Iranian Journal of Management Studies (IJMS) 2023, 16(1): 125-138
RESEARCH PAPER

Adaptive Market Hypothesis: Evidence From the Cryptocurrency Market

Yunus Karaömer[1*], Songül Kakilli Acaravci[2]

1. Assistant Professor, Department of Business Administration, Faculty of Economics and Administrative Sciences, Hatay Mustafa Kemal University, Hatay, Turkey
2. Professor, Department of Business Administration, Faculty of Economics and Administrative Sciences, Hatay Mustafa Kemal University, Hatay, Turkey

(Received: January 4, 2022; Revised: April 5, 2022; Accepted: April 11, 2022)

Abstract
This study aimed to evaluate whether the efficiency of the cryptocurrency market varies over time according to the Adaptive Market Hypothesis. It investigated the varying cryptocurrency market efficiency by applying daily historical data to Bitcoin, Ethereum, Litecoin, Ripple, and Cardano. The conformity of cryptocurrencies to the normal distribution was examined by the Jarque-Bera test and their stationarity was tested by unit root tests. The cryptocurrency daily return predictability was measured using the Automatic Portmanteau and Wild Bootstrap Automatic Variance Ratio tests. Besides, the daily returns of cryptocurrencies were analyzed using the 500-days rolling window approach to capture the time-varying nature of the cryptocurrency market efficiency. Findings are consistent with the Adaptive Market Hypothesis and indicate that the cryptocurrency market efficiency varies over time. Besides, the cryptocurrency market efficiency varies and generally corresponds to positive or negative news/events.

Keywords: adaptive market hypothesis, cryptocurrency, efficient market hypothesis.

1. Introduction

The development and use of information technology has initiated a cultural change all over the world. The Internet, introduced by information technology, has become an indispensable part of our lives. With the spread of Internet-based electronic markets, there has been a change in the financial system. Thanks to Internet-based electronic markets, users can transact more quickly with low transaction costs on an online platform. Bitcoin, which entered the financial market with an article titled “Bitcoin: Peer-to-Peer Electronic Cash Payment System” published by Satoshi Nakamoto in 2008, has attracted the attention of many people (Zhang et al., 2021).

Bitcoin was created as a decentralized digital currency in January 2009. After Bitcoin, a large number of cryptocurrencies have emerged. These cryptocurrencies basically use blockchain technology and reward mechanism, but typically live on isolated transaction networks. Many of them are basically clones of Bitcoin, although with different parameters such as transaction validation times, different supplies, etc. (ElBahrawy et al., 2017). Data from Coinmarketcap (2021b) indicate that as of September 07, 2021, the combined market capitalization of cryptocurrencies was $2.37 trillion, with Bitcoin worth $991 billion (41.8 % of the overall market cap), followed by Ethereum worth $461 billion, Litecoin worth $11 billion, and Ripple worth $64 billion.

* **Corresponding Author, Email:** yunuskaraomer@mku.edu.tr

Market efficiency is one of the important concepts widely researched in neoclassical finance. The Efficient Market Hypothesis (EMH) is based on the original contributions from Bachelier (1900), Cowles (1933), Kendall (1953), Samuelson (1965), and Fama (1965). These authors asserted that in an information efficient market, price changes cannot be predicted if the prices of securities reflect all the expectations of the investors and all the available information in the market. More specifically, Fama (1970) defined the efficiency of a market such that stock or security prices always fully reflect all the information available in the market. According to the hypothesis, there is a correlation between stock or security prices and information, because stock or security prices are always formed according to the new information announced. Fama (1970) examined the efficiency of the markets with three test forms: weak-form efficiency, semi-strong market efficiency, and strong-form efficiency. In weak-form efficiency, prices include all the historical information. In the semi-strong form efficiency, prices include all historical information and publicly disclosed information. In strong-form efficiency, prices include historical price information and publicly disclosed information as well as private insider information from certain privileged persons. Therefore, it is not possible for the actors in the market to earn abnormal returns by using the available information. Past researchers have emphasized the importance of analyzing market efficiency for the cryptocurrency market. Therefore, it is essential to understand the time-varying market efficiency in order to analyze variations in cryptocurrency prices over time (Khursheed et al., 2020).

There is a large literature on Fama's (1970) weak form of the EMH for cryptocurrency markets, particularly the Bitcoin market. For instance, Jakub (2015), Urquhart (2016), Nadarajah and Chu (2017), Bariviera (2017), Tiwari et al. (2018), Aggarwal (2019), and Lade and Yi (2020) have concluded that the Bitcoin market inferred strong evidence regarding the weak-form of efficiency, while Cheah et al. (2018) and Vidal-Tomás and Ibáñez (2018) have claimed against it. For the other cryptocurrencies, Caporale et al. (2018) and Kang et al. (2021) have concluded that the cryptocurrency market is consistent with the weak-form of efficiency. In contrast, Alam (2017) and Vidal-Tomás et al. (2019) have come to the conclusion that the cryptocurrency market is inconsistent with the weak-form of efficiency. The EMH has been studied by researchers in many research projects in the literature. However, there is no consensus among researchers on whether the markets are efficient or not.

The EMH has been an important research topic for most researchers since the beginning of financial markets. Recently, market efficiency and investor rationality have been the main subject of discussion among the thinkers of efficient market and behavioral finance in the interpretation of many empirical findings (Tseng, 2006). The EMH explains the concept of "effective economic world" with homo economicus, which is one of the basic concepts of classical economic theory. The main features of homo economicus are as follows: economic man is rational, preferences are fixed, he always has full knowledge, and he tries to optimize wealth or income (Lofthouse & Vint, 1978). However, there is mounting experimental and empirical evidence (including the recent financial crisis) to suggest that human do not always act rationally but often make seemingly random and suboptimal decisions (Brennan & Lo, 2012). Although behavioral finance states that it is not possible for investors to be completely rational and therefore it is not possible to force financial markets to be efficient all the time, it has not been able to put forward a new theory against the EMH (Verheyden et al., 2013). Lo (2017) stated that individuals are not always rational, homo sapiens (human) and homo economicus are not the same, and markets are not always efficient.

Lo (2004) introduces the Adaptive Market Hypothesis (AMH), which evaluates market efficiency from an evolutionary perspective. In order to better explain the real market and investor behaviors, the AMH reconciles the EMH and behavioral finance by adapting some evolutionary principles such as competition, mutation, reproduction, adaptation, survival of living things, and natural selection to financial markets. The EMH evaluates the efficiency of the market as either 100% efficient or 100% inefficient. Contrary to the EMH, the AMH argues that markets are adaptive, evolve over time, and therefore switch between efficiency and inefficiency at different points in time. In other words, it argues that financial markets have a dynamic structure.

The AMH is qualitative and inherently intangible; therefore, no formal definition of AMH is available in the literature. However, concrete practical implications have been obtained for testing AMH (Patil & Rastogi, 2019). There are several implications of the AMH as pointed out by Lo (2004). The first implication is the risk-reward relationship. The risk-reward relationship changes over time due to the preferences and demographic characteristics of the participants in the market (Hiremath & Kumari, 2014). Second, unlike EMH, arbitrage opportunity appears from time to time in the markets for AMH. The AMH suggests more complex market dynamics, with cycles, panics, trends, bubbles, breaks, bankruptcies, and other events that can routinely be seen in real markets and require active management, rather than the idea that markets would become more and more efficient, which EMH suggests (Lo, 2005). APH argues that arbitrage opportunities arise from time to time due to changing market conditions (Boya, 2019). Third implication is an investment strategy. Depending on the conditions of the market, the success of investment strategies may increase from time to time and decrease from time to time. Unlike EMH, AMH states that an investment strategy that performs well in one market may perform poorly in other markets. Thus, investment strategies need to be adapted to suit changing market conditions (Lo, 2012). Fourth, innovation is the most important factor to survive in the markets. The final implication is that survival is the only goal. According to AMH, the primary goal of all market participants is to maintain their presence in the markets (Lo, 2005).

This study provided several contributions to the literature. First, this study aimed to evaluate whether the degree of cryptocurrency market efficiency varies over time according to the AMH. Second, this study evaluated the general effect of the sentiment of news and other factors (events) on market efficiency. Third, the AMH has become one of the most important and remarkable issues for academic circles in the financial world in recent years. In contrast with empirical studies (see Table 1), this study applied the foregoing model not only to Bitcoin but also to Ethereum, Litecoin, Ripple, and Cardano. Finally, this study is expected to make a significant contribution to researchers, analysts, portfolio managers, and market participants.

The rest of this study is organized as follows: Section 2 presents a review of the relevant literature. Section 3 explains the methodology. Section 4 describes the data and computational details. Empirical results are discussed in section 5. Finally, section 6 is the conclusion.

2. Literature Review

A limited number of studies have analyzed the time-varying return predictability. Yet, they have found strong support for the AMH using various methods in different country markets in the literature. The empirical studies in the context of the AMH are summarized in Table 1.

The AMH has become one of the most important and remarkable issues for academic circles in the financial world in recent years. When the studies on the AMH were examined, it was determined that the studies on the time-varying market efficiency of the AMH are mostly focused on financial markets such as stocks, foreign exchange, commodities, and real estate investment trusts, and there are very few studies on the crypto money market. Moreover, there are even fewer market activity studies, especially on Ripple, Litecoin and ADA cryptocurrencies.

Table 1. Empirical Studies

Study	Period	Sample	Methodologies	Results
Panel A		**Cryptocurreny market**		
Khuntia & Pattanayak (2018)	2010-2017	Bitcoin	Dominguez–Lobato (DL) test	The AMH is valid.
Jabeen et al. (2018)	2010-2016	Bitcoin	Run test and BDS test	The AMH is not valid.
Chu et al. (2019)	2017-2018	Bitcoin, Ethereum	DL test	The AMH is valid.
Noda (2019)	2010-2015	Bitcoin, Ripple, Ethereum	Time-Varying AR (TV-AR) model	The AMH is valid.
Khursheed et al. (2020)	2014-2018	Bitcoin, Monaro, Litecoin, Steller	DL test, Generalized spectral (GS) test, Automatic Portmanteau (AP) test	The AMH is valid.
Ghazani & Jafari (2021)	2015-2019	Bitcoin, Ethereum, Ripple	GS test, AP test	The AMH is valid.
Panel B		**Other markets**		
Todea et al. (2009)	1997-2008	Stock markets (Australia, China, India, Malaysia, Singapore and Japan)	Run test and BDS test	The AMH is valid.
Charles et al. (2012)	1974-2009	Exchange rates	DL test, WBAVR test,GS test	The AMH is valid.
Popović et al. (2013)	2004-2011	Stock market (Montenegro)	Rolling-window	The AMH is valid.
Zhou & Lee (2013)	1980-2009	ABD real estate investment trusts.	Automatic Variance ratio (AVR) test and AP test	The AMH is valid.
Urquhart & McGroarty (2014)	1900-2013	Dow Jones Industrial Index	Rolling-window	The AMH is valid.
Noda (2016)	1991-2015	Stock market (Japan)	TV-AR model	The AMH is valid.
Gyamfi (2018)	2011-2015	Stock market (Ghana)	Rolling-window	The AMH is valid.
Ertas & Ozkan (2018)	1988-2018	Borsa Istanbul 100 index; Standard and Poor’s 500 index	Variance ratio test	The AMH is valid.
Boya (2019)	1988-2018	Stock market (France)	Variance ratio test	The AMH is valid
Patil & Rastogi (2020)	1995-2019	Stock market (India)	Multifractal Detrended Fluctuation Analysis (MFDFA) and Multifractal Detrended Cross-Correlation Analysis (MFDCCA	The AMH is valid
Okoroafor & Leirvik (2021)	1987-2020	Brent and WTI crude market	Adjusted Market Inefficiency Magnitude, TV-AR model	The AMH is valid
de Souza et al. (2021)	2000-2018	Sector-specific indicators and institutional factors	Regression model	The AMH is valid
Asif & Frömmel (2022)	2000-2019	Exchange rates	Hurst exponent	The AMH is valid

3. Methodology

In this study, Bitcoin, Ethereum, Litecoin, Ripple, and Cardano were used to evaluate whether the degree of the cryptocurrency market efficiency varies over time according to the AMH. The conformity of cryptocurrencies to normal distribution was examined by the Jarque-Bera test and their stationarity was inspected by unit root tests. The predictability of cryptocurrency returns was measured using the AP and WBAVR tests. To reveal the behavior of cryptocurrency returns over time, the 500-day rolling window method was used.

3.1. Variance Ratio Tests

Ljung and Box's (1978) Portmanteau and Lo and MacKinlay's (1988) Variance Ratio tests are widely used in empirical finance studies to test the weak-form efficiency of financial markets and to evaluate the predictability of financial asset returns. However, these tests are known to be inadequate, especially in small samples with conditional heteroscedasticity, which is often observed in financial data. In addition, the fact that the lag length requires temporal choices in determining the durations worsens the small sample characteristics. To overcome the problem of temporary selection of the lag length, Escanciano and Lobato (2009) used the AP test, in which the selection of the lag length is automatically based on the available data, and Kim (2009) the WBAVR test, in which the optimal retention time is automatically selected (Charles et al., 2017).

3.1.1. Automatic Portmanteau Test

The portmanteau test developed by Box and Pierce (1970) is designed to test if the initial p autocorrelations of a series (possible residuals) are zero. It is thought that the number of p is constant or grows with the sample size n (Escanciano & Lobato, 2009).

If $\{Y_t\}_{t=1}^{n}$ represents financial time series return rates, $\bar{Y}$ shows the sample mean, and $\gamma_j = \frac{1}{n-j}\sum_{t=1+j}^{n}(Y_t - \bar{Y})(Y_{t-j} - \bar{Y});\ j = 0,\ldots,n-1$ is determined as the sample autocovariance (Q_p), the test statistic can be written as follows:

$$Q_p = n\sum_{j=1}^{p}\hat{\rho}_j^2, \tag{1}$$

Here, $\hat{\rho}_j = \hat{\gamma}_j/\hat{\gamma}_0$ denotes the j^th order sample autocorrelation.

However, this test has been generally ignored in the literature, and it has been suggested that the approach proposed as the reason only depends on the condition that the returns are independently and identically distributed (Charles et al., 2012). Thus, Lobato (2001) modified this test statistic because financial returns generally exhibit conditional heteroscedasticity variance:

$$Q_k^* = n\sum_{j=1}^{k}\hat{\rho}_j^2 \tag{2}$$

where $\tilde{\rho}_j^2 = \hat{\gamma}_j^2 / \hat{\tau}_j^2$ and $\hat{\tau}_j^2 = \frac{1}{n-j}\sum_{t=1+j}^{n}(Y_t - Y)^2(Y_{t-j} - \hat{Y})^2$ are the sample autocovariance of Y_t. $\tilde{k}$ is the optimal delay order selected according to the combination of Akaike Information Criteria (AIC) and Bayesian Information criterion (BIC). In other words, $\tilde{p}$ = min {m: 1≤ m ≤ p_n; $L_m \geq L_h$, h=1,2,…, p_n}, where L_p = Q_p^* - π(p,n,q), and p_n is an upper bound that grows slowly to infinity with n.

$$\pi(p,n,c) = \begin{cases} plogn, & if \quad max_{1\le j\le p_n} \left|\frac{\tilde{p}_j^2}{\tau_j}\right| \le \sqrt{qlogn} \\ 2p, & if \quad max_{1\le j\le p_n} \left|\frac{\tilde{p}_j^2}{\tau_j}\right| > \sqrt{qlogn}, \end{cases} \tag{3}$$

where q is a constant positive number. Escanciano and Lobato (2009) suggest q = 2.4 after a simulation study showing that this value provides the best combination of the two information criteria. Small values of q result in the choice of Akaike's criterion, while large q's lead to the choice of Schwarz's criterion.

The AP test is defined as follows:

$$AQ_p^* = n\sum_{j=1}^{\tilde{p}} \tilde{\rho}_j^2 \tag{4}$$

The AP statistic follows the Chi-square distribution with one degree of freedom under the null hypothesis that the rate of return cannot be predicted asymptotically.

3.1.2. Wild Bootstrap Automatic Variance Ratio Test

The variance ratio test developed by Lo and MacKinlay (1988) is often used in the random walk hypothesis (RWH) literature. The statistical feature of the variance ratio test suggests a random walk in asset prices when the variance of k-period returns equals the variance of a period's return. Therefore, the variance ratio VR(k), defined as the ratio of 1/k times the variance of the k-period return to the one-period return, must be equal to one for all k. To apply the test (holding periods), a choice must be made between the k-values, e.g., a popular choice for daily returns (2, 5, 10, 20, 40) and for weekly returns (2, 4, 8, 16, 32) (Kim, 2009). For instance, a return series with the variance ratio r_t (2) for two-period returns is said to follow RWH when VR (2) = 1. VR can be calculated for any number of periods. Here, considering r_t as the return of a financial asset in time period t, VR for holding period q is defined as (Khuntia et al., 2018).

$$VR(q) = \frac{\sigma^2[r_t(q)]}{\sigma^2 q[r_t]} = 1 + 2\sum_{k=1}^{q-1}\left(1 - \frac{k}{q}\right)\rho^k \tag{5}$$

Here $\rho^k$is the kth order autocorrelation coefficient of the returns [r_t]. Equation (5) states that the data generation process is random when VR is equal to one at a selected q. The main limitation of the VR test is to choose the retention time q arbitrarily and without any statistical justification. Statistical implications of VR test statistics based on asymptotic theory can be misleading for small samples. To overcome this situation, Choi (1999) proposed the automatic ratio of variance (AVR) test. The most important statistical feature of the AVR test is that it allows the automatic and optimal selection of a holding period q based on data-dependent operations. The null hypothesis of AVR test is that the returns of a series are not serially correlated. the AVR test statistics are expressed as:

$$AVR(\hat{k}) = \sqrt{\frac{T}{k}} \frac{[VR(\hat{K}) - 1]}{\sqrt{2}} \xrightarrow{d} N(0,1) \tag{6}$$

where $(\hat{k})$ is the optimal holding time and T is the sample observations. Kim's (2009) Monte Carlo simulations show how the AVR test causes size distortion when the sample size is small and the return series show conditional heteroscedasticity variance. To solve this problem, Kim (2009) proposed the Wild Bootstrap version of the AVR test and a three-step procedure to estimate the AVR statistic (Gyamfi, 2018):

(1) a bootstrap sample of n observations is formed from the returns data,

(2) calculate the AVR statistic, $AVR(\hat{k})$ for the bootstrap sample,

(3) repeat steps 1 and 2 N times to form a bootstrap distribution of AVR statistics.

4. Data

In order to evaluate the efficiency of the cryptocurrency market, the daily closing values of Bitcoin, Ethereum, Litecoin, Ripple, and Cardano in US dollars, which are the cryptocurrencies with the highest market value and transaction volume, were used. The data were obtained from the data of the Binance cryptocurrency exchange from the CryptoDataDownload website daily until 25.02.2021. Start dates varied depending on the availability of data for the cryptocurrencies studied. As each cryptocurrency started on a different start date, the number of observations differed between cryptocurrencies, as shown in Table 2. $R_t = \ln(P_t) - \ln(P_{t-1})$, daily return data were obtained by taking the natural logarithmic first differences of the daily closing prices of cryptocurrencies.

Figure 1 indicates the plots of cryptocurrency daily returns. The plots indicate the feature of volatility clustering.

Table 2. Variable Definations

Cryptocurrency	Abbreviation	Start date	Observation number
Bitcoin	BTC	18/08/2017	1,289
Ethereum	ETH	18/08/2017	1,289
Litecoin	LTC	15/12/2017	1,170
Ripple	XRP	05/05/2018	1,028
Cardano	ADA	18/04/2018	1,045

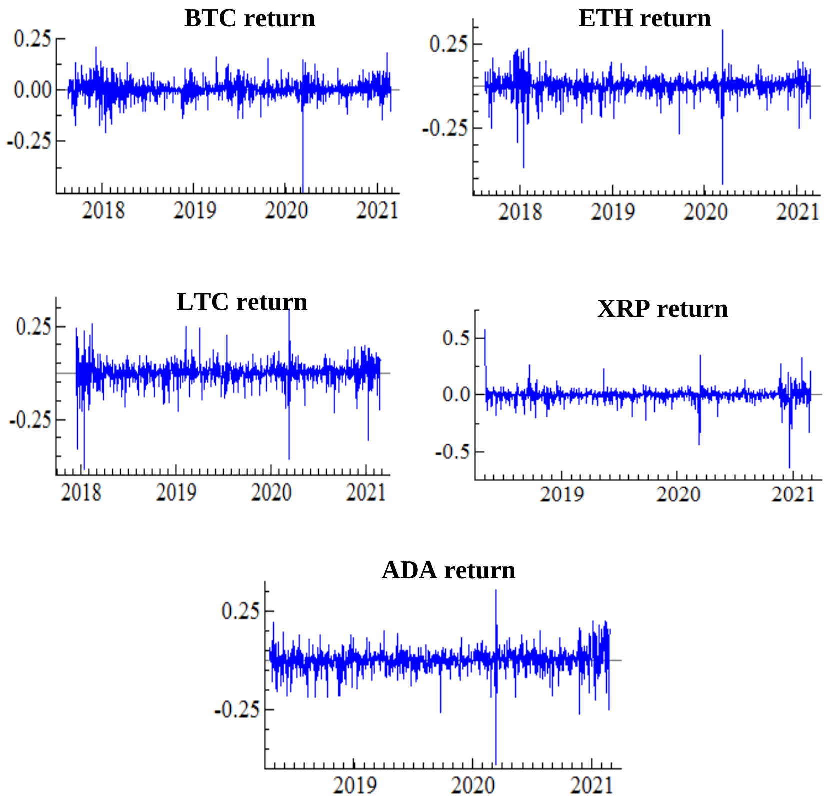

Figure 1. Cryptocurrencies' Return Plots

Table 3 reports the descriptive statistics for cryptocurrency returns. The results indicate that the highest return belongs to the BTC and the lowest return belongs to the LTC and XRP variables while the highest standard deviation belongs to the XRP and the lowest standard deviation belongs to the BTC variable. The variables' high kurtosis values show the fat tails or outliers. The non-normality is also verified by the rejection of Jarque-Bera (JB) test statistics' null hypothesis at the 1% level of significance. The heteroscedasticity is verified by the rejection of ARCH-LM test statistics' null hypothesis of no conditional heteroscedasticity at the 1% level of significance. The Augmented Dickey-Fuller (ADF) (1979) and KPSS (Kwiatkowski et al., 1992) tests indicate that all variables are stationary at the level.

Table 3. Descriptive Statistics of Cryptocurrency Returns

	BTC	ETH	LTC	XRP	ADA
Mean	0.002	0.001	-0.000	-0.000	0.001
Std. Dev.	0.046	0.057	0.059	0.060	0.059
Skewness	-1.557	-1.713	-1.380	-0.768	-0.916
Kurtosis	18.450	18.643	15.966	30.698	12.501
Jarque-Bera	23.610*	13.774*	8.568*	32.962*	4.076*
ARCH-LM	9.794769*	9.594*	9.389*	32.473*	15.335*
ADF test	-36.081*	-27.375*	-26.614*	-25.842*	-23.747*
KPSS test	0.150*	0.342*	0.429*	0.099*	0.095*

Note: * denotes statistical significance at 1% level. ARCH-LM denotes the Lagrange Multiplier test for Autoregressive Conditional Heteroskedasticity with 10 lags.

5. Empirical Results

In order to analyze the behaviors of cryptocurrency returns, we used the 500-day rolling window method. The rolling window is important in terms of capturing variations in cryptocurrency return predictability over time. Figure 2 indicates the probability (p) values (horizontal lines) for the AP and WBAVR tests on the rolling window of returns for cryptocurrency. The red and blue horizontal lines indicate the 5% and 10% levels of significance, respectively. A p-value below the horizontal line shows the rejection of the null hypothesis of returns unpredictability at the 5% and 10% significance levels, which are statistical evidence of significant returns predictability (i.e., market inefficiency).

Figure 2 indicates that the null hypothesis of returns unpredictability is rejected for all cryptocurrencies during some periods. Khuntia and Pattanayak (2018) and Chu et al. (2019) state that some important positive news or events in the cryptocurrency market increase the market efficiency, while some important negative news or events decrease the market efficiency. Here are some of the important news and events that may be attributed to the returns of cryptocurrency in predictable and unpredictable periods.

The BTC rose from $1,000 at beginning of 2017 to around $6,000 in October 2017, and the BTC pushed the $19,783 mark at the end of 2017 (Coinmarketcap, 2021a). From the third quarter of 2017 to the first quarter of 2018, the p-values of BTC and ETH returns above the horizontal line show the acceptance of the null hypothesis. In addition, p-values of LTC returns above the horizontal line show the acceptance of the null hypothesis from the third quarter of 2017 to December 2017. The increase in the interest of people, investors, and companies in cryptocurrencies and the greater coverage of cryptocurrencies in the media may have caused the prices of cryptocurrency to increase. Goczek and Skliarov (2019), Zhang et al. (2018), and Kjærland et al. (2018) stated that popularity has a positive effect on cryptocurrency prices. Sensoy (2019) found that the Bitcoin market is efficient from January 2016 to March 2018.

In January 2018, the p-values of LTC, XRP, and ADA returns below the horizontal line show the rejection of the null hypothesis. The cryptocurrencies may have been negatively impacted by the news that the South Korean government was planning to ban cryptocurrency trading and the Chinese government's negative sentiment towards cryptocurrencies (Kharpal, 2018). In addition, the p-values of BTC and ETH returns above the horizontal line show the acceptance of null hypothesis. This may indicate that both the BTC and ETH may be more sensitive to local markets, such as the American and European markets, as well as local factors and events compared to others (Chu et al., 2019).

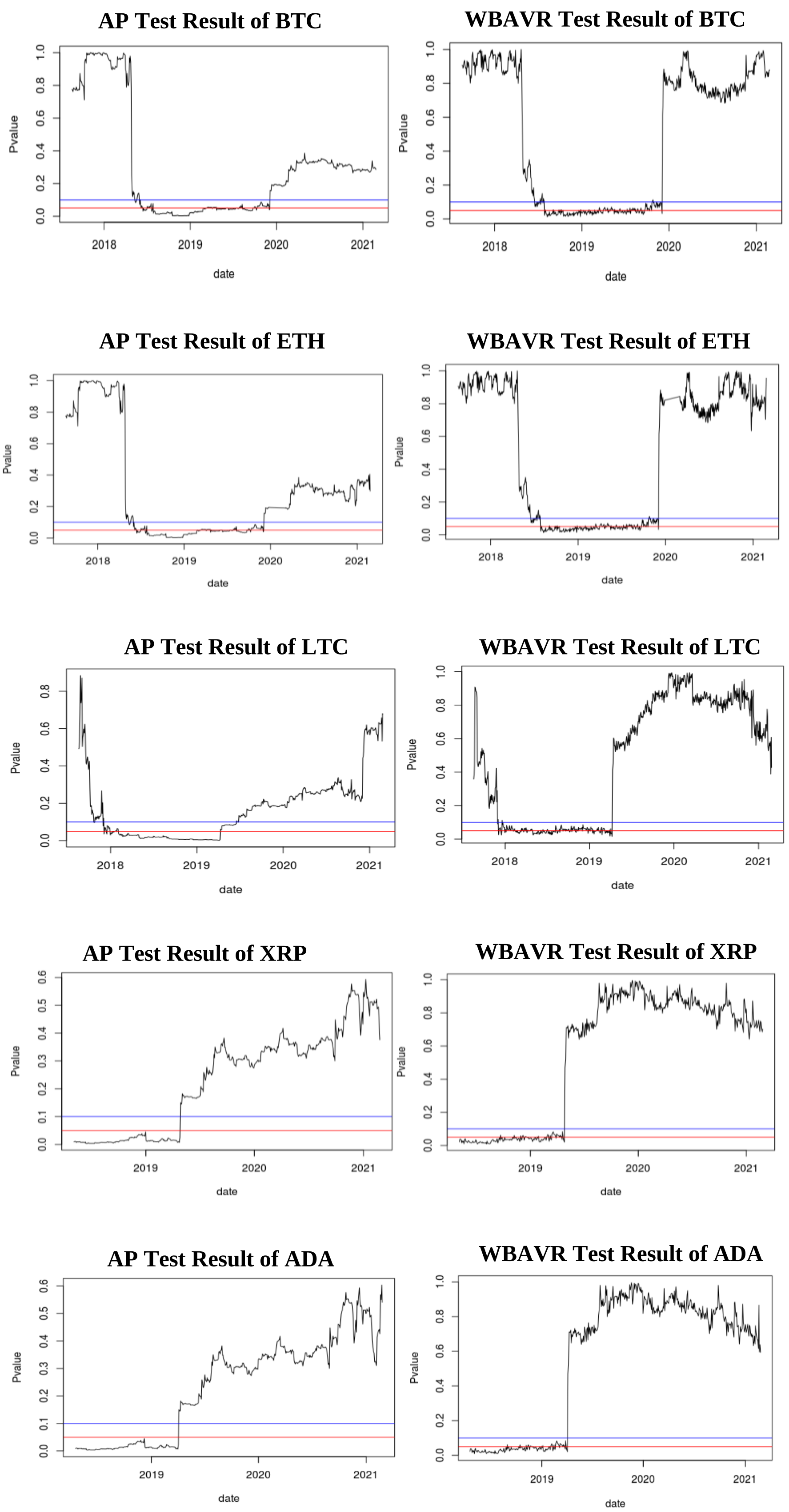

Figure 2. Cryptocurrencies' AP and WBAVR Test Results

In Figure 2, an extended period of inefficiency for cryptocurrencies is seen from May 2018 to December 2018. In 2014, Mt. Gox, a Tokyo-based cryptocurrency exchange, went bankrupt. But, at the end of April 2018, 16,000 BTC (approximately $140 million) was moved from the vaults of Mt Gox to an unknown address. Thus, the possible crash in the value of BTC may have created fear and panic among investors (Independent, 2018). In July 2018, the announcement of an advertising ban for cryptocurrencies and initial coin offerings on Google search platforms may have also taken this inefficiency period even further (Sean, 2018). The US Securities and Exchange Commission's (SEC) approval of exchange-traded funds (ETFs) for cryptocurrencies, which started in August 2018, was delayed once again in December 2018, which had a negative impact on the market. As investors are especially focused on decisions from the SEC, negative news may have affected cryptocurrencies negatively (Finadium, 2018).

In 2019, 12 major cyber attacks were carried out on cryptocurrency exchanges. These attacks included Binance, the world's largest cryptocurrency exchange with transaction volume. On May 7, 2019, The 7,000 BTC, equivalent to $40 million at the time, was stolen from the Binance cryptocurrency exchange. Similarly, on November 27, 2019 the Upbit cryptocurrency exchange was hacked for nearly $49,116,778 in ETH (Thompson, 2020). Both of these events may have increased investor uncertainty, leading to a sell-off in cryptocurrencies and significant predictability in their prices. Thus, these events appear to have contributed to an increase in the inefficiency in the market of cryptocurrency. The Coronavirus (Covid-19) pandemic, which started in Wuhan, China in December 2019 and grew in mid-January 2020, was announced a global outbreak (a pandemic) by the World Health Organization (WHO) on March 11, 2020. The p-values of cryptocurrency returns above the horizontal line show the acceptance of the null hypothesis. Mnif et al. (2020) stated that the Covid-19 had a positive impact on cryptocurrency market efficiency. Wang and Wang (2021) stated that the Bitcoin market was active during the Covid-19 process and could be considered as a safe haven asset in risk management. In addition, Demir et al. (2020) found that the BTC, ETH, and XRP initially had a negative impact on the number of reported cases and deaths, but had a positive impact in the later period, and they stated that cryptocurrencies showed the role of hedging against the uncertainty caused by the Covid-19.

Jakub (2015), Urquhart (2016), Nadarajah and Chu (2017), Bariviera (2017), Tiwari et al. (2018), Aggarwal (2019), and Lade and Yi (2020) have concluded that the Bitcoin market inferred strong evidence regarding the weak-form of efficiency. Besides, for the other cryptocurrencies, Caporale et al. (2018) and Kang et al. (2021) have concluded that the cryptocurrency market is consistent with a weak form of efficiency. This study found that the cryptocurrency market reacts differently to varying market conditions over time. In other words, this study supports the AMH, which assumes that market efficiency is time-varying in contrast with EMH.

6. Conclusion

Studies in the literature on weak-form market efficiency are divided into classical (EMH) and adaptive (AMH). Classical studies focus on the proposition that markets move towards efficiency over time, while adaptive studies focus on the varying or dynamic nature of markets over time (Patil & Rastogi, 2019).

In this study, the BTC, ETH, LTC, XRP, and ADA were used to evaluate whether the efficiency of the cryptocurrency market varies cyclically over time according to the AMH. The conformity of cryptocurrencies to normal distribution was examined by the Jarque-Bera test and their stationarity was investigated by unit root tests. The predictability of cryptocurrency returns was measured using the AP and WBAVR. To reveal the behavior of cryptocurrency returns over time, the study used the 500-day rolling window method. The empirical analysis confirmed that cryptocurrency market is dependent on market conditions and, unlike the EMH, market efficiency varies over time. In other words, the AMH is valid in the cryptocurrency market. This result is consistent with Noda (2019), Khursheed et al. (2020), and Ghazani and Jafari (2021), but in contrast with Jabeen et al. (2018). Besides, it was found that the cryptocurrency market varies between efficiency and inefficiency at different times, and variations in these activities generally correspond to negative or positive news/events. The reasoning for variations in the efficiency of cryptocurrency market falls in line with those suggested in Khuntia and Pattanayak (2018) and Chu et al. (2019), who also found that variation in the efficiency of the cryptocurrency market corresponded to negative or positive news/events – e.g., negative news reduced the efficiency of cryptocurrency market whilst positive news appeared to increase the efficiency of cryptocurrency market. The impact of the variation in market conditions was found to be greater on BTC and ETH compared to LTC, XRP, and ADA. In this case, LTC, XRP, and ADA can be preferred by portfolio managers and market participants in various ways as the optimum investment option. According to the results of the analysis, even if it is determined that the AMH is valid for each cryptocurrency, it should be evaluated separately as each cryptocurrency interacts differently according to market conditions. Therefore, market investors need to evaluate each cryptocurrency independently and adapt their investment strategies to changing market conditions. In addition, investors who trade in the cryptocurrency market and seek profit can make predictions about the prices of the future period by using the prices of the past periods of cryptocurrencies with many analysis methods, especially technical and fundamental analysis. They can earn abnormal return from the market, although not always.

This study indicated that the cryptocurrency market has a more suitable characterization for the dynamic market hypothesis rather than the static efficient market hypothesis. However, this study clearly revealed the impact of the type of news and events on the cryptocurrency market efficiency. Moreover, the AMH has become one of the most important and remarkable issues for academic circles in the financial world in recent years. When the studies on the AMH were examined, it was determined that the AMH is mostly used in financial markets such as stocks, foreign exchange, commodities, and real estate investment trusts, and there are very few studies on the cryptocurrency market. Due to the limited number of studies on the cryptocurrency market, it is thought that this study can fill a gap in the finance literature.

In future studies, researchers may consider high-frequency data rather than daily data as there may be short-term variations in cryptocurrency market efficiency that are masked. They can also investigate the validity of the AMH using other cryptocurrencies traded in the cryptocurrency market and use different econometric methods to test the validity of the AMH. Besides, the empirical results presented in this study open an avenue for further research on cryptocurrency market efficiency.

References

Aggarwal, D. (2019). Do bitcoins follow a random walk model? *Research in Economics*, *73*(1), 15-22.

Alam, S. (2017). Testing the weak form of an efficient market in cryptocurrency. *Journal of Engineering and Applied Sciences*, *12*(9), 2285-2288.

Asif, R., & Frömmel, M. (2022). Testing Long memory in the exchange rates and its Implications for the adaptive market hypothesis. *Physica A: Statistical Mechanics and its Applications*, *593*(2022), 1-17.

Bachelier, L. (1900). *The random character of stock market prices*. MIT Press.

Bariviera, A. F. (2017). The inefficiency of bitcoin revisited: A dynamic approach. *Economics Letters, 161*(2017), 1-4.

Box, G. E., & Pierce, D. A. (1970). Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. *Journal of the American Statistical Association*, *65*(1970), 1509-1526.

Boya, C. M. (2019). From efficient markets to adaptive markets: Evidence from the French stock exchange. *Research in International Business and Finance*, *49*(2019), 156-165.

Brennan, T. J., & Lo, A. W. (2012). An evolutionary model of bounded rationality and intelligence. *PLOS ONE*, *7*(11), 1-8.

Caporale, G. M., Gil-Alana, L., & Plastun, A. (2018). Persistence in the cryptocurrency market. *Research in International Business and Finance*, *46*(2018), 141-148.

Charles, A., Darné, O., & Kim, J. H. (2012). Exchange-rate return predictability and the adaptive markets hypothesis: Evidence from major foreign exchange rates. *Journal of International Money and Finance, 31*(6), 1607-1626.

Charles, A., Darné, O., & Kim, J. H. (2017). Adaptive markets hypothesis for islamic stock indices: Evidence from Dow Jones size and sector-indices. *International economics*, *151*(2017), 100-112.

Cheah, E. T., Mishra, T., Parhi, M., & Zhang, Z. (2018). Long memory interdependency and inefficiency in Bitcoin markets. *Economics Letters*, *167*(2018), 18-25.

Choi, I. (1999). Testing the random walk hypothesis for real exchange rates. *Journal of Applied Econometrics*, *14*(3), 293-308.

Chu, J., Zhang, Y., & Chan, S. (2019). The adaptive market hypothesis in the high frequency cryptocurrency market. *International Review of Financial Analysis*, *64*(2019), 221-231.

Coinmarketcap (2021a). *Bitcoin*. https://www.coinmarketcap.com

Coinmarketcap (2021b). *Today's cryptocurrency prices by market cap*. https://www.coinmarketcap.com

Cowles, A. (1933). Can stock market forecasters forecast? *Econometrica, 1*(3), 309-324.

de Souza, P. V. S., Silva, C. A. T., & Lima, F. G. (2021). Evidence of the adaptive market hypothesis in shares traded by B3 listed banking companies. *Managerial Finance*, *48*(1), 113-125.

Demir, E., Bilgin, M. H., Karabulut, G., & Doker, A. C. (2020). The relationship between cryptocurrencies and COVID-19 pandemic. *Eurasian Economic Review*, *10*(3), 349-360.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427-431.

ElBahrawy, A., Alessandretti, L., Kandler, A., Pastor-Satorras, R., & Baronchelli, A. (2017). Evolutionary dynamics of the cryptocurrency market. *Royal Society Open Science*, *4*(11), 1-16.

Ertas, F. C., & Ozkan, O. (2018). Piyasa etkinliği açısından adaptif piyasa hipotezi'nin test edilmesi: Türkiye ve ABD hisse senedi piyasaları örneği [Testing theadaptive market hypothesis in terms of market efficiency: the case of Turkey and the US stock markets.] *Finans Politik & Ekonomik Yorumlar*, *642*(2018), 23-40.

Escanciano, J. C., & Lobato, I. N. (2009). *Testing the martingale hypothesis*. Palgrave Macmillan.

Fama, E. F. (1965). Random walks in stock market prices. *Financial Analysts Journal*, *51*(1), 75-80.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, *25*(2), 383-417.

Finadium (2018). *Crypto in 2018 infographic- What happened?* https://www.finadium.com/crypto-in-2018-infographic-what-happened

Ghazani, M. M., & Jafari, M. A. (2021). Cryptocurrencies, gold, and WTI crude oil market efficiency: A dynamic analysis based on the adaptive market hypothesis. *Financial Innovation*, *7*(1), 1-26.

Goczek, Ł., & Skliarov, I. (2019). What drives the bitcoin price? A factor augmented error correction mechanism investigation. *Applied Economics*, *51*(59), 6393-6410.

Gyamfi, E. N. (2018). Adaptive market hypothesis: Evdience from ghanaian stock market. *Journal of African Business*, *19*(2), 195-209.

Hiremath, G., S., & Kumarı, J. (2014). Stock returns predictability and the adaptive market hypothesis in emerging markets: Evidence from india. *SpringerPlus*, *3*(1), 1-14.

Independent (2018). *Cryptocurrency price crash predicted as bankrupt bitcoin exchange Mt Gox moves $144m worth of coins*. https://www. independent.co.uk/life-style/gadgets-and-tech/news/bitcoin-cryptocurrency-pricecrash predicted-mt-gox-exchange-latest-a8324026.html

Jabeen, S., Sattar, A., & Ateeq, A. (2018). Behavior of bitcoin returns and adaptive market hypothesis (AMH). *Asia Pacific Journal of Emerging Markets*, *2*(2), 113.

Jakub, B. (2015). Does Bitcoin follow the hypothesis of efficient market. *International Journal of Economic Sciences*, *4*(2), 10-23.

Kang, H. J., Lee, S. G., & Park, S. Y. (2021). Information efficiency in the cryptocurrency market: The efficient-market hypothesis. *Journal of Computer Information Systems*, 1-10.

Kendall, M. G. (1953). The analysis of economic time-series-part 1: Prices. *Journal of the Royal Statistical Society*, *116*(1), 11-34.

Kharpal, A. (2018). *Over $100 billion wiped off global cryptocurrency market following talk of South Korea trading ban*. https://www.cnbc.com/2018/01/11/south-korea-cryptocurrency-justice-ministry-softened-stance.html

Khuntia, S., & Pattanayak, J. K (2018). Adaptive market hypothesis and evolving predictability of bitcoin. *Economics Letters*, *167*(2018), 26-28.

Khuntia, S., Pattanayak, J. K., & Hiremath, G. S. (2018). Is the foreign exchange market efficiency adaptive? the empirical evidence from india. *Journal of Asia-Pacific Business*, *19*(4), 261-285.

Khursheed, A., Naeem, M., Ahmed, S., & Mustafa, F. (2020). Adaptive market hypothesis: An empirical analysis of time–varying market efficiency of cryptocurrencies. *Cogent Economics & Finance*, *8*(1), 1-15.

Kim, J. H. (2009). Automatic variance ratio test under conditional heteroskedasticity. *Finance Research Letters*, *6*(3), 179-185.

Kjærland, F., Meland, M., Oust, A., & Øyen, V. (2018). How can bitcoin price fluctuations be explained? *International Journal of Economics and Financial Issues*, *8*(3), 323-332.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of econometrics*, *54*(1-3), 159-178.

Lade, S., & Yi, J. (2020). Does the South Korea bitcoin market is efficient? *International Journal of Management*, *11*(9), 1592-1597.

Ljung, G. M., & Box, G. E. (1978). On a measure of lack of fit in time series models. *Biometrika*, *65*(2), 297-303.

Lo, A. W., & MacKinlay, A. C. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test. *The Review of Financial Studies*, *1*(1), 41-66.

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *Journal of Portfolio Management*, *30*(2004), 15-29.

Lo, A. W. (2005). Reconciling efficient markets with behavioral finance: The adaptive markets hypothesis. *Journal of Investment Consulting, 7*(2), 21-44.

Lo, A. W. (2012). Adaptive markets and the new world order. *Financial Analysts Journal, 68*(2), 18-29.

Lo, A. W. (2017). *Adaptive markets: Financial evolution at the speed of thought*. Princeton University Press.

Lobato, I. N. (2001). Testing that a dependent process is uncorrelated. *Journal of the American Statistical Association*, *96*(455), 1066-1076.

Lofthouse, S., & Vint, J. (1978). Some conceptions and misconceptions concerning economic man. *Rivista Internazionale di Scienze Economiche E Commerciali*, *25*(7), 586-615.

Mnif, E., Jarboui, A., & Mouakhar, K. (2020). How the cryptocurrency market has performed during covid 19? A multifractal analysis. *Finance Research Letters, 36*(2020), 1-13.

Nadarajah, S., & Chu, J. (2017). On the inefficiency of Bitcoin. *Economics Letters*, *150*(2017), 6-9.

Noda, A. (2016). A test of the adaptive market hypothesis using a time-varying ar model in Japan. *Finance Research Letters*, *17*(2016), 66-71.

Noda, A. (2019). On the time-varying efficiency of cryptocurrency markets. *arXiv preprint arXiv:1904.09403*. researchgate.net, 1-11.

Okoroafor, U. C., & Leirvik, T. (2021). Time varying market efficiency in the Brent and WTI crude market. *Finance Research Letters*, 102191.

Patil, A. C., & Rastogi, S. (2019). Time-varying price–volume relationship and adaptive market efficiency: A survey of the empirical literature. *Journal of Risk and Financial Management*, *12*(105), 1-18.

Patil, A. C., & Rastogi, S. (2020). Multifractal analysis of market efficiency across structural breaks: Implications for the adaptive market hypothesis. *Journal of Risk and Financial Management*, *13*(248),1-18.

Popović, S., Mugoša, A., & Đurović, A. (2013). Adaptive markets hypothesis: Empirical evidence from Montenegro equity market. *Economic Research-Ekonomska Istraživanja*, *26*(3), 31-46.

Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randomly. *Industrial Management Review*, *6*(2), 41-49.

Sean B. (2018). *Google bans ads for bitcoin and other cryptocurrencies.* https://www.thewrap.com/google-bitcoin-ban-ads

Sensoy, A. (2019). The inefficiency of bitcoin revisited: A high-frequency analysis with alternative currencies. *Finance Research Letters*, *28*(2018), 68-73.

Thompson, P. (2020). *Most significant hacks of 2019 - new record of twelve in one year*. https://www.cointelegraph.com/news/most-significant-hacks-of-2019-new-record-of-twelve-in-one year?_ga=2.50113888.770597633.1615270779-1421920406.1615025470

Tiwari, A. K., Jana, R. K., Das, D., & Roubaud, D. (2018). Informational efficiency of Bitcoin-an extension. *Economics Letters, 163*(2018), 106-109.

Todea, A., Ulici, M., & Silaghi, S. (2009). Adaptive markets hypothesis: Evidence from Asia-Pacific financial markets. *The Review of Finance and Banking*, *1*(1), 7-13.

Tseng, K. C. (2006). Behavioral finance, bounded rationality, neuro-finance, and traditional finance. *Investment Management and Financial Innovations*, *3*(4), 7-18.

Urquhart, A., & McGroarty, F. (2014). Calendar effects, market conditions and the adaptive market hypothesis: Evidence from long-run U.S. data. *International Review of Financial Analysis*, *35*(2014), 154-166.

Urquhart, A. (2016). The inefficiency of bitcoin. *Economics Letters*, *148*(2016), 80-82.

Verheyden, T., Van den Bossche, F., & De Moor, L. (2013). Towards a new framework on efficient markets: A rolling variance ratio test of the adaptive markets hypothesis. *HUB Research Papers*, *4*(2013), 1-13.

Vidal-Tomás, D., & Ibañez, A. (2013). Semi-strong efficiency of bitcoin. *Finance Research Letters, 27*(2013), 259-265.

Vidal-Tomás, D., Ibáñez, A. M., & Farinós, J. E. (2019). Weak efficiency of the cryptocurrency market: A market portfolio approach. *Applied Economics Letters*, *26*(19), 1627-1633.

Wang, J., & Wang, X. (2021). COVID-19 and financial market efficiency: Evidence from an entropy-based analysis. *Finance Research Letters*, *42*(2021), 1-7.

Zhang, W., Li, Y., Xiong, X., & Wang, P. (2021). Downside risk and the cross-section of cryptocurrency returns. *Journal of Banking & Finance*, *133*(2021), 1-18.

Zhang, W. P. Wang, X. L., & Shen D. (2018). Quantifying the cross-correlations between online searches and bitcoin market. *Physica A: Statistical Mechanics and Its Applications*, *509*(2018), 657–672.

Zhou, J., & Lee, J. M. (2013). Adaptive market hypothesis: Evidence from the reit market. *Applied Financial Economics*, *23*(21), 1649-1662.