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Cryptocurrency Market: Overreaction to News and Herd Instincts

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Abstract: *The present research focuses on the phenomenon of cryptocurrency market overreactions, especially examining the behavior of Bitcoin, DASH, EOS, Ethereum, Lisk, Litecoin, Monero, NEO, Quantum, Ripple, Stellar, and Zcash from January 2, 2018, to March 1, 2023. The findings show that there are both positive and negative autocorrelations, which might result in lowered volatility and more moderate fluctuations in prices. These results possess the potential to assist investors in making well-informed choices since they are less susceptible to being influenced by exaggerated reactions to news or information hitting the market. However, before investing in cryptocurrency markets, investors should exercise caution and carefully examine their risk tolerance, since market circumstances may change quickly, making it impossible to perform consistently profitable trades.*

1. INTRODUCTION

The efficient market hypothesis posits that stock prices include all relevant information, thereby making the prediction of future returns and the attainment of abnormal gains challenging for investors. Nevertheless, several academic investigations conducted since the mid-1980s have presented arguments against this assumption. Bondt and Thaler (1985) conducted a study that demonstrated the potential for achieving abnormal returns over the long term through the investment in stocks with a history of poor performance (extreme initial losers) and the divestment of those that have exhibited strong performance (extreme initial winners). The authors suggest that adopting a "contrary" investing strategy yields positive returns since investors tend to exhibit exaggerated reactions to information, resulting in an excessive level of both optimism and pessimism within the market.

According to author Urquhart (2018), the volatility of cryptocurrency prices is an example of exaggerated reactions that lasted for six months and drew the attention of investors, regulators, and policymakers, among others. According to the authors, Amini et al. (2013), exaggerated reactions may occur in shorter periods of a few minutes on different asset classes, leading to a repeated pattern of high prices followed by decreases (or vice versa) in financial markets. Therefore, it is essential to do thorough research aimed at examining the occurrence of exaggerated price reactions in cryptocurrencies.

Traditional research has focused on stock markets, but the purpose of this study is to investigate the behavior of digital currencies, which have emerged as a new asset class that has attracted the interest of investors and gained recognition in financial circles in recent years. In this study, we have conducted an analysis and presented empirical evidence about the prevalence

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of exaggerated reactions throughout digital currency markets, including Bitcoin (BTC), DASH, EOS, Ethereum (ETH), Lisk (LSK), Litecoin (LTC), Monero (XMR), NEO, Quantum (QUA), Ripple (XRP), Stellar, and ZCASH.

This manuscript presents a significant contribution to the existing literature concerning overreaction behavior in digital currency markets. It introduces a novel modeling method that eliminates the need for explicit limit parameters. In our investigation, we used a modeling approach to represent the exaggerated price reactions by considering price changes with a time lag ranging from 16 days. This method differs from other studies that have relied on statistical modeling of exaggerated reactions, which requires the arbitrary selection of one or more parameters. Given the significance of selecting these parameters, the resultant findings may exhibit a certain tendency. Therefore, our research expands upon the existing empirical literature by using a rigorous and unbiased methodology to evaluate the prevalence of exaggerated reaction patterns across different digital currencies.

The article is organized into five sections. Section 2 provides a review of the literature on the overreactions of investors in global markets. Section 3 describes the methodology and data of the study. Section 4 presents the results of the analysis. Finally, Section 5 summarizes the conclusions.

2. LITERATURE REVIEW

Exaggerated reactions in financial markets have been more common in recent decades, as shown by academic studies and Wall Street views. Several writers have investigated the behavior of investors in different financial markets as well as their propensity to overreact. Bondt and Thaler (1985) argue that the typical reversal in stock prices is demonstrated by exaggerated responses; however, Chen and Zhu (2005), who studied the Chinese stock market, argue that investors tend to overreact to positive news and underreact to negative news. Antweiler and Frank (2011) observed evidence of reversal or exaggerated reaction in abnormal, pre-, and post-event corporate news returns, which supports the efficient market hypothesis. Later, De Bondt and Thaler (2012) demonstrate that high returns to first losers are not due to risk, tax effects, or tiny anomalies but rather to unpleasant expectations of future returns. In researching the 1987 stock market crash, author Shiller (2022) shows that investors were motivated by each other's conduct rather than by negative economic news. In more recent research, the authors Diaconaşu et al. (2022), Schaub (2022), and Wen et al. (2022) studied whether investors react to each other's behavior or information entering the digital currency market. According to Diaconaşu et al. (2022), the Bitcoin market matures with time as investor behavior fits with the uncertain information hypothesis of positive and negative events. Furthermore, the analysis suggests that Bitcoin's efficiency increased throughout the COVID-19 pandemic. According to Schaub (2022), Bitcoin and Ethereum overreact to such situations, but Tether has a significant value reversal following atypically positive events. Wen et al. (2022) provide evidence of intraday return predictability in the digital currency market. Other actively traded digital currencies, such as Ethereum, Litecoin, and Ripple, show evidence of intraday timing. The research also demonstrates that a timing strategy based on intraday predictors outperforms reference techniques in terms of economic value. The late-informed investor theory explains the evidence of intraday timing.

Understanding the cryptocurrency market dynamics requires assessing how investors react to each other's behavior or information received. This is important because of the risk of herd behavior, asset price bubbles, and crashes caused by irrational investor decisions influenced by others in the market. Furthermore, the digital currency market's extreme volatility and lack of regulation underscore the necessity to investigate the influence of information on investor behavior. This information may be used to make better investment decisions and to help establish more effective regulatory frameworks for the cryptocurrency market.

3. METHODOLOGY

3.1. Data

The time series comprises daily data from January 2, 2018, to March 1, 2023, including a sample of 12 digital currencies, namely Bitcoin (BTC), DASH, EOS, Ethereum (ETH), Lisk (LSK), Litecoin (LTC), Monero (XMR), NEO, Quantum (QUA), Ripple (XRP), Stellar, and ZCASH. It is important to note that the period in question includes exogenous events of considerable complexity for the global economy, such as the COVID-19 outbreak, the subsequent oil price conflict among OPEP members, and the Russian invasion of Ukraine in 2022. The data was obtained from Thomson Reuters Eikon and is represented in U.S. dollars.

3.2. Methodology

The development of research will occur in multiple phases. The characterization of the sample used in the study was carried out using descriptive statistics as well as the Jarque and Bera (1980) adherence test. In order to assess the stationarity of the time series, we will use the panel unit root tests proposed by Levin et al. (2002) and Im et al. (2003). Additionally, to validate the obtained results, we will apply the Dickey and Fuller (1981) and Phillips and Perron (1988) tests, using the Fisher Chi-square transformation. In order to answer the research question regarding the possible existence of exaggerated reactions in the price series of cryptocurrencies, we will use the non-parametric test proposed by Wright (2000). This test includes the Position Test (Rankings) as well as the Signal Test, which is specifically designed for heteroscedastic series. According to Vats and Kamaiah (2011), these methods provide more accurate estimations when dealing with smaller sample sizes and exhibit more statistical power compared to standard variance ratio tests in the context of serial correlation. The ratio of variances may be expressed as the quotient of the variance of q periods divided by the variance of a single period, resulting in a value of 1. In this context, when $VR(q) = 1$, the series exhibits characteristics of a random walk process. When the null hypothesis is rejected, yet the variance ratio $VR(q) > 1$, it suggests the presence of a positive correlation. Conversely, when the variance ratio $VR(q) < 1$, it implies negative correlations in the series.

4. RESULTS

Figure 1 shows the evolution of the 12 cryptocurrencies under consideration, namely Bitcoin (BTC), DASH, EOS, Ethereum (ETH), Lisk (LSK), Litecoin (LTC), Monero (XMR), NEO, Quantum (QUA), Ripple (XRP), Stellar, and ZCASH, between January 2, 2018, and March 1, 2023. The first months of 2020 saw the convergence of the first wave of the COVID-19 pandemic and the oil price war between Russia and Saudi Arabia. The behavior of the cryptocurrencies under investigation exhibits heightened volatility throughout the second and third quarters of 2021, highlighting significant structural breaks. As early as 2022, the time series analysis of the cryptocurrencies under investigation reveals visible fluctuations, which can be attributed to the impact of the Russian invasion of Ukraine and the resulting uncertainty surrounding inflation. These fluctuations indicate the presence of structural breaks, but with lesser significance when compared to the global COVID-19 pandemic. The authors Pardal et al. (2022), Dias et al. (2022), and Teixeira et al. (2022) have also presented these findings in the context of international financial markets.

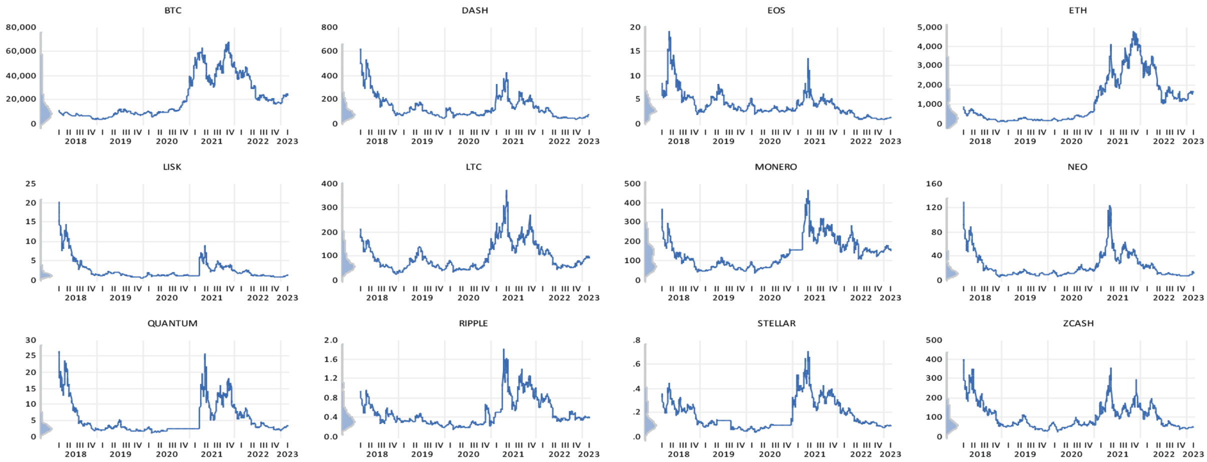

Figure 1. Evolution, in levels, of the cryptocurrencies under analysis, from January 2, 2018, to March 1, 2023

Source: Own elaboration (Software: Eviews12)

Table 1 is a summary of the main descriptive statistics, measured in returns, of the 12 cryptocurrencies studied in this research for the whole sample period. It also shows the results of the Jarque and Bera (1980) adherence test. In relation to the mean returns, it is seen that just 2 cryptocurrencies, namely BTC (0.000571) and ETH (0.000467), exhibit positive mean returns, while the other digital currencies experience negative mean returns. In relation to the standard deviation, it is seen that the LSK (0.075517) exhibits the highest level of dispersion, while the BTC (0.042613) has a comparatively lower and less volatile standard deviation. By conducting a validation of the assumption of a Gaussian distribution, we ascertain that the values of skewness and kurtosis for all digital currencies differ from 0 and 3, respectively. The confirmation of the Jarque and Bera (1980) adherence test additionally suggests that the time series under study deviates from a strictly normal distribution.

Table 1. Summary table of descriptive statistics, in returns, in respect of the cryptocurrencies under analysis, from January 2, 2018, to March 1, 2023

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability	Observations
BTC	0.000571	0.042613	-0.474092	7.963501	1388.487	0.000000	1305
DASH	-0.001657	0.064197	-0.002465	9.467086	2274.138	0.000000	1305
EOS	-0.001529	0.066729	-0.146585	8.249220	1502.939	0.000000	1305
ETH	0.000467	0.056324	-0.359280	7.468006	1113.568	0.000000	1305
LSK	-0.002177	0.075517	5.579036	121.0497	764525.1	0.000000	1305
LTC	-0.000624	0.058194	-0.536404	7.605415	1215.867	0.000000	1305
XMR	-0.000562	0.055398	-0.504036	10.21548	2886.192	0.000000	1305
NEO	-0.001811	0.066035	-0.202070	7.828584	1276.646	0.000000	1305
QUA	-0.001604	0.073484	3.630120	73.43264	272607.3	0.000000	1305
XRP	-0.000684	0.062772	0.674267	15.81223	9024.711	0.000000	1305
STELLAR	-0.001049	0.061881	-0.801490	24.18074	24533.64	0.000000	1305
ZCASH	-0.001714	0.065196	-0.314126	6.004688	512.3676	0.000000	1305

Source: Own elaboration

In order to verify the assumption of stationarity for the time series pertaining to the cryptocurrencies Bitcoin (BTC), DASH, EOS, Ethereum (ETH), Lisk (LSK), Litecoin (LTC), Monero (XMR), NEO, Quantum (QUA), Ripple (XRP), Stellar, and ZCASH, we will employ a panel unit root test. Specifically, we will use the Levin et al. (2002) test as well as the Im et al. (2003) test. To validate the obtained results, we will also apply the Dickey and Fuller (1981) test and the Phillips and Perron (1988) test with the Fisher Chi-square transformation. To achieve stationarity, the decision was made to apply a logarithmic transformation to the first differences in the time series. This was done to align the time series in a way that would exhibit the characteristics of white noise, namely an average of 0 and a constant variance. By doing this, the assumption of stationarity was proven correct, as shown by the fact that the null hypothesis H_0 was rejected at a significance level of 1% (Table 2).

Table 2. Summary table of panel unit root tests, in returns, concerning the cryptocurrencies under analysis, from January 2, 2018, to March 1, 2023

Group unit root test: Summary				
Method	**Statistic**	**Prob.***	**Cross-sections**	**Obs.**
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t	-101.661	0.0000	12	15608
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-91.7055	0.0000	12	15608
ADF - Fisher Chi-square	1653.61	0.0000	12	15608
PP - Fisher Chi-square	1107.54	0.0000	12	15636

Note: * Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality

Source: Own elaboration

In order to answer the research question, we used Wright's (2000) non-parametric test, which comprised the variance tests of Ranking and Signals, from January 2, 2018, to March 1, 2023. The proposed approach involves the use of two separate tests: one for homoscedastic series, referred to as the ranking test, and another for heteroscedastic sets, known as the signal test. These tests are applied to lag periods ranging from 2 to 16 days. The digital currencies BTC, ETH, LSK, NEO, QUA, and STELLAR exhibit positive serial autocorrelation in both the Rankings and Signals tests, indicating that cryptocurrency price movements are not entirely random and are influenced by previous price fluctuations. These indicators may point to exaggerated investor reactions to new market information. In such a case, any positive news or information regarding a certain cryptocurrency has the potential to induce a rise in its value as investors cultivate a heightened sense of optimism over its future potential. Consequently, a further rise in purchases might be expected, thus contributing to further price escalations. The DASH, EOS, and LTC cryptocurrencies exhibit a balanced performance in the Rankings test while showing negative serial autocorrelation in the Signals test. The cryptocurrencies XMR and XRP exhibit negative autocorrelation in the Ranking test and positive autocorrelation in the Signals test. On the other hand, ZCASH displays both positive and negative autocorrelation in both the homoscedastic and heteroscedastic tests. In pragmatic terms, the movements in bitcoin prices are driven by previous upward and downward price trends. In the given context, investors may exhibit different reactions to both positive and negative news or information related to a certain cryptocurrency. The dissemination of favorable information might potentially result in an increase in the value of the coin as investors exhibit heightened optimism toward its future possibilities. Nevertheless, the extent of the price increase can be comparatively lesser in the presence of only positive serial autocorrelation. Likewise, spreading negative news may result in a sale, as investors' outlook on the future potential of the coin becomes gloomier. In summary, the presence of positive and negative serial autocorrelation in cryptocurrencies may contribute to lower volatility and more rational price fluctuations. This may facilitate enhanced decision-making for investors since it reduces the likelihood of being swayed by exaggerated reactions to news or information. The findings show the presence of both positive and negative autocorrelations within the cryptocurrency markets, which have the potential to result in more moderated price fluctuations and a lower level of volatility. This may assist investors in making better-informed decisions since it reduces the possibility of being influenced by exaggerated reactions to news or information.

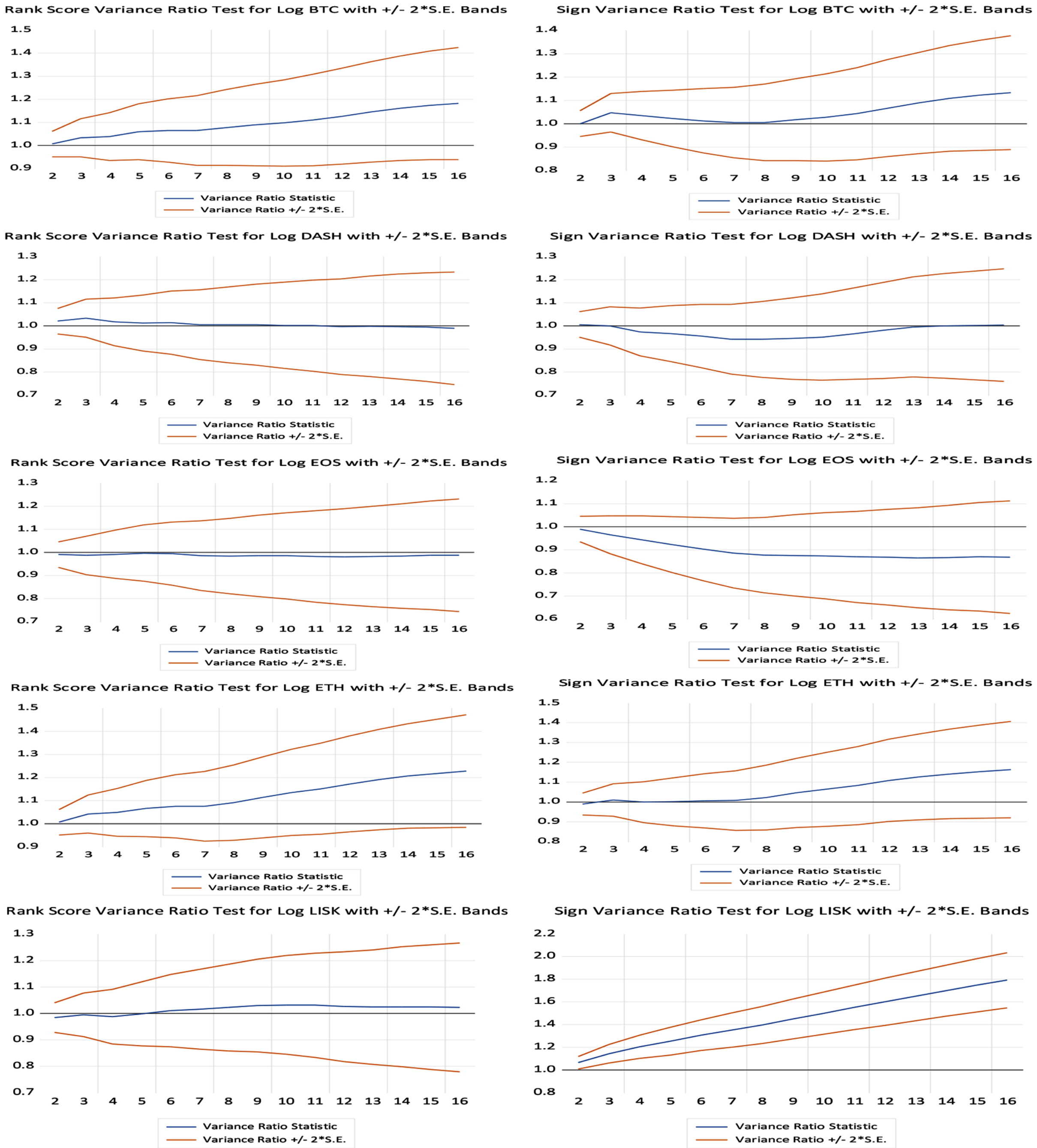

Figure 2. Results of the Rank and Sign Variance Ratio tests in respect of the cryptocurrencies under analysis, from January 2, 2018, to March 1, 2023

Source: Own elaboration (Software Eviews12)

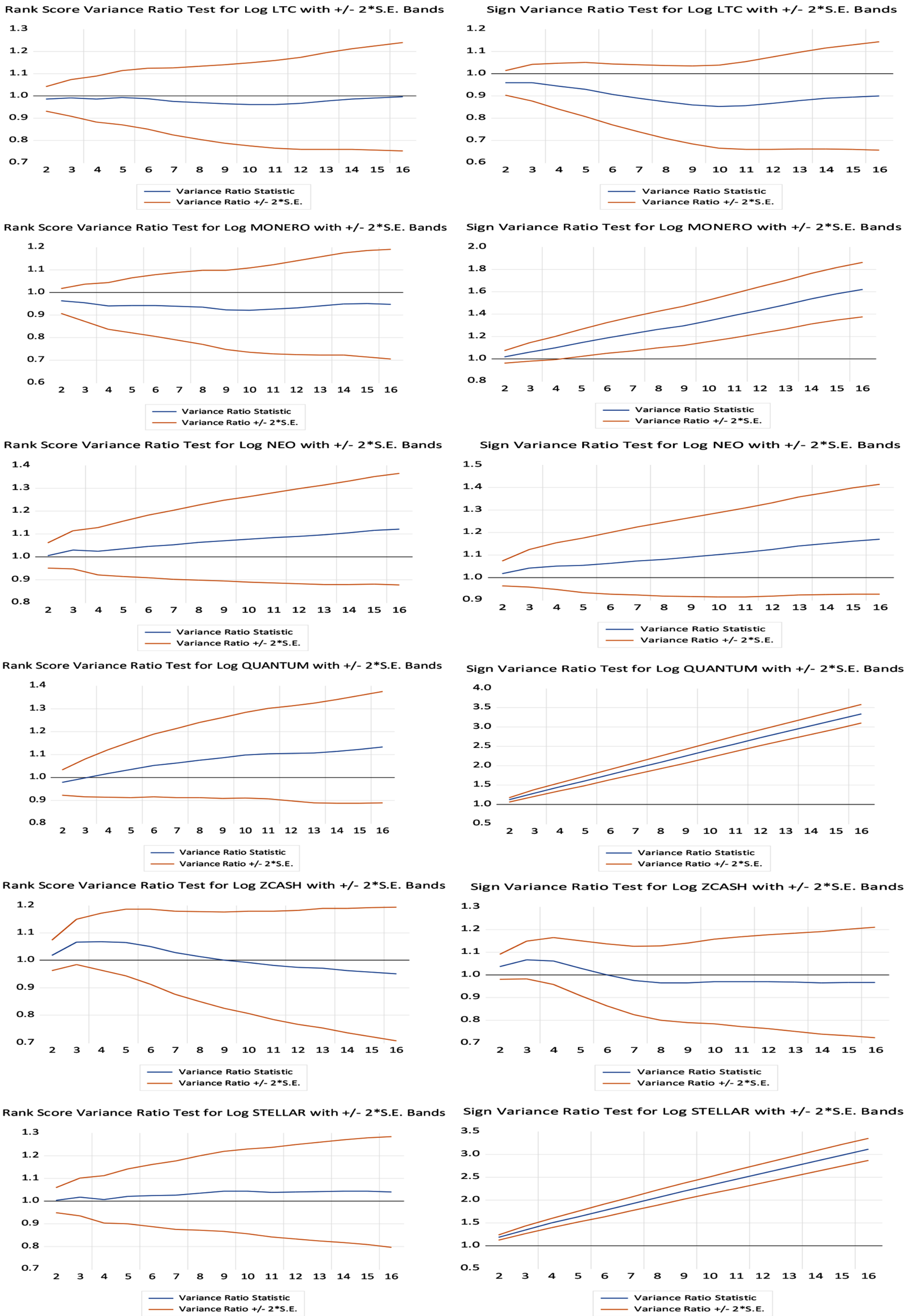

Figure 2. Continued

Source: Own elaboration (Software Eviews12)

5. CONCLUSION

This study aimed to examine if the prices of Bitcoin (BTC), DASH, EOS, Ethereum (ETH), Lisk (LSK), Litecoin (LTC), Monero (XMR), NEO, Quantum (QUA), Ripple (XRP), Stellar, and ZCASH are subject to exaggerated investor reactions. The findings show the presence of both positive and negative autocorrelations within the cryptocurrency markets, which have the potential to result in more moderated price fluctuations and a lower level of volatility. This may assist investors in making better-informed decisions since it reduces the possibility of being influenced by exaggerated reactions to news or information. Nevertheless, the cryptocurrency markets exhibit a high degree of complexity and volatility, whereby several variables exert influence on pricing, hence making the execution of consistently lucrative trades a challenging task. Consequently, before diving into cryptocurrency markets, investors are advised to exercise prudence and assess their capacity to bear risks. Consequently, it is advisable for investors to constantly watch market fluctuations and adjust their investment strategies accordingly.

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