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INVESTOR HAPPINESS AND CRYPTOCURRENCY RETURNS: FRESH EVIDENCE FROM TOP FIVE CRYPTOCURRENCIES

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Abstract

The study aims to investigate the causality relationship between investor happiness and cryptocurrency returns. The study is focused on the five largest cryptocurrencies, specifically Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), and Cardano (ADA). Twitter-based Happiness Index is used to measure investor happiness. The sample period covers the period between January 1, 2019, and October 2, 2021. The Zivot-Andrews test is employed to detect stationary of covariates. After ensuring that all variables are stationary at levels, the Granger causality test is adopted to understand the relationship between the happiness index and cryptocurrency returns. The impulse-response functions are illustrated. The results indicate that there is a uni-directional relationship from BTC to Happiness Index, and Happiness Index to ETH. Considering that the causal relationship between cryptocurrency returns and investor happiness differs between cryptocurrencies, it is thought that investors should closely monitor the happiness index and make adjustments in their portfolios in response to changes in investor happiness.

Keywords: *Investor happiness, Cryptocurrency, Granger causality, Impulse-response analysis.*

YATIRIMCI MUTLULUĞU VE KRİPTO PARA GETİRİLERİ ARASINDAKİ İLİŞKİ: EN BÜYÜK İLK BEŞ KRİPTO PARA BİRİMİNDEN KANITLAR

Öz

Çalışma, yatırımcı mutluluğu ile kripto para getirileri arasındaki nedensellik ilişkisini ortaya çıkarmayı amaçlamaktadır. Bu amaç doğrultusunda piyasa değeri bakımından ilk sırada yer alan Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP) ve Cardano (ADA)'ya odaklanılmıştır. Yatırımcı mutluluğunu ölçmek için ise Twitter tabanlı Mutluluk Endeksi kullanılmıştır. Çalışmanın örneklemi 1 Ocak 2019 ile 2 Ekim 2021 arasındaki dönemi kapsamaktadır. Çalışmada ortak değişkenlerin durağanlığını tespit etmek için Zivot-Andrews testinden faydalanılmıştır. Tüm değişkenlerin seviyelerde durağan olduğundan emin olduktan sonra, mutluluk endeksi ile kripto para getirileri arasındaki ilişkiyi anlamak için Granger nedensellik testi uygulanmıştır. Ayrıca etki-tepki analizi ile kripto para getirileri ve mutluluk endeksinde meydana gelecek şokların etkileri analiz edilmiştir. Bulgular, BTC'den Mutluluk Endeksi'ne ve Mutluluk Endeksi'nden ETH'ye tek yönlü bir ilişki olduğunu göstermektedir. Kripto para getirileri ile yatırımcı mutluluğu arasındaki nedensellik ilişkisinin kripto para birimleri arasında farklılık gösterdiği düşünüldüğünde, yatırımcıların mutluluk endeksini yakından takip etmeleri ve yatırımcı mutluluğundaki değişimlere karşılık portföylerinde ayarlamalar yapmaları gerektiği düşünülmektedir.

Anahtar kelimeler: *Yatırımcı mutluluğu, Kriptopara birimi, Granger nedensellik, Etki-tepki analizi.*

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1.INTRODUCTION

Cryptocurrencies are the new emerging assets that allow online payments without the need for a higher authority thanks to their peer-to-peer system. The cryptocurrency market has grown at a fairly rapid rate following the introduction of Bitcoin in 2008 (Nakamoto, 2008). The total market capitalization of cryptocurrencies has increased more than 600 times from April 2013 to June 2022 (www.coinmarketcap.com). The increasing market share of cryptocurrencies in the financial system and unprecedented ups and downs experienced in cryptocurrency prices caused a shift of academic and political attention to this new asset class. Among other issues (such as regulation, cyber criminality, and diversification benefits), cryptocurrency pricing is one of the key aspects of academic research (Corbet et al., 2019).

There are two mainstream theories regarding asset pricing in the finance literature pointing to different drivers of asset prices. The traditional financial theory argues that asset prices are determined by fundamental value considering that the financial markets are efficient. In particular, the traditional model contends that rational investors, who are not driven by their emotions, counteract the effect of irrational investors on asset prices, and thereby force asset prices to reflect their underlying values. The traditional financial theory has been applied to well-known financial models including modern portfolio theory (Markowitz, 1952), Capital Asset Pricing Model (Sharpe, 1974), and Arbitrage Pricing Model (Ross, 2013). However, the traditional model has failed to explain the dramatic changes in asset prices as in Tulipmania, the Crash of 1929, dot.com bubble. Therefore, the behavioral finance theory based on cognitive psychology points also out investor sentiment as one of the determinants of asset prices under the assumption that investors are not fully rational and their investment decisions are affected by their beliefs and attitudes (De Long et al., 1990). The behavioral model also assumes that betting against transactions of irrational investors is both costly and risky. In other words, the behavioral model propounds that asset prices are determined by two types of investors, rational arbitrageurs, and irrational investors affected by sentiment. Irrational investors make an investment based on their emotions and moods rather than fundamentals, causing mispricing in financial markets. However, rational investors have limited ability to correct the mispricing due to short time horizons and trading risk. Overall, behavioral finance theory asserts that asset prices often deviate from their fundamental value, and two factors induce mispricing, a change in irrational investors' sentiment and limited arbitrage.

As the key element in behavioral finance, investor sentiment is an attitude reflecting the willingness of market participants to invest. Since investor sentiment is shaped by moods and emotions, it is quite hard to observe. Nevertheless, investor sentiment is attempted to measure using different approaches (Baker and Wurgler, 2007). One approach, called a bottom-up approach, addresses individuals' psychological prejudices including overconfidence, loss aversion, and anchoring to account for deviations of asset prices from fundamentals at the aggregate level. The bottom-up procedure takes sentiment as an internal factor and provides a base for change in investor sentiment. However, focusing on one or two biases remains incapable to explain why asset prices deviate from their fundamentals. Alternatively, the top-down approach attempts to explain how individual stocks are affected by sentiment rather than addressing the impact of sentiment on aggregate stock prices. The top-down approach is based on two assumptions; (1) not all asset prices are equally affected by investor sentiment and (2) arbitrage is more difficult for speculative assets compared to stable ones. Unlike the former approach, the top-down approach considers investor sentiment as an external factor. Adopting a top-down approach, researchers generate various proxies to measure investor sentiment either based on consumer surveys or by searching market data such as Baker and Wurgler's (2006) sentiment index, Tetlok's (2007) news-based sentiment measure, and Buchman et al. (2020)'s Daily News Sentiment Index, CNN Business Fear & Greed Index, S&P 500 Twitter Sentiment Index, and Happiness Index. Investor sentiment is addressed in the finance literature to explain the prices of various asset classes including stocks (Brown and Cliff, 2004; Baker and Wurgler, 2007), bonds (Laborda and Olmo, 2014), mutual funds (Da et al., 2015), precious metals (Balcilar et al., 2017); and energy (Luo et al., 2022).

In the case of cryptocurrencies, there is no accepted pricing methodology. Several studies apply the classical pricing model originally generated for stocks (Shen et al., 2020; Shahzad et al., 2021; Wang and Chong, 2021; among others) and address factors such as size, market, momentum, and liquidity. However, cryptocurrency pricing is more complicated than those of traditional assets because neither they have fundamental value nor they provide cash flows. Furthermore, cryptocurrencies seem speculative investment rather than a medium of exchange, which further complicate the detection of cryptocurrency prices by applying the traditional pricing model. In addition, the cryptocurrency market is still immature, and therefore there is too much concern about its efficiency. A bulk of studies also provided empirical evidence regarding the inefficiencies in the cryptocurrency market. For instance, Urquhart (2016) showed that Bitcoin, a cryptocurrency with the largest market capitalization, fails to meet the requirements of the Efficient Market Hypothesis. Zhang et al. (2018) also analyzed the informational efficiency of nine cryptocurrencies and reveal that all cryptocurrencies covered in the study seem inefficient. More recently, Al-Yahyaee et al. (2020) provided evidence regarding the inefficiency of the cryptocurrency market. Overall, immature market dynamics dampen arbitrage opportunities in the cryptocurrency market. Last but not least, investors in cryptocurrency markets have a low level of cryptocurrency knowledge (Cardify, 2021), suggesting crypto investors make investment decisions based on their feelings rather than fundamentals. Accordingly, a bulk of studies have addressed investor sentiment as one of the most important factors in cryptocurrency pricing (Anamika et al. 2021; Guler, 2021). Several papers questioned the relationship between investor sentiment and cryptocurrency returns (Kraaijeveld and Smedt, 2020; Naeem et al., 2021; Akyildirim et al.2021) while others linked investor sentiment with cryptocurrency volatility (Bouri et al. 2021; Zhang and Zhang, 2022).

However, the studies addressing the impact of investor sentiment on cryptocurrency prices remain limited, suggesting that more research should be conducted to ascertain the relationship between investor sentiment and cryptocurrency prices. Given this setting, the main purpose of the present study is to investigate the causal relationship between investor happiness and cryptocurrency returns. The study contributes literature on two fronts. *First*, cryptocurrency pricing is still an immature area, so the present study contributes to cryptocurrency pricing by analyzing the price dynamics of the top five cryptocurrencies. *Second*, investor sentiment is expected to be one of the most dominant drivers because neither cryptocurrency has fundamental value nor do investors have a sufficient level of cryptocurrency knowledge. By investigating the causality between investor sentiment and cryptocurrency return, this study shed light on this issue.

The remainder of the paper is organized as follows. Section 2 summarizes the prior literature, Section 3 describes the data and methodology, Section 4 reports empirical findings and Section 5 gives concluding remarks and policy recommendations.

2.LITERATURE REVIEW

There is a growing body of literature on cryptocurrencies, much of which centres on Bitcoin, the world's largest and best-known cryptocurrency. Along with several subjects such as cryptography, regulatory framework, illegal use, and security risk; cryptocurrency pricing has been one of the major topics of academic studies. Price swings that have been experienced in cryptocurrencies in recent years have also triggered researchers to explore the dynamics of cryptocurrency prices. Market efficiency (Urquhart, 2016; Zhang et al., 2018; Al-Yahyaee et al., 2020), bubble formation (Corbet et al., 2018; Kyriazis et al., 2020; Gronwald, 2021; Haykir and Yagli, 2022; Waters and Bui, 2022), integration (Bouri et al., 2019; Keilbar and Zhang, 2021; Apergis et al., 2021), volatility (Teker et al., 2020; Abakah et al., 2020), and factors affecting cryptocurrency prices (Shen et al., 2020; Shahzad et al., 2021; Wang and Chong, 2021) are among the most emphasized issues regarding economic aspects of cryptocurrencies.

Several factors have been addressed as influencing cryptocurrency prices. These include macroeconomic factors such as interest rates, inflation, exchange rates, and market volatility (Sovbetov, 2018; Basher and Sadorsky, 2022; Wang et al., 2022), as well as microeconomic factors such as supply and demand, trading volume, and size (Abraham, 2019; Gregoriou, 2019; Shen et al., 2019; Wang and Chong, 2021). Additionally, investor attention, news events, regulatory announcements, and technological advancements have also been found to affect cryptocurrency prices (Flori, 2019; Guindy, 2021; Li et al., 2021; Dunbar and Owusu-Amoako, 2022; Lee and Jeong, 2023). One factor that has been gaining increasing attention is the role of investor sentiment. This literature review aims to examine the existing research related to cryptocurrency pricing, with a focus on the impact of investors' sentiment on cryptocurrency prices.

Investor sentiment refers to the overall emotional and psychological state of investors towards a particular asset or market. The concept of investor sentiment is not a new phenomenon, and it has been extensively studied in traditional financial markets (Baker and Wurgler, 2007, Laborda and Olmo, 2014; Balcilar et al., 2017; among others). However, the nexus between investor sentiment and cryptocurrency pricing is a relatively new field of study. Several studies analyzed the impact of investor sentiment on cryptocurrency returns. For instance, Jo et al. (2020) investigated the relationship between investor sentiment and Bitcoin returns. Adopting the logic of Baker and Wurgler (2007), they revealed that Bitcoin behaves similarly to high sentiment beta stock, and investor sentiment has an indirect impact on Bitcoin returns through traditional factors. Anamika et al. also (2021) examined the effect of investor sentiment on cryptocurrency returns using survey-based measures, and their findings indicate that when investors are optimistic about Bitcoin, the price of Bitcoin rises. In another study, Koutmos (2023) explored the relationship between investor sentiment and Bitcoin returns using sentiment measure constructed with the bid and ask orders data obtained from Coinbase's order book, and revealed that investor sentiment is positively related to Bitcoin returns. Guler (2021) also analyzed the impact of investor sentiment on Bitcoin returns and their volatility amid the Covid-19 pandemic and found that cryptocurrency returns and their volatility are positively related to both rational and irrational investor sentiments, particularly during the Covid-19 outbreak pandemic. Kraaijeveld and Smedt (2020) addressed the aforementioned relationship for a larger sample of cryptocurrencies and analyzed the predictive ability of Twitter sentiment on the nine largest cryptocurrency returns. Their results ascertained that investors can use Twitter sentiment as a predictor of Bitcoin, Bitcoin Cash, and Litecoin returns. Naeem et al. (2021) analyzed the relationship between investor sentiment and cryptocurrency returns, using the Fears index and Twitter Happiness sentiment. They concluded that even though both happiness and fear indexes can predict cryptocurrency returns, the predictive ability of the Happiness index is more powerful. Akyildirim et al. (2021) also researched the nexus between investor sentiment and cryptocurrency prices and revealed that information transmission is from cryptocurrency returns to investor sentiment. Zhang and Zhang (2022) also revealed that both cryptocurrency prices and trading volume give a positive reaction to Twitter sentiments while the reaction of trading volume is in a shorter period. Banerjee et al. (2022) examined the nonlinear relationship between Covid-19 news sentiment and returns for the top 30 cryptocurrencies. Their findings showed that the aforementioned relationship is uni-directional, from sentiment to returns.

In conclusion, investor sentiment seems to be an important factor in cryptocurrency pricing. Positive investor sentiment is associated with increased cryptocurrency prices, while negative sentiment has been associated with lower prices. Additionally, investor sentiment can influence other market indicators such as trading volume and volatility. However, cryptocurrency pricing is still a topic of debate, and therefore the literature should be enlarged to comprehend the relationship between investor sentiment and cryptocurrency returns.

3.DATA AND METHODOLOGY

The main purpose of the current study is to investigate the causality relationship between investor sentiment and cryptocurrency returns. We focus on the largest five cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), and Cardano (ADA). To proxy the investor sentiment, we use Happiness Index calculated based on tweets by the Hedonometer team (www.hedonometer.org). The sample consists of daily data that spans from January 1, 2019, to October 2, 2021. Even though a longer time frame would be appropriate for this study; data is limited to our sample in the happiness index data portal. The happiness index is constructed by combining the top 5,000 words from Google Books, New York Times articles, Music Lyrics, and Twitter tweets. The index is created as a composite set of about 10,000 unique words to measure the happiness of language atoms. Each of these 10,000 words is graded on a nine points happiness scale using Amazon Mechanical Turk: (1) sad to (9) pleased. We use STATA statistical software program to employ analyses.

Several factors motivate us to employ the Happiness Index as a proxy of investor happiness. The first factor is the use of social media by a large part of the global population. According to the Digital 2022 Global Overview Report, 4.62 billion people, 58.4% of the global population, use social media and spend more than 2 hours every day. Twitter is one of the most frequently used social media platforms. Moreover, cryptocurrency investors are highly keen on Twitter (Shen et al., 2019). Therefore, we believe it is suitable to proxy investor happiness with the Happiness Index based on tweets. The second reason for adopting the Happiness Index as a proxy of investor sentiment is its high frequency. The Happiness Index is a search-based sentiment measure calculated on a daily base. Therefore, it provides a timelier measure of investor happiness than the survey-based sentiment measures. The third factor is its high correlation with traditional measures of well-being (Mitchell et al., 2013), indicating that it is a reliable measure to capture happiness.

Asset prices, especially those whose underlying value is difficult to determine, are more prone to investor sentiment. Given that cryptocurrencies have no fundamental value and cryptocurrency investors have limited cryptocurrency knowledge, we expect that cryptocurrencies generate higher returns when investor sentiment increases. However, herding behavior in the cryptocurrency market is quite common (Ballis and Drakos, 2020). Therefore, it is also possible that higher returns can trigger investors to invest in cryptocurrencies, suggesting causality from cryptocurrency returns to investor sentiment. Overall, the relationship between investor sentiment and cryptocurrency returns might be bi-directional.

Accordingly, the present paper aims to ascertain the direction of investor happiness and cryptocurrency returns. To do so, the study employs the Granger causality test. In this regard, first, we determine the stationary of covariates using the Zivot-Andrews (1992) structural break unit root test. Second, we examine the Granger causality among variables. Finally, we show the impulse-response functions of each covariate.

We use the daily return of the five cryptocurrencies using the formula (1).

$$Return_{i,t} = ln(\frac{Price_{i,t}}{Price_{i,t-1}}) \tag{1}$$

where is the $Return_{i,t}$ of each cryptocurrency *i* in day *t*. $Price_{i,t}$ refers to the price of each cryptocurrency *i* in day *t*, and $Price_{i,\, t-1}$ indicates the price of each cryptocurrency *i* in day *t-1.*

In order to have a similar magnitude among variables, we also use the growth of happiness index which is calculated as in equation 2.

$$Happiness\ growth_t = ln(\frac{Happiness_t}{Happiness_{t-1}}) \tag{2}$$

where $Happiness\ growth_t$ is the growth of the happiness index in day *t*. $Happiness_t$ refers to the index of happiness in day *t*, and $Happiness_{t-1}$ refers to the index of happiness on day *t-1.*

To determine the Granger causality between variables, we first need to identify the order of integration of the variables. If the series is not stationary in the level, the estimation result of the Ordinary Least Squares (OLS) is superior which means they are not reliable. Moreover, Granger (1969) states that the variables should be stationary to capture the Granger causality between variables. Otherwise, the causality relation changes based on the sample period. In addition, the stationary of the variables leads us to understand which time-series estimation model we can implement. If the variables are stationary at the level, we adopt Vector Autoregression (VAR) model. If the variables are stationary at the first difference, one should employ Cointegration techniques. If the stationary level is mixed, we implement Autoregressive Distributed Lag (ARDL) model. Thus, it is vital to detect the stationary of the variables. To do so, we examine the stationary of the variables as a first step of the analysis.

Several approaches can determine the stationary of the variables in the time-series analysis. The traditional models, specifically Augmented Dickey-Fuller (ADF, 1979), Phillips-Perron (PP, 1988), Kwiatkowski-Phillips-Schmidt-Shin (KPSS, 1992), and Augmented Dickey-Fuller Generalized Least Squares (ADF-GLS, 1996) tests, detect the presence of a unit root when there is no structural break in the time-series data. Unlike the traditional models, structural break unit-root test such as Zivot-Andrews allows having a structural break in the series. We adapt two-unit root tests, namely Phillips-Perron (1988) and Zivot-Andrews structural break unit root tests.

The Phillips-Perron (1988) test is an extension of the augmented Dickey-Fuller (ADF) test, and it addresses some of the limitations of the ADF test. The test statistic is computed based on the estimated coefficient of an autoregressive model, which is fitted to the differenced time series.

$$\Delta Y_t = \alpha + \rho y_{t-1} + \sum_{i=1}^{\rho-1} \beta_i \Delta y_{t-i} + \varepsilon_t \tag{3}$$

In the Phillips-Perron test, you would estimate this regression model and examine the coefficient estimate p to determine if it is statistically significant. A significant p suggests the presence of a unit root and indicates that the time series is non-stationary.

Zivot-Andrews (1992) unit-root test consists of three models as follows:

Model 1: $$y_t = \hat{\mu}^A + \hat{\alpha}^A y_{t-1} + \hat{\beta}^A t + \hat{\theta}^A DU_t(\hat{\lambda}) + \sum_{j=1}^{k} \hat{c}_j^A \Delta y_{t-j} + \hat{\varepsilon}_t \tag{4}$$

Model 2: $$y_t = \hat{\mu}^B + \hat{\alpha}^B y_{t-1} + \hat{\beta}^B t + \hat{\gamma}^B DT_t^*(\hat{\lambda}) + \sum_{j=1}^{k} \hat{c}_j^B \Delta y_{t-j} + \hat{\varepsilon}_t \tag{5}$$

Model 3: $$y_t = \hat{\mu}^C + \hat{\alpha}^C y_{t-1} + \hat{\beta}^C t + \hat{\theta}^C DU_t(\hat{\lambda}) + \hat{\gamma}^C DT_t^*(\hat{\lambda}) + \sum_{j=1}^{k} \hat{c}_j^C \Delta y_{t-j} + \hat{\varepsilon}_t \tag{6}$$

Model 1 DU_t refers to the break in only intercept whereas DT_t represents the break in only trend in model 2. In the last model, we allow a break in intercept and trend.

Once we determine the stationary of the variables using the Phillips-Perron and Zivot-Andrews structural break unit-root test, we employ the VAR estimation model to understand the causal link between covariates. The Granger causality test determines whether a time series helps us to forecast another. In other words, if the Granger causality exists, it means the independent variable (X) variable provides statistically significant information regarding the future values of the dependent variable (Y). The traditional model of Granger causality can be formulated as follows:

$$Y_t = \sum_{j=1}^{m} \delta_j Y_{t-j} + \sum_{j=1}^{m} \gamma_j X_{t-j} + \varepsilon_t \tag{7}$$

$$X_t = \sum_{j=1}^{m} \theta_j X_{t-j} + \sum_{j=1}^{m} \mu_j Y_{t-j} + \vartheta_t \tag{8}$$

4.EMPIRICAL FINDINGS

The empirical evidence regarding the causality relationship between investor sentiment and five cryptocurrency returns is reported in this section. Before estimation results, we show the descriptive statistics and correlation matrix of the variables. Table 1 presents the descriptive statistics and the correlation matrix of the variables. BNB has the highest average return (60%), and the XRP has the lowest average return (30%) during the sample period. Similarly, BNB has the highest daily increase, and ETH has the lowest daily decrease in the sample period. BTC, ETH, and Happiness have a negative skewness whereas BNB, XRP, and ADA have positive skewness. Since kurtosis values of the variables are higher than 3, it is recognized as leptokurtic distribution. When we turn our attention to the correlation matrix, BTC and ETH have the highest correlation among variables. The correlation coefficients between cryptocurrency returns and the happiness index are negative.

Table 1. Descriptive Statistics and Correlation Matrix

Panel A: Descriptive Statistics							
Variable	Obs	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
BTC	998	0.331992	3.94181	-37.1695	18.74646	-0.4711024	13.52576
ETH	998	0.450262	5.047877	-42.3462	25.94864	-0.502828	10.89571
BNB	998	0.600703	5.985933	-41.8886	69.76472	1.566201	26.59897
XRP	998	0.304411	6.431198	-42.3283	55.98866	1.582555	20.02087
ADA	998	0.570619	5.881935	-39.5713	32.23881	0.2797679	7.459418
Happiness	998	0.001103	0.50633	-3.2937	2.555535	-0.641686	8.987798
Panel B: Correlation Matrix							
	BTC	ETH	BNB	XRP	ADA	Happiness	
BTC	1						
ETH	0.802[a] (0.000)	1					
BNB	0.621[a] (0.000)	0.651[a] (0.000)	1				
XRP	0.560[a] (0.000)	0.612[a] (0.000)	0.493[a] (0.000)	1			
ADA	0.652[a] (0.000)	0.733[a] (0.000)	0.579[a] (0.000)	0.583[a] (0.000)	1		
Happiness	-0.034 (0.276)	-0.009 (0.789)	-0.002 (0.939)	-0.002 (0.939)	-0.013 (0.677)	1	

Notes: Panel A of Table 1 presents the descriptive statistics, and Panel B shows the correlation coefficients of our variables. BTC refers to Bitcoin returns, ETH refers to Ethereum returns, BNB indicates Binance Coin, XRP indicates Ripple returns, ADA refers to Cardano returns and Happiness refers to Happiness Index growth. P-values are in the parenthesis. a, b, and c represent the significance at the 1, 5, and 10 percent levels, respectively.

We begin the estimation section by examining the stationary of the variables to determine which time-series methodology we should conduct. Table 2 shows the test statistics of the Phillips-Perron and Zivot-Andrews unit-root tests and the order of integration of the variables. We employ intercept but no trend analysis for Phillips-Perron since there is a trend in the data and analyze three different Zivot-Andrews tests which allow a break in intercept, trend, and both separately as shown in equations 4-6. The null hypothesis states that the variable is not stationary whereas the alternative hypothesis states that the variable is stationary in both tests. The critical values are given at the bottom of Table 2. Since the test statistics are higher than the critical values at 1% for all covariates, we can conclude that all series are stationary at levels.

Table 2. Phillips-Perron and Zivot-Andrews Unit Root Test

	Phillips-Perron Test	**Zivot-Andrews Test**			
Variables	**Including Intercept**	**Break in Intercept**	**Break in Trend**	**Break in Both**	**Order of Integration**
BTC	-34.010[a]	-15.284[a]	-15.099[a]	-15.429[a]	I (0)
ETH	-34.810[a]	-15.166[a]	-15.078[a]	-15.214[a]	I (0)
BNB	-33.686[a]	-20.595[a]	-20.547[a]	-20.996[a]	I (0)
XRP	-32.387[a]	-32.613[a]	-32.476[a]	-32.634[a]	I (0)
ADA	-33.114[a]	-15.058[a]	-14.946[a]	-15.262[a]	I (0)
Happiness	-33.924[a]	-21.005[a]	-20.858[a]	-20.994[a]	I (0)
Critical Values	1%: 3.43	1%: -5.34	1%: -4.93	1%: -5.57	

Notes: Table 2 presents the results of the Phillip-Perron and Zivot-Andrews Unit Root Test. Test statistics and Critical values are given in the table. BTC refers to Bitcoin returns, ETH refers to Ethereum returns, BNB indicates Binance Coin, XRP indicates Ripple returns, ADA refers to Cardano returns and Happiness refers to Happiness Index growth. a, b, and c represent the significance at the 1, 5, and 10 percent level, respectively.

In the second step of the analysis, we employ the Granger causality test (1969) to determine the causality between variables. To apply the analysis, we use Akaike Information Criteria (AIC) to select the optimal lag for the vector autoregression (VAR) model. Granger causality tests are modelled as follows:

$$Cryptocurrency_t = \sum_{j=1}^{6} \delta_j Happiness_{t-j} + \sum_{j=1}^{6} \gamma_j Cryptocurrency_{t-j} + Covid_t + \varepsilon_t \tag{9}$$

$$Happiness_t = \sum_{j=1}^{6} \theta_j Happiness_{t-j} + \sum_{j=1}^{6} \mu_j Cryptocurrency_{t-j} + Covid_t + \vartheta_t \tag{10}$$

$Cryptocurrency_t$ indicates the return of each cryptocurrency, and the $Happiness_t$ refers to the growth of the happiness index. We consider the pandemic announcement as the beginning of Covid-19 and define our dummy variable as $Covid_t$ gets one if the date is 12 March 2020, the announcement date of the pandemic, otherwise zero. Based on the AIC, we use six lags in the Granger causality analyses.

Table 3 reports the results of Granger causality among variables. Chi-squares and p-values of each Granger causality test are given in Table 3. Our findings indicate that the causal relation between individual cryptocurrencies and the happiness index differs. There is a uni-directional relationship between BTC and the happiness index which runs from BTC to the happiness index. The result indicates that when BTC begins to increase or decrease, the investor starts tweeting regarding Bitcoin. Therefore, knowing the BTC movement helps us to forecast investor sentiment. In addition, there is a uni-directional link between ETH and the happiness index; however, the Granger causality runs from the happiness index to ETH, unlike the BTC. There is also a bi-directional link between BNB and the happiness index. In addition, Granger causality results for XRP and ADA are insignificant. Overall, the results indicate that the Twitter-based happiness index follows the movements of Bitcoin.

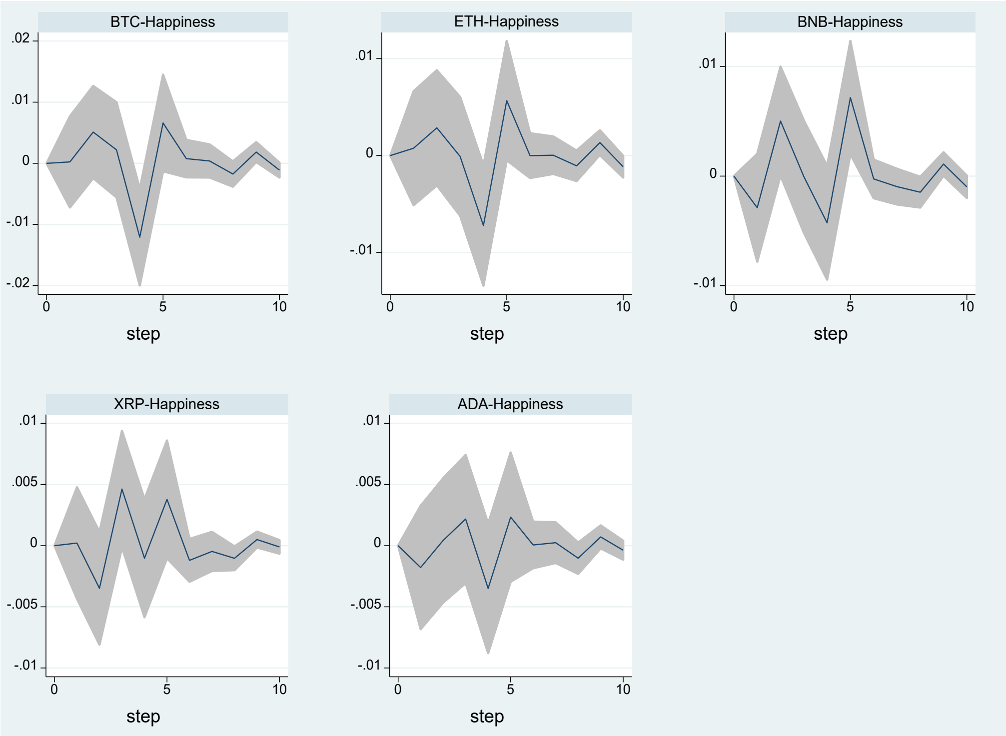
Table 3. Granger Causality Result

Variables	Chi-Squares	P-value
BTC → Happiness	13.022[b]	0.023
Happiness→ BTC	4.009	0.548
ETH→ Happiness	8.752	0.119
Happiness→ ETH	13.600[b]	0.018
BNB → Happiness	15.818[a]	0.007
Happiness→ BNB	12.702[b]	0.026
XRP→ Happiness	8.913	0.113
Happiness→ XRP	3.069	0.689
ADA → Happiness	3.680	0.596
Happiness→ ADA	8.930	0.112

Notes: a, b, and c show the statistical significance at the 1, 5, and 10 percent levels, respectively.

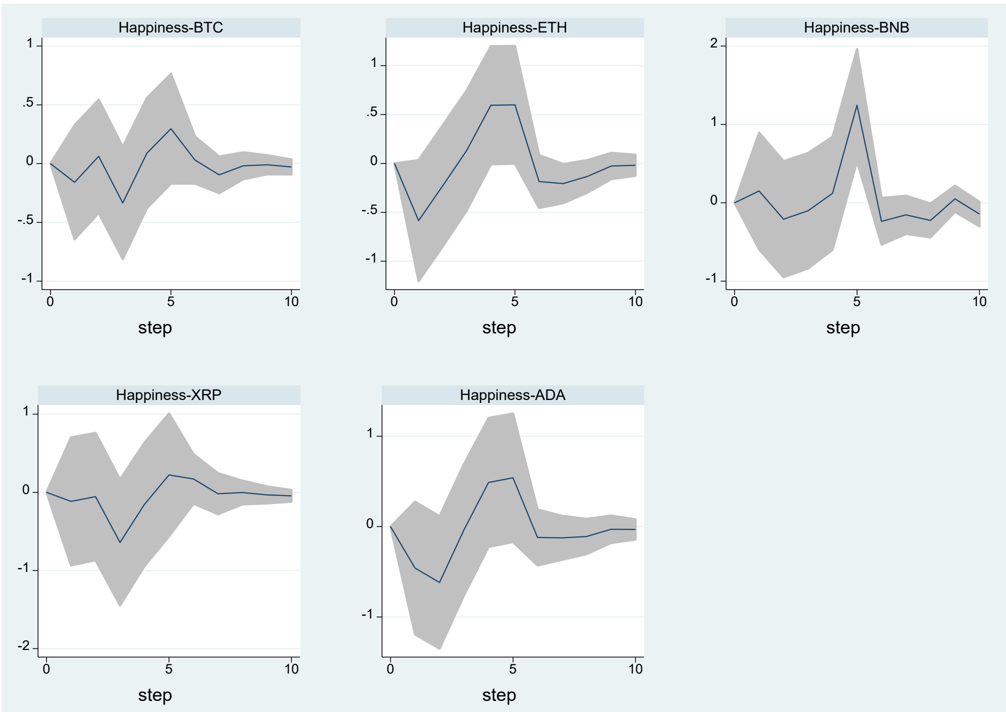
As a final step, we determine the impulse-response function between variables to capture the effect of one standard deviation shock to one of the covariates on the current and future values of the endogenous variables in the short run.

Graph 1 illustrates the response of the happiness index to the one-unit standard deviation shock to cryptocurrency returns. The graphs show that the response of the Happiness Index is similar to the shock in BTC, and ETH. The happiness index reacts negatively on the fourth day after the shock in BTC and ETH and quickly recovers around the sixth day. On the other hand, the happiness index increases on the second day and moves back to where it was before the shock in BNB and XRP on the seventh day. Moreover, the happiness index decreases on the fourth day after the shock in ADA and comes back to pre-level on the sixth day.



Graph 1. Impulse (Cryptocurrencies Returns) – Response (Happiness Index) Function

Graph 2 depicts the response of the cryptocurrencies to the one-unit standard deviation shock to the happiness index. The BTC graph shows that Bitcoin decreases around the fourth day after the shock and moves back to its pre-level on the seventh day. On the other hand, the responses of ETH, BNB, and ADA are stronger. At the initial level, ETH declines but on the third day, it goes up quickly and comes to the initial level after the seventh day of the shock. A positive response to BNB can be seen on the fifth day, and it comes back immediately. XRP negatively responds to the shock on the third day. ADA reacts similarly to the ETH and diminishes at the beginning and recovers after the seventh day.



Graph 2. Impulse (Happiness Index) – Response (Cryptocurrencies Returns) Function

5.DISCUSSIONS AND CONCLUSION

Asset pricing is one of the well-addressed topics in the finance literature. Accordingly, several asset pricing models such as the capital asset pricing model, and arbitrage pricing model are generated. These models mostly concentrate on classical financial assets with fundamental value. However, cryptocurrency, the new asset class, has neither fundamental value nor government support. Even though these drawbacks, the cryptocurrency market has experienced rapid growth that attracted investors and regulators. In parallel with this growth, a bulk of studies have been conducted regarding the cryptocurrency market.

The present study addresses the causality relationship between investor happiness and cryptocurrency returns to contribute to the cryptocurrency pricing literature. In this regard, we focused on five major cryptocurrencies, namely BTC, ETH, BNB, XRP, and ADA. Using daily data from January 1, 2019, to October 2, 2021, we investigate the causality between the Twitter Happiness Index and the returns of five cryptocurrencies by employing the Granger causality test.

The findings show that there is a uni-directional Granger causality running from Bitcoin returns (BTC) to the growth of the happiness index. It is significant at the 5% level. On the other hand, we do not find Granger causality from investor sentiment to BTC returns. Our results differ from Jo et al.'s study (2020), which reports that investor sentiment does Granger-cause Bitcoin returns, whereas Bitcoin returns do not Granger-cause investor sentiment. This difference may arise from either the investor sentiment measure used or the sample period adopted in the studies. Our investor sentiment measure is derived from social media data, whereas Jo et al.'s (2020) sentiment measures are survey-based (American Association of Individual Investors Sentiment Index) and market-based (VIX). Besides, our investor sentiment measure is constructed daily, while their investor sentiments are weekly and monthly bases. For Ethereum, we reveal that a uni-directional Granger causality exists from the happiness index to the Ethereum returns (ETH). This finding is parallel to those of Akyildirim et al. (2021) and Banerjee et al. (2022), which indicate that investor sentiment does Granger-cause cryptocurrency returns. On the other hand, there is a bi-directional Granger causality from Binance Coin (BNB) and happiness index. This finding endorses the results of Naeem et al. (2021), that implies investor happiness has a more powerful impact on cryptocurrency returns than investor fears. The impulse-response function shows that a one-unit standard deviation shock to BTC and ETH negatively affects the happiness index whereas a one-standard deviation shock to the happiness index increases the BTC and ETH in the short run. The impact of one-unit standard deviation shock to BNB and XRP on the happiness index is mixed.

In conclusion, our findings reveal that investor happiness is an important factor affecting cryptocurrency prices; indicating that investors can use sentiment analysis tools to make more informed investment decisions in the cryptocurrency market, and can adjust their portfolios according to the movements in the sentiment index. The Granger causality between investor sentiment and cryptocurrency returns may imply that cryptocurrency investors fear missing out on a potentially profitable investment. However, our results show that the investor sentiment-cryptocurrency returns relationship differs among individual cryptocurrencies. Therefore, an investor should also be careful about the shock in the happiness index which has a diverse impact on the top five cryptocurrencies.

The findings should be interpreted given the limitations of the study. First, the study considers the largest five cryptocurrencies. Thereby, investors should be aware that the investor sentiment-return relationship may vary for cryptocurrencies with smaller market capitalization (altcoins). Second, the investor sentiment indicator in the study is measured by investor happiness and derived from social media data. Employing alternative investor sentiment measures such as fear index, market- or survey-based investor sentiment indicators should be beneficial regarding the robustness of the results. Third, the sample period covered in the study spans from January 1, 2019, to October 2, 2021. Given these limitations, future studies can examine the investor sentiment-return relationship for a larger sample of cryptocurrencies adopting various investor sentiment indicators. Moreover, different sample periods may be used to capture the relationship.

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