Egyptian Bitcoin Investments: A Comprehensive Examination of Investor Sentiment Effects on Bitcoin Returns

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Abstract

This research investigates how Egyptian investor sentiment affects cryptocurrency returns, focusing specifically on Bitcoin. We utilized an enhanced investor sentiment index in Egypt, constructed through factor analysis of various literature-based variables. Our study's findings revealed a notable positive correlation between the investor sentiment index, lagged by one order, and Bitcoin returns, as per the estimation and analysis using VAR models. Analysis indicates that a one standard deviation change in the investor sentiment index leads to an alteration in the influence of each standard deviation of the original positive variable, resulting in a switch from positive to negative and vice versa in the medium and long term. Regarding variance decomposition, the short-term variance error of 100% is primarily explained by Bitcoin returns themselves. However, in the medium to long term, besides Bitcoin returns, the investor sentiment index emerges as the most influential variable affecting Bitcoin returns. Causality tests reveal a unidirectional short-term impact from the investor sentiment index to Bitcoin returns via Granger causality tests. Additionally, using the Toda-Yamamoto causality test, long-term bidirectional effects between Bitcoin returns and the investor sentiment index were observed.

Keywords: Cryptocurrency Behavior; Bitcoin, Egypt; Investor Sentiment; Factor Analysis; Vector Autoregressive (VAR) Model; Impulse Response Function (IRF); Forecast Error Variance Decomposition (FEVD); Granger Causality Test; and Toda-Yamamoto causality test

1. Introduction

The world has witnessed accelerated electronic development, which has brought about a radical change in the economic lifestyle, as several phenomena such as e-commerce and the digital economy have emerged. This did not stop to this extent but entered the world of cryptography, which increased the interest of financial researchers, physicists, and artificial intelligence pioneers in all their specialties to research the encryption mechanism. In addition to that, several virtual currencies appeared. During the past ten years, more than 2,000 virtual currencies were estimated in 2019. The most famous and successful of which was Bitcoin, which appeared in 2009. Many economists and financial analysts as a technological boom and revolution considered it. It came because of many circumstances dictated by the state of great development in all fields, especially in the fields of informatics, communications, software, and the development of international electronic trade.

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Bitcoin, which was launched by a programmer or a group of anonymous programmers, has turned into a parallel virtual economy that exceeds the size of the economies of stand-alone countries. This is because of the fact that many companies and global financial institutions have benefited from the rise of Bitcoin by accepting online payment in these currencies on the one hand. On the other hand, investing in it through its own wallet. This increasing spread of the currency was accompanied by a large fluctuation in its price, whether rising or falling within short periods and effects of skepticism in governments. Major companies and a large section of financial and business pioneers thought about the reality of Bitcoin and the extent of confidence in its trading, and about whether it is safe and the extent of its continuity and survival in the market. A large number of global economists differed and agreed upon supporting the emergence of such a type of electronic currency. However, in all ways, it simulates terrible technological progress and promises of a prosperous future although opponents and fears of such an intangible and unrecognized type. These fears can be overcome through neutral monitoring its movements and indicators.

The effects of the growing use of Bitcoin and the large fluctuations in its prices are a wide controversy among investors, economists, and regulators alike. This is especially true since it operates in an unclear regulatory environment, and the most dangerous thing is that it does not have a tangible physical presence. Therefore, price fluctuations do not directly affect global financial stability because they are not linked to any assets. Their fragile nature on the one hand and the increase in demand for them on the other hand can cause heavy losses to investors because of price fluctuations. Surprisingly, as many economists such as the Nobel Prize-winning economists, Joseph Stiglitz and Robert Shiller pointed out when they said that Bitcoin is a bubble that will soon burst causing an economic collapse - especially since human behavior is one of the main determinants of its price. Therefore, the contribution of this study is to examine to what extent can investor sentiment affect the movements of the virtual currency Bitcoin? The paper aims to understand the technical and financial aspects of Bitcoin, and know the most important factors determining it to avoid expected risks and effects; Study the behavior and volatility of Bitcoin yields; and Measure the impact of investor sentiment on Bitcoin.

The importance of the study lies in its treatment of a topic that is one of the focuses of interest on several levels, which is the trading of the virtual currency Bitcoin. It has spread in the countries of the world, where its price has witnessed a significant increase, and its total market value reached about $ 220 billion in 2021, representing about 51% of the virtual currency market, thus exceeding the market value of international companies (www.coinmarketcap.com). Identifying and analyzing the fundamental factors that lead to the high volatility of this currency and in particular the behavioral factors of investors has become important. This will help the engaged investors and financial managers in facilitating task of making expectations about this currency, and thus better-managing currency risk.

2. Literature Review

Several academic studies aimed to ascertain the impact of investor behavior on Bitcoin. Bukovina & Marticek's (2016) investigation into investor sentiment's effect on Bitcoin's volatility from 12/12/2013 to 31/12/2015 found minimal influence initially, but the explanatory power of sentiment notably increased during periods of heightened volatility. It emphasized the greater influence of positive investor sentiment on Bitcoin's volatility. Blau (2017) sought to link unusual Bitcoin volatility from 2010-2014 to speculation using the GARCH model. However, the study concluded that the extraordinary rise and fall in Bitcoin's value were not due to speculation. Conversely, Cheah & Fry's (2015) study suggested speculative bubbling in Bitcoin, indicating a zero-base price for Bitcoin. Estrada's (2017) research investigated Bitcoin's price and volatility, seeking causal links between Bitcoin's price, S&P index, Vix fear index, and blockchain technology measured via Google Trends data from 2010 to 2017. The findings revealed causal relationships between Bitcoin's price and blockchain technology, and a bidirectional causal link between Bitcoin's volatility, the Vix fear index, and the S&P 500 index at a 5% significance level. Jo Park & Shefirin's (2018) study, conducted from 2010-2012, used FAMA and French's contemporary capital asset pricing model to explore Bitcoin's resemblance to stocks with high sentiment beta. It concluded that Bitcoin returns exhibit similarities to sentiment-influenced stock returns, suggesting a susceptibility of Bitcoin to investor sentiment.

Perry & Carrera (2018) investigated the relationship between investor sentiment and Bitcoin prices by analyzing sentiment in over 500,000 tweets related to Bitcoin using the VADER method between 12/1/2017 and 31/31/2017. The study found a negative association between gold futures/market volatility and Bitcoin prices, but a positive link between Bitcoin prices and sentiment, indicating that Twitter sentiment analysis could forecast future currency returns. Om, Kazoji, Kang, & Pichl's (2019) research examined Bitcoin return characteristics and their ability to predict return volatility from 2011-2017. They observed a distinct distribution pattern in Bitcoin's returns, emphasizing the

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significant role of investor sentiment in predicting Bitcoin prices and volatility. Baig, Blau, & Sabah's (2019) study explained Bitcoin price fluctuations' concentration using various Bitcoin sentiment metrics from 2010-2018. The outcome highlighted a robust a beneficial association between sentiment and the concentration of Bitcoin volatility. Bianchi et al. (2020) explored the connection between significant bitcoin pairs and stable-coin connects using an extensive Bayesian vector autoregression (BVAR) model. This model, an extension of the classical VAR model, employs estimating a trajectory of autoregression using Bayesian techniques by Considering the parameters being entered to be independent variables and providing them with previous probabilities.

Regarding the extensive publications examining the connection between cryptocurrencies and investor sentiment, a comprehensive overview is available in various studies encompassing the development and ongoing study on cryptocurrencies (Corbet, Lucey, Urquhart, & Yarovaya, 2019; Bariviera & Merediz-Sol`a, 2021). The uncertainty surrounding cryptocurrency prices, returns, and the factors influencing them has been a focal point of investigation. Numerous studies have tied Bitcoin to investor sentiment, with different sentiment indices potentially exerting varied consequences and forecasting capabilities concerning the bitcoin industry, particularly evident during tumultuous periods like the latest worldwide epidemic (COVID-19) catastrophe. Anamika and Subramaniam (2021) highlighted that optimistic investor sentiment toward Bitcoin tends to correlate with increased Bitcoin prices, demonstrating the significant predictive power of Bitcoin sentiment even after controlling for relevant factors. Gaies, Nakhli, Sahut, and Guesmi (2021) studied the effect of sentiment among traders evaluated by the Cryptocurrency suffering indicator on the return of Bitcoin, revealing that pessimistic shocks have a more profound long-term impact on the rebound of bitcoin compared to optimistic shocks.

During the COVID-19 crisis, Hoang and Baur (2021) compared the influence of investor sentiment on cryptocurrency returns and volatility, finding that heightened coronavirus fears led to decreased returns and increased volatility. They also indicated the lack of a safe refuge provided by Bitcoin, while Google searches could predict cryptocurrency trends. Studies have consistently highlighted the usefulness of investor sentiment in forecasting the unpredictability and yields of cryptocurrencies. Corbet, Larkin, Lucey, Meegan, and Yarovaya (2020) developed a sentiment index based on news surrounding macroeconomic indicators, displaying that Bitcoin's reactions to news differ from those of the stock market. They argued that the cryptocurrency market's response to news could change based on the kind of electronic documents., suggesting that currency-based digital assets are more influenced by US monetary policy announcements compared to applications or digital resources founded on protocols. This trend also applies to mineable and non-mineable currencies, indicating different responses to uncertainties compared to Bitcoin returns.

The global COVID-19 outbreak significantly affected bitcoin investor sentiment and behavior, leading to increased volatility during periods of widespread lockdowns. Recent studies, including Guzmán et al. (2021) and Huynh et al. (2021), indicated increased investors in the pandemic's digital currency marketplace, particularly on days with limited mobility due to lockdown measures. These studies suggested that the rise in frequency and instability of trade in Bitcoin was prompted by increased uncertainty related to the pandemic, resulting in herding behavior among cryptocurrency investors. (Evrim Mandaci & Cagli, 2021; and Lee et al., 2021). Akyldirim, Corbet, Lucey, Sensoy, and Yarovaya (2020) discovered that heightened investors' fear correlates with increased volatility in cryptocurrency markets. Dwita Mariana et al. (2021) based on the WHO COVID-19 pandemic announcement, suggested Bitcoin and Ethereum served as short-term safe havens, despite their increased volatility during the crisis. Chen et al. (2021) applying the technique of extended quantitative regression found that only elevated quantiles of the Chinese Economic Strategy Amidst the COVID-19 circumstance, the returns of bitcoin were tremendously positively impacted by ambiguity. Hasen et al. (2021) investigated twelve securities between COVID-19 and the world's economic downturn of 2008, revealing that Bitcoin and gold acted as strong safe havens during extremely bearish market conditions. Ben Khelifa et al. (2021) examined the, observing an impact on conventional hedge fund strategies. Melki and Nefzi (2021) analyzed the advantages of Ethereum, Ripple, and Bitcoin beyond equities for security refuges and hedges, commodity, and foreign exchange markets during the COVID-19 pandemic, highlighting Bitcoin and Ripple's safe haven traits in the marketplaces for commodities and foreign exchange, with Ethereum showing stronger safe-haven attributes than Bitcoin. However, recent research by Chemkha et al. (2021) with the use of a multidimensional asymmetric static conditional correlation framework revealed Bitcoin, while serving as a hedging asset, contributed to reducing international portfolio risk but could not give elevated risk throughout the COVID-19 epidemic, it was viewed just a refuge. These findings suggest that there is tremendous instability in the digital currency marketplace. May become more vulnerable to fluctuations in pricing and investor thoughts, where behavioral elements like investor sentiment might play a significant role.

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Numerous studies in behavioral finance have focused on measuring investor sentiment in cryptocurrency markets. Works by L´opez-Cabarcos et al. (2019), Urquhart (2018), Shen, Urquhart, and Wang (2019), Ibikunle, McGroarty, and Rzayev (2020), and Lin (2020) have established investor sentiment as a key factor in explaining and predicting returns and volatility in cryptocurrency markets. Some studies have established a bi-directional causal relationship between investor focus and the results on Cryptocurrencies (Dastgir, Demir, Downing, Gozgor, & Lau, 2019). Additionally, the use of search volume, particularly from Twitter trends, has shown promise in short-term Bitcoin market prediction (Garcia & Schweitzer, 2015; Karalevicius, Degrande, & De Weerdt, 2018). Recent research has further endorsed the use of Twitter for explaining adjustments in a number of Cryptocurrency market variables such as return, volatility, and liquidity (Shen et al., 2019; Philippas, Rjiba, & Guesmi, 2019; Choi, 2021). There have also been efforts to discover new variables for measuring investor attention beyond Twitter and Google Trends, with these new variables being identified as crucial for understanding yields as well as turbulence (Sabah, 2020).

Moreover, there is an expanding body of research on empathy and Cryptocurrency. There are three primary theoretical justifications that motivate this paper. Identified in previous studies. First, different categories of investors may be attracted to specific cryptocurrencies like Bitcoin, with its speculative nature appealing more to Individual investors that view data accessible to everyone in an alternative manner than do major financial institutions. Second, there is a need to analyze the determinants of cryptocurrency prices, returns, and volatility. Third, sentiment remains relatively underexplored in the cryptocurrency market. As such, various approaches, including brand-new sentiment metrics proposed by Anamika and M., Subramaniam, S (2021), Hoang and Baur (2021), Gaies et al. (2021), and Corbet et al. (2020), have been suggested to capture the sentiment. However, research connecting the state of the cryptocurrency market and investors' mental state has been limited, often simplistic, and has not thoroughly explored the comprehensive predicting and descriptive ability of sentiment toward investors.

3. Theoretical Framework

Bitcoin has been able to reach all parts of the world due to its low cost, ease of use, speed in dealing, and prompt payment. It was defined as an encrypted digital "token" that is mined, and the code is given in exchange for discovering a solution to a digital dilemma as an incentive in exchange for hardware, energy and time. This contributes to the execution of transactions, encryption and preservation of their information record". It has been characterized as "a means of storing value, facilitating transfers among blockchain network participants, and being purchasable, sellable, or tradable for various currencies on dedicated exchanges. It represents an optimal form of online currency due to its speed, security, and boundless nature" (Owaisi, 2017, p. 42). Additionally, the European Central Bank has delineated it as a form of decentralized digital currency typically generated and managed by its creators, employed, and acknowledged within the Virtual Community by its members (European Central Bank, 2019).

We can see from the above definitions that Bitcoin is a cryptographic electronic virtual currency, not printed and not physical, but is dealt with electronically via the Internet. Central banks or any central issuing authority because it relies on a computer program designed to find and manage the currency offer, and is not creates this. In addition, due to the absence of a regulatory body for it, and trading operations are carried out in the peer-to-peer network between users directly without an intermediary or monitor, it can be convertible for additional international money including the dollar, the euro. The basic idea behind it is to dispense with the central authority when completing electronic transactions and to provide an innovative solution to a common problem in all payment systems and digital transactions, which is double payment.

The way this currency can be obtained is either to buy it from some companies or people via the Internet, or through an electronic process called mining. The latter is done through the Internet, which refers to the act of producing the computer to perform calculations and mathematical operations for the benefit of the cryptocurrency networking in order to increase security. These are complex calculations through which the operations that take place between electronic currency wallets are documented, audited and recorded. Processing cryptography algorithms and using a capacity measured by Hash Rate, and therefore whoever has a high Hash ability can decode and get the so-called Bitcoin units as a reward for this service (Abu Omaria, Shadid and Jaradat 2018: page 6). Recently, the concept of cloud mining has emerged, which works to help investors conduct the mining process without exposure to risks and without costing a lot of time and effort. The mining process depends on the computer processing power of those who participate in the virtual currency network and deal with a large amount of data, and at the same time compete with other senses of individuals and companies that mostly own devices specialized in the mining process. All operations are recorded and stored within a database, which is called Block chain. This chain is designed to preserve stored data

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so that it cannot be erased or modified and allows the recording any events, operations or activities. Therefore, it serves as a special ledger for currency and prevents double spending. In addition, no operation can be undone after payment except with the consent of the seller and the buyer. There are no litigation laws other than the blockchain law (Abu Omaria Shadid and Jaradat 2018).

Bitcoin represents a distinctive digital currency that has the potential to revolutionize digital transactions. It empowers consumers by enabling direct electronic inter-peer exchanges without the regard of the necessity of an in between, akin to cash transactions (Brito et. al., 2014). Through BTC transactions in the digital realm, individuals can seamlessly transmit payments to merchants without divulging personally identifiable information, thus reducing the risk of interception by cybercriminals for fraudulent purposes. However, a significant concern regarding BTC's widespread adoption as a currency lies in its security aspect. The absence of an intermediary raises apprehensions about the lack of coverage in case of BTC theft (Brito et. al., 2014). Given the notable 63% Year-to-Date (YTD) appreciation in 2016 and an 87% YTD increase in 2020, scrutinizing previous tendencies could aid in comprehending the potential behavior of BTC security, along with similar cryptocurrencies, since their beginning.

3.1. Bitcoin Ledger

Within the distributed ledger of Cryptocurrency, each block comprises an overview of each transaction within the utilize a Merkle tree for obstruction (also known as a binary hash tree). Initially, each transaction enters an assortment of outstanding transactions and then becomes part of the exchanges with the network, forming the blockchain (Antonopoulos, 2014). The blocks are interconnected through references to previous header hashes, and the inclusion of a transaction in the chain occurs via a process resembling a "mathematical lottery" (United States Securities and Exchange Commission, 2017). Miners solve mathematical problems through cryptographic hashing, facilitating the addition of transactions to the chain. This mathematical process aids wallet holders in determining the transaction order and accessing past transaction details.

3.2. Bitcoin Development Process

As new digital currencies seek to perform similar decentralized tasks, they encounter risks from inception to maturity. The three main attributes define a sound of an electronic currency, considering its success factors (Barski and Wilmer, 2015):

3.2.1. The Network Effect

The fundamental concept involves the willingness of individuals to use a currency as long as some people take it in exchange for money. Unless the method of payment method has been backed via a robust network. a cryptocurrency's liquidity might deter people from using it.

3.2.2. Cryptocurrency Volatility

For a newly established bitcoin used as a mode of payment, stability in it's determine worth is crucial for consumer confidence. BTC, as a relatively new asset, requires buyers and sellers to agree upon its value. BTC's historical volatility, fluctuating from as low as $355 in 2016 to $15,000 in 2020, raises concerns among consumers, despite comparable volatility in some traditional currencies, like the Zimbabwean hyperinflation.

3.2.3. Cryptocurrency-Pegging Technology

With a capped supply of 21,000,000 BTC, increased adoption has somewhat reduced its volatility. BTC's established user network has conferred credibility, aiding its acceptance and minimizing volatility compared to other digital currencies. New e-coins entering the market might benefit from pegging their stability to more established cryptocurrencies like BTC.

3.3 Market Participants

Several market participants warrant deeper analysis due to their roles in the market:

1. Miners: Responsible for providing data about transactions to the open blockchain of Bitcoin and supporting BTC supply.
2. Individual investors: Acquire digital assets to use for purchasing goods or services.
3. Payment mechanism: Facilitates international business transactions through BTC.

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4. Retail investors: Incorporate the currency into portfolios for hedging, mirroring traditional currency market exposure.

3.4 Stakeholders

The adoption of cryptocurrencies impacts various stakeholders, both formal and informal, including savers/investors, government entities, cryptographers, BTC exchanges/brokers, illegal markets, BTC miners, and the public. Stakeholders seek consistency and potency in any transaction medium, but some may oppose BTC's widespread adoption due to its decentralized nature, where no single entity controls its value, raising concerns for governments and certain cryptographers.

3.5 The development of Bitcoin and its returns

The purchase price of Cryptocurrency has witnessed a remarkable fluctuation over the past few years, as its first trading price reached 0.001 US dollars per bitcoin, as the exchange activity of this currency at the beginning of its emergence was very slow. Then exceeded one dollar for the first time in February 2011 to reach $ 1.1. It began to grow during the years to reach $ 1131.97 by the end of 2013. But it returned sharply to reach about $ 428 by the end of 2015. Since the beginning of 2017 and because Investors as well as the journalists have contributed great focus on the currency as a result of the technical solutions it has given in the execution of operations, rising and achieving record 50% levels reaching $19,497 in December. During 2018, the price fell more than $ 13657.20 in January to $ 3742.70 at the end of December, to witness a rise in June 2019 to exceed $ 13700, which is the highest level since the last significant rise in 2017. Finally, the highest level over the research period was in November 2021 exceeding $ 64978.89 (www.coinmarketcap). The following figure shows its development:

3.6 Factors affecting Bitcoin

3.6.1 Regulatory and legislative regulations, and international recognition: Many empirical studies have indicated that prices respond quickly to any decision regarding the regulation of electronic currencies or their official recognition, since the emergence of these currencies, governments have made great efforts to give a regulatory framework to virtual currencies, so they were welcome, and some of them took an aggressive position towards virtual currencies such as China and Korea, and therefore the lack of clarity in regulation increases price fluctuations.

3.6.2 Technical factors: Although Bitcoin is a decentralized currency, some decisions related to the way it works, circulates, and develops affect its price The programs in which Bitcoin is traded are usually created by developers, and managed by miners, and therefore a rise in the mining workforce of the currency and the rise in mining result in a rise in its number and affects its value, due to the high costs associated with hardware and electrical energy consumption in addition to competition with devices specialized in mining.

3.6.3 News and statements: News related to Bitcoin is one of the most important determinants of the currency, and these events and statements from important figures are a double-edged sword, as bad news leads to investors skeptical of Bitcoin and therefore investors tend to sell it, which results in the currency taking a downward curve, and the opposite is true when good news and support Bitcoin.

3.6.4 Behavioral factors: Economists pointed out that the behavioral factors of investors and their morale play a pivotal role when making an investment decision in general and in Bitcoin in particular, in some periods the performance of Bitcoin is not related to the relevant circumstances, and is linked to the behavioral biases committed by the investor, most notably herd behavior, as the main goal of investors and speculators, especially small ones, is to achieve the greatest profit in the least possible time, so once Bitcoin rises, they rush to offer the currency for sale, which causes A severe drop in its price, and if the price falls, they rush to buy, which raises its price again, in the future, and behavioral biases are also optimism, pessimism and fear, in addition to rumors that are complex and high-risk, as well as their rapid viral spread, and the effects of their rapid and large spread are clearly reflected.

4. Methodology

The study is focused on the entire population of cryptocurrencies traded in Egypt. Specifically, it utilizes Bitcoin's returns data as a case study to test the two primary hypotheses. The analysis spans from October 2010 to December 2021, establishing a time-series based on monthly data sourced from the internet (www.investing.com) considering the availability of data in the choice of the beginning period month. The monthly returns of the Bitcoin are calculated

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by using the monthly close prices of the Bitcoin. In other words, return is calculated by taking the naturel logarithm of the result obtained from dividing the t's close price by that of t-1 (Campbell et al., 1997). In addition, the used data is available in dollar terms. We converted it into Egyptian pound terms depending upon the Close price of Dollar-Egyptian Pound exchange rate extracted from the internet (www.bloomberg.com).

This study assesses Egyptian investors' behavior using a sentiment index indicating two conditions: optimistic (bull) or pessimistic (bear) attitudes (El-Gayar, 2021). To enhance this index, four proxies are utilized, focusing on the primary constituent subject based on data availability. These proxies capture variations in four underlying sentiment indicators, obtained from consumer transactions, equities funds that are open-end, closed-end mutual fund reductions, and risk tolerance indexes (Kumar and Persaud, 2002; Bandopdhyaya and Jones, 2006; El-Gayar, 2021). However, evaluating and quantifying investor sentiment remains a challenge in academic research (Baker and Wurgler, 2007). There is no universally decided to definitive measure for investor sentiment, leading to ongoing debates on the effectiveness of each proxy.

Prior studies have employed diverse methods to quantify investor sentiment. One approach involves direct sentiment measures, such as surveys designed to capture market participants' outlook. For instance, US-oriented research (Brown and Cliff, 2004; Fisher and Statman, 2000) focused on surveys like the American Association of Individual Investors (AAII) sentiment index and the Investor Intelligence services (II) to categorize various investor types. Conversely, indirect sentiment indicators, observed through variables such as savings on willingness to take risks indexes, retail trading, stock funds, and restricted bond funds, are utilized in much of the literature. While these indirect measures lack a strong theoretical connection to investor sentiment, they mitigate issues related to direct measurement, such as sample size limitations and statistical representativeness. Additionally, indirect measures are often obtained more frequently (e.g., monthly) and offer real-time insights into market participants' strength of optimism or pessimism (Brown and Cliff, 2004). The advantages of using indirect measures include their simplicity, ease of establishment, and real-time reflection of market participants' sentiments and attitudes. (Shams, 2018):

Table 1: Summary of Measures of Sentiment Used in Prior Research

Measure (s)	Definition (s)	Prior Research
Put-Call Ratio **Mutual Fund Cash Position**	Puts outstanding/Calls outstanding Net cash flow into MF's Survey of individual investors	Dennis and Mayhew (2002) Randall *et al.* (2003) Fisher and Statman (2000, 2003)
Price %	Gross annual equities issued/Gross annual debt & equity issued	Baker and Wurgler (2006, 2007)
IPOs Volume	Average annual first-day returns on IPOs	Baker and Wurgler (2006, 2007)
Turn Over "Market Activity"	Reported share volume/Average # of listed shares	Baker and Wurgler (2006, 2007)
Closed-End Fund Discounts	$\Delta\ VWD_t = VWD_t - VWD_{t-1}$	Lee *et al*, (1991) and Doukas and Milonas (2004)
Seat prices	Trading volume or quoted bid-ask spread	Keim and Madhavan (2000)
Risk Appetite index Investor Fear Gauge	Spearman Rank correlation volatility versus excess returns Implied option volatility	Kumar and Persaud (2002) Whaley (2000)

(Source: Abdel Hameed, 2012)

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Table 1 summarizes measures of sentiment employed in prior research as the approach outlined by Baker and Wurgler in 2006 and 2007 emphasizes the absence of a flawless index specifically representing investor sentiment. Instead, they advocate for employing various accessible yet imperfect proxies for sentiment that likely encompass aspects of investor sentiment to some extent. Given this perspective, the optimal strategy is to integrate multiple available proxies, considering as many as possible, and construct a composite index based on common characteristics shared among these proxies.

El-Gayar (2021) found a significant positive direct impact of his used investor sentiment index as well as liquidity in the stock market. This asserts that we can also add any measure of stock market liquidity to his index to denote investor sentiment more precisely. Thus, we used the trading volume of Egx30 to during our used period to capture the liquidity part of the sentiment index. The researchers can initially introduce all of their 5 used indices in bigger detail below:

1. CLOSED-END MUTUAL FUND DISCOUNT INDEX

Closed-end funds, which issue a set quantity of units that can be traded on the market for securities, have long been considered a barometer of investor confidence through their discounts. The pricing discrepancy between these funds' stock prices and their net asset value (known as the "closed-fund mystery") is believed to reflect individual investors' sentiment (Lemmon and Portniaguina, 2006). Researchers like Lee et al. (1991), Neal and Wheatley (1998), and Swaminathan (1996) found a connection among fund reductions, fragile stock returns, and accessibility. They recommend that during the event that retail investors mostly hold closed funds; the average discount of these funds could serve as a sentiment indicator.

However, recent evidence questions the accuracy of closed-end fund discounts as a reliable gauge of the general attitude of investors. Qiu and Welch (2006) demonstrate that these discounts do not consistently correspond with sentiment about investors' information from UBS/Gallup or customer trust metrics. Brown and Cliff (2004) similarly find a weak correlation among sentiment among investors and fund price reductions measured by the American Association of Individual Investors.

A Closed-End Fund Discount (CEFD) measures the disparity within the permanent asset's net asset value of capital funds' shares and their market price. This metric has been linked to sentiments in previous studies. Zweig (1973) used CEFD to predict Dow Jones stock reversals, while Lee et al. (1991) attributed various characteristics of closed-fund discounts to sentiments.

Li et al. (1991) and Doukas and Milonas (2004) developed a weighted discount index primarily based on closed funds. This study also employs this technique, consistent with numerous sentiment-related studies in the literature. The cumulative discounted index's development is outlined as follows:

$$\mathbf{VWD_t} = \sum_{t=1}^{n_t} \mathbf{W}_i\, \boldsymbol{Disc_{it}} \qquad (1)$$

Where,
* VWD_t is the value-weighted index of month-t discounts.
* Disc is the closed-end fund discount, and

$$\mathbf{w_i} = \frac{NAV_{it}}{\sum_{t=1}^{n_t} NAV_{it}} \qquad (2)$$

* NAV_{it} is the net asset value of fund i at end of month t.

$$\boldsymbol{Disc_{it}} = \frac{\mathbf{NAV_{it}} - SP_{it}}{\mathbf{NAV_{it}}}\ \mathbf{X\ 100}, \qquad (3)$$

* SP_{it} is the Market Price of fund i at the end of month t.
* n_t = the number of funds with available Disc $_{it}$ and NAV_{it} data at the end of period t.

Furthermore, alterations in the value-weighted index of monthly discounts are calculated. To compute this measure, the researcher follows a methodology akin to that used for the weighted discount index. However, it is necessary for every fund included within the index to possess available DISC (discount) and NAV (net asset value) data for both month t and t - 1. This ensures that the monthly changes within the index are computed over the same asset base across consecutive months. The researchers then define $\Delta\ VWD_t$ to be:

$$\boldsymbol{\Delta VWD_t = VWD_t - VWD_{t-1}} \qquad (4)$$

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2. EQUITY OPEN-END MUTUAL FUND FLOWS INDEX

Information regarding how mutual fund investors distribute their investments across fund categories is readily accessible (Baker and Wurgler, 2007). Studies conducted by Brown and Cliff (2004, 2005), Lee et al. (1991), Malkiel (1977), and Neal and Wheatley (1998) have established that the Mutual funding movement can serve as an indicator of investor sentiment. Brown and Cliff (2005) examined investor sentiment in both the United States and Japan by employing investor sentiment index statistics on the daily movement of mutual funds, discovering its significance in both markets. Frazzini and Lamont (2006) found supportive evidence indicating that the movement of funds could reflect the sentiment surrounding individual stocks. Their study revealed that stocks experiencing substantial inflows from funds tended to perform relatively poorly in subsequent periods. Previous scholarly work has established a beneficial association between mutual fund flows and investor sentiment. Additionally, researchers have devised various methods for calculating mutual fund flows, as demonstrated by Sirri and Tufano (1998):

$$\boldsymbol{FLOW_{it}} = \frac{\boldsymbol{TNA_{i,t} - TNA_{i,t-1}\,(1 + R_{i,t})}}{\boldsymbol{TNA_{i,t-1}}} \tag{5}$$

Where, the term $FLOW_{it}$ represents the flow of fund *i* at the end of month *t*, and $TNA_{i,t}$ stands for the total net assets of fund *i* at the end of month *t*;

$$\boldsymbol{R_{i,t}} = \frac{\boldsymbol{P_{i.t}}}{\boldsymbol{P_{i,t-1}}} - \boldsymbol{1}, \tag{6}$$

Where, the two terms $P_{i.t}$ and $P_{i,t-1}$ represent the share prices of fund *i* at the end of months *t* and *t – 1*, respectively. The average flow of all A-type mutual funds can be computed as below:

$$\boldsymbol{AFLOW_t} = \frac{\boldsymbol{1}}{\boldsymbol{n}}\sum_{\boldsymbol{i-1}}^{\boldsymbol{n}} \boldsymbol{FLOW_{i,t}}. \tag{7}$$

3. RETAIL TRADES (BUY-SELL IMBALANCE) INDEX

Novice retail Traders are thought to be more impacted by the attitude of investors compared to professional institutional investors. A growing body of empirical evidence suggests that the security returns moving together is linked to the trading behaviors of various investor groups. For instance, Barber et al. (2006) analyzed trading volume and observed the fact that ordinary investors consistently purchase stocks with strong current results and a substantial trade volume, indicating a shared psychological bias that affects their trading decisions. These biases collectively affect stock prices.

Kumar and Lee (2006) examined micro-trade data and found that retail investors tend to buy and sell shares together, aligning with the sentiment of the market, which is crucial for individual actions to influence prices. They provided direct evidence that the transactions of individual investors are linked to stock returns, particularly regarding equities where a significant portion of investors are buying at the retail level.

Analyzing individual investor orders on the New York Stock Exchange, Kaniel et al. (2004) discovered that these transactions could predict market-wide stock returns. Stocks that garnered the most interest from investors in a given week exhibited an average excess return of 1.4% over the subsequent 20 days.

Boyer (2006) suggested that similar trading patterns might account for some relationships between stocks with comparable book value-market value ratios. Meanwhile, Soeren (2008) used micro-transaction trading volume to investigate the correlation between retail investors' trading behavior and future equity returns. His main finding indicated that stocks with low trading volume prompted by intense selling outperformed those with low trading volume driven by strong buying. This performance gap persisted for up to three years, indicating that stocks favored by retail investors after an extended period of underperformance could yield better returns.

Kumar and Lee (2006) proposed the use of Buy Imbalance (BSI) as a measure of total investor trading activities within a specific period. BSI determines whether retail investors are net buyers (stock BSI > 0, indicating an overall positive sentiment) or net sellers (stock BSI < 0, indicating an overall negative sentiment) during a given period. Monthly BSI can be calculated to ascertain the period's directional sign of net consumer demand:

$$\boldsymbol{BSI_{it}} = \frac{\sum_{\boldsymbol{j=1}}^{\boldsymbol{D_t}}(\boldsymbol{VB_{ijt} - VS_{ijt}})}{\sum_{\boldsymbol{j=1}}^{\boldsymbol{D_t}}(\boldsymbol{VB_{ijt} + VS_{ijt}})} \tag{8}$$

Where in the equation provided, 'Dt' represents the number of days in the month 't'. 'VB_{ijt}' signifies the dollar-

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denominated buy volume for stock '*i*' on day '*j*' of month '*t*', while 'VS_{ijt}' denotes the dollar-denominated sell volume for the same stock '*i*' on day '*j*' of month '*t*'.

4. RISK APPETITE INDEX

In prior research, indicators such as the Put Call Ratio and VIXInvestor Fear Gauge were utilized to gauge investor sentiment in the stock market. However, Kumar and Persaud (2002) demonstrated that these measures might capture shifts in potential market risks or changes in investors' perceptions of these risks, making it challenging to distinguish between these two phenomena.

On the other hand, the Risk Appetite Index (RAI) developed by Persaud (1996) and the Stock Market Sentiment Index (EMSI) based on Bandopadhyaya and Jones (2006) offer advantages in this context. RAI and EMSI are structured in a manner that separates potential market risks from their impact on these measures. Consequently, these indices more accurately portray alterations in market attitudes toward risk. They particularly focus on the risk versus reward balance inherent in pricing, aiming to represent the market's willingness to embrace the inherent risks at a given moment.

It seems like the construction of the Risk Appetite Index (RAI) involves several steps based on the methodology developed by Bandopdhyaya and Jones (2006). Here is an attempt to rephrase and complete the provided information: The creation of the Risk Appetite Index (RAI) involved utilizing daily market price data spanning from 2004 to 2021. To formulate RAI, the first step was to compute the average monthly return derived from EGX 30. Subsequently, the average standard deviation of returns, also known as "historical volatility," was determined for every month during the designated sample period.

Following this, a categorization of monthly returns and historical volatility was conducted. This involved determining the Spearman interval correlation coefficient between the monthly income interval of each company and the historical volatility interval on a monthly basis, as follows:

$$\mathbf{RAI} = \frac{\sum(\boldsymbol{R_r}-\bar{R}_r)(\boldsymbol{R_v}-\bar{R}_v)}{[\sum(\boldsymbol{R_r}-\bar{R}_r)^2\sum(\boldsymbol{R_v}-\bar{R}_v)^2]^{1\backslash 2}} \quad \mathbf{*\ 100}\ ; \qquad -100 \leq EMSI \leq +100 \qquad (9)$$

Where, R_r, and R_v, are the rank of the monthly return and the historical volatility, respectively. In addition, $\bar{R}_r$ and $\bar{R}_v$ are the population mean return and historical volatility rankings, respectively.

5. TRADING VOLUME

The trading volume, often referred to as liquidity, has a critical function in financial market interactions among different investors. It represents the average daily volume of shares exchanged within a specified period. This volume of transactions is indicative of market liquidity and is influenced by various economic forces. Analyzing trading volume can provide valuable insights into the functioning of market liquidity, and it can be calculated on a daily, weekly, yearly, or other suitable time interval for analysis.

In the context of investor sentiment, trading volume is considered an essential indicator. According to Baker and Wrugler (2007), high trading volumes or liquidity can reflect investor sentiment. For instance, Baker and Stein (2004) highlighted that when short-selling costs exceed the expenses of opening and closing long positions (as often occurs in practice), irrational investors are more inclined to trade when optimistic about rising stock prices, contributing to increased liquidity. Scheinkman and Xiong (2003) noted that trading volume reveals differing opinions among investors, which can be linked to valuation levels, especially in situations where short selling is challenging. Market turnover, described as the proportion of the volume of trade to all shares registered at the Stock Exchange, serves as a straightforward proxy for this concept.

Additionally, two control variables, namely Gold Return and Bitcoin Bid-Ask Spread, were employed in this study to control for other potential influential factors on the dependent variable, Bitcoin Return. Gold Return represents a macroeconomic factor used to control for the influence of the metal market on cryptocurrency prices (Bouoiyour and Selmi, 2015). Cryptocurrency prices are influenced significantly by market participants and are affected by market microstructure factors. Baek and Elbeck (2015) used Bitcoin bid-ask spread as an indicator of liquidity in their analysis of cryptocurrencies. Table 2 shows the summary of research variables and their measurements.

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Table 2: Summary of Research Variables and their Measurements

Measure	Calculation
Dependent Variable (Bitcoin Return)	
The monthly closing prices for each Bitcoin are used to compute the average monthly gains. In other words, return is calculated by taking the naturel logarithm of the result obtained from dividing the t's close price by that of t-1. In addition, the used data is available in dollar terms. We converted it into Egyptian pound terms depending upon the Close price of the Dollar-Egyptian Pound exchange rate.	
Independent Variable (Investor Sentiment)	
1. Closed-End Mutual Fund Discount Index	$VWD_t = \sum_{t=1}^{n_t} W_i \, Disc_{it}$ Where, A) VWD_t is the value-weighted index of month t discounts. B) Disc is the closed-end fund discount: B.1 $Disc_{it} = \frac{NAV_{it} - SP_{it}}{NAV_{it}}$ X 100, B.2 NAV_{it} is the net asset value of fund i at end of month t. B.3 SP_{it} is Market Price of fund i at the end of month t. C) $w_i = \frac{NAV_{it}}{\sum_{t=1}^{n_t} NAV_{it}}$ D) n_t =the number of funds with available Disc $_{it}$ and NAV_{it} data at the end of period t. E) $\Delta VWD_t = VWD_t - VWD_{t-1}$
2. Equity Open-End Mutual Fund Flows Index	$$FLOW_{it} = \frac{TNA_{i,t} - TNA_{i,t-1}\left(1 + R_{i,t}\right)}{TNA_{i,t-1}}$$ Where, A) $FLOW_{it}$ is the flow of fund i at the end of month t. B) $TNA_{i,t}$ is the total net assets of fund i at the end of month t. C) $R_{i,t} = \frac{P_{i.t}}{P_{i,t-1}} - 1,$ where $P_{i.t}$ and $P_{i,t-1}$ are the share prices of fund i at the end of months t and t – 1, respectively. D) The average flow of all A-type mutual funds is computed as below: $$AFLOW_t = \frac{1}{n}\sum_{i-1}^{n} FLOW_{i,t}.$$
3.Retail Trades Index (Buy-Sell Imbalance)	$$BSI_{it} = \frac{\sum_{j=1}^{D_t}(VB_{ijt} - VB_{ijt})}{\sum_{j=1}^{D_t}(VB_{ijt} + VB_{ijt})}$$ Where, A) D_t is the number of days in month t. B) VB_{ijt} (VS_{ijt}) is the dollar-denominated buy (sell) volume for stock *i* on day *j* of month *t*.
4. Risk Appetite Index	RAI = $\frac{\sum(R_r - \bar{R}_r)(R_v - \bar{R}_v)}{[\sum(R_r - \bar{R}_r)^2 \sum(R_v - \bar{R}_v)^2]^{1\backslash 2}}$ * 100 ; $-100 \leq EMSI \leq +100$ Where, A) R_r, and R_v, are the rank of the monthly return and the historical volatility, respectively. B) Return = (Close Price-Open Price/Open Price) * 100 & $$\text{Volatility} = \sigma = \sqrt{\frac{\sum_{i=1}^{n}(R_i - R_{avg})^2}{n-1}}$$ C) $\bar{R}_r$ and $\bar{R}_v$ are the population mean return and historical volatility rankings, respectively.

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5. Trading Volume Index	The average number of shares traded per day during month t-1.
Control Variables Affecting Dependent Variable (Bitcoin Return)	
1. Gold Return	- The monthly returns are calculated by using the monthly close prices of the Gold. - In other words, return is calculated by taking naturel logarithm of the result obtained from dividing the t's close price by that of t-1. - Also, the used data is available in dollar terms. - We converted it into Egyptian pound terms depending upon the Close price of the Dollar-Egyptian Pound exchange rate.
2.Bitcoin Bid-Ask Spread	The B*id-Ask Spread* for the Bitcoin is calculated as the difference between the monthly close (sell) and open (buy) prices of the Bitcoin.

The research is conducted in an analytical manner utilizing long-term collected second-hand information from October 2010 until December 2021 using four statistical techniques, namely factor (1st. principal component) analysis, method selection for the time-series data analysis, Vector Autoregressive (VAR) analysis, and causality tests.

4.1 Factor (1st. Principal Component) Analysis:

4.1.1 Constructing Index:-

Because there is no consensus among researchers regarding a precise definition of sentiment, given its multiple contextual interpretations, agreement remains elusive. Even if one researcher comprehends sentiment transparently, others may differ in their views. For instance, some may link sentiment with investor optimism, while others may associate it with a broader concept like general risk appetite. The measurement methods for sentiment also diverge widely among scholars. Evaluating investor sentiment proves challenging, with numerous measures proposed, spanning from direct surveys by analyzers of markets to indirect assessments using financial information, valuations, and stock kinds. Baker and Wurgler (2006, 2007) similarly approached sentiment analysis concerning the New York Stock Exchange mood.

Considering the findings that unrelated elements coexist within each sentiment measure, Principal Component Analysis (PCA), as introduced by Brown and Cliff (2004) and Baker and Wurgler (2006, 2007), aims to disentangle these shared elements. This study incorporates various sentiment indicators proposed in recent research and amalgamates them into a comprehensive sentiment index using their primary principal component. The selected sentiment indicators—such as Closed Funds Discount (CEFD), variable capital mutual funds flow, Retail Trade Index (BSI), and risk appetite index (RAI)—might intermingle elements of sentiment with other disparate components. Hence, PCA is employed to discern common elements and construct the sentiment indicator using the main idea constituent method.

The first principal component represents a linear set of parameters and factors selected to obtain the most significant collective variation within the series. PCA streamlines the variables by reducing redundancy among them, revealing the principal elements that explain most of the variance. These components can serve as predictive or standard variables in result analyses. PCA is not tied to any specific causal model and aims to reduce variables into a smaller set of components that explain the observed variance. Ultimately, PCA is a technique for variable reduction, typically yielding a handful of components explaining most variance in the observed dataset.

4.1.2 Assessment of the Suitability of the Data for Factor Analysis:-

Principal Component Analysis (PCA) is typically conducted on a sizable dataset to ensure reliable outcomes. For robust results, it is suggested that a minimum of 100 subjects providing usable data or several subjects at least 5 times greater than the variables under analysis should be employed. Analyzing a small dataset often yields different factors compared to those derived from a larger sample. However, some researchers emphasize that the total sample size alone is not the sole focus when assessing data decomposition.

Two statistical measures are commonly utilized to evaluate the appropriateness of the data for factor analysis: Bartlett's sphericity test (Bartlett, 1954) and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Kaiser, 1960, 1970, 1981; Kaiser and Rice, 1974). Bartlett's test should yield a significant result ($p < 0.10$) to be deemed suitable for factor analysis. On the other hand, the KMO index, which ranges from 0 to 1, serves as a metric for adequate

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sampling. A minimum value of 0.5 is recommended for conducting a reliable Principal Component Analysis (Tabachnick and Fidell, 2001; SPSS Survival Manual, 2005).

4.2 Method Selection for the Time-Series Data Analysis:

4.2.1 Method Selection Framework:-

Selecting the suitable techniques for time series investigation is crucial as it directly affects the reliability of the estimates. The selection process typically relies on unit root tests to ascertain the stationarity of the variable under examination. Different methods are employed based on whether the variables are stationary or non-stationary. If all the variables of interest exhibit stationarity, simpler methods like Ordinary Least Squares (OLS) or Vector Autoregressive (VAR) models can be used to derive unbiased estimates. However, when all variables are non-stationary, these models might not be suitable to analyze their relationships. Challenges also arise when dealing with a mix of variable types – some stationary and others non-stationary.
A comprehensive methodology for longitudinal analysis follows. The parameters for technique selection in Figure 1 offer a basic approach, but it is important to note that time series involve several additional factors models beyond these criteria.

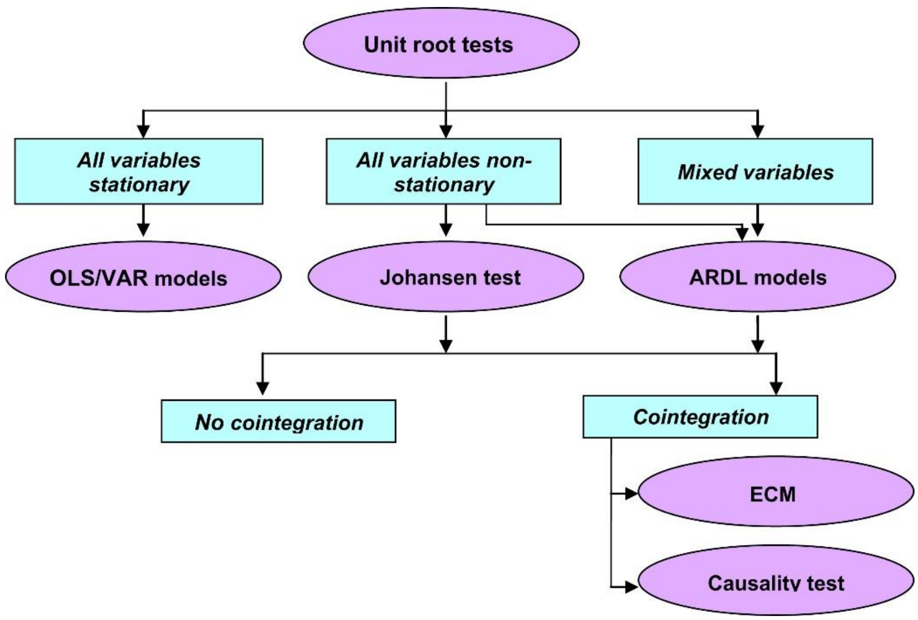

Figure 1. Method selection for time series data. OLS: Ordinary least squares; VAR: Vector autoregressive; ARDL: Autoregressive distributed lags; ECM: Error correction models.
(Source: Shrestha & Bhatta, 2018)

4.2.2 Time-Series Adjustment (KPSS Stationarity Test):-

Many time series, especially financial ones like stock price indices, often display non-stationary behavior or trends. When a series is non-stationary, using it in regressions without transforming it into a stationary form or establishing a stationary co-integration relationship with other non-stationary series might lead to spurious regression (Xu and Sun, 2010). As the research period spans about eleven years, structural modifications to the market, technology, competition, and financial market activities could cause the data series to become non-stationary. Consequently, the researcher may conduct various unit root assessments for every series to ascertain if transformations are required to achieve stationarity. Among the popular approaches to assessing if time series information is stationary are the Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992) test.

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In this research, given that the ADF and PP tests usually yield similar conclusions, the researcher opts to conduct the ADF and KPSS tests. One drawback of the Augmented Dickey-Fuller (ADF) test is its minimal power consumption while almost irregular, meaning the process is close to being stationary but with a root near the non-stationary boundary (Brooks, 2002). Consequently, the researcher solely employs the KPSS test, where the null hypothesis posits that the sequence does not move.

To determine whether a unit root is present, the study calculates the T-statistic and compares it to critical values at different significance levels. If the test statistic is lower or greater than the edge of the values at the selected significant level, the null hypothesis of stationarity for the series is not rejected. Rejection of the null hypothesis suggests the series contains a unit root. However, before performing the KPSS test, the researcher must decide whether to consist of in the analysis of regress, a permanent and an exponential trend, or neither. One feasible approach is to conduct the test with a tendency that is both steady and linear, encompassing the other two cases as special instances of this broader specification (Verbeek, 2004).

The conventional KPSS test can be excessively large for extremely autoregressive systems as it uses an estimator that estimates the procedure's long-run variance that is semi-parametric and by autocorrelation and heteroskedasticity (HAC), which introduces notable limited sampling bias that is beneficial. However, different bandwidths can be chosen for the HAC estimator than those suggested by KPSS. The choice of bandwidth in finite samples involves a trade-off: selecting a larger bandwidth overestimates the long-run variance, resulting in an understated test statistic and reduced power, while a smaller bandwidth, when the process is highly autoregressive, underestimates the long-run variance, leading to an inflated test statistic. Even with a more appropriate estimator for the long-run variance under the null hypothesis, the KPSS-type test might not be rectified. A limited number of long-term variance estimations that perform well under the null can cause the KPSS-type test to be inconsistent for random walk alternatives, implying that its power for certain relevant alternatives doesn't reach 1 as the sample size increases. This study proposes an automated form of the KPSS-test to mitigate the size distortion without encountering inconsistency (Hobijn, Franses, & Ooms, 2004).

4.3 Vector Autoregressive (VAR) Model:

4.3.1 Optimum Number of Lags Order Selection:-

The VAR lag order selection approach, as utilized in this research, involves choosing the best number of lags for the Vector Autoregressive (VAR) model. To determine this optimal number of lags, the study employed VAR lag order selection criteria, as outlined by Braun and Mittnik in 1993.

4.3.2 Vector Autoregression Analysis Estimation:-

Vector Autoregressive (VAR) models play a crucial role in describing the dynamic relationships among economic, financial, and even meteorological variables. They are instrumental in studying interactions, analyzing relationships, forecasting various metrics including earnings, sales, and foreign exchange rates, and predicting changes in consumer behavior over time. These models offer flexibility and success in the realm of multivariate time series analysis (Abdullah, 2022).

The inception of Vector Autoregressive models dates back to Sims' introduction in 1980, and they have since become a cornerstone in economic research. Lutkepohl's work in 1991 stands as a primary citation for VAR models and their implementations. In the financial domain, Hamilton (1994) and Tsay (2005) have significantly contributed to their utilization and understanding.

VAR models expand upon univariate autoregression models by incorporating multiple variables treated as endogenous factors. In these models, each variable forms an equation comprising lagged values of that same variable and lagged values of all other variables within the model (Mohr, 2018).The VAR(p) model of order p can be represented in the following formula:

$$y_t = c + A_1 y_t{=}1 + A_2 y_{t-2} + \dots + A_p y_{t-p} + \varepsilon_t \qquad (10)$$

As,

- $y_t = (y_{1t} \dots\dots y_{kt})'$ denote an $(k\, x 1)$ vector of time series variables,
- **c** is a k-vector of constants serving as the intercept of the model,
- $A_i = (i = 1.2 \dots\dots p)$ denote an $(k\ x\ k)$ matrices of parameters, and
- ε_t denote an $(k\, x 1)$ vector of random error

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$\varepsilon_t = (\varepsilon_{1t} \ldots \varepsilon_{kt})'$ with mean zero and variance covariance matrix $\sum(\varepsilon_{1t}\varepsilon_t)'$. Moreover, to ensure stability in a Vector Autoregressive (VAR) model, the Eigenvalues of the matrix A_i should be less than one. Additionally, the random error vector ought to exhibit a normal distribution with a mean of zero and a variance-covariance matrix ($\sum$). In the VAR model, the diagonal elements of matrix A represent the identical variable's autoregression settings throughout time. On the other hand, the off-diagonal elements denote cross-autoregression parameters, illustrating the impact of each variable at time '*t*' on another variable at time '*t - 1*'.

A bivariate VAR (1) model can be represented as follows:

$$y_t = c + A_1 y_{t-1} + \varepsilon_t \qquad (11)$$

As,

- $Y_t = \binom{y_{1t}}{y_{2t}}$,
- $A_t = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$, and
- $\varepsilon_t = \binom{\varepsilon_{1t}}{\varepsilon_{2t}}$, $C = \binom{C_{1t}}{C_{2t}}$

Thus,

$$\binom{y_{1t}}{y_{2t}} = \binom{c_{1t}}{c_{2t}} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \binom{y_{1t-1}}{y_{2t-1}} + \binom{\varepsilon_{1t}}{\varepsilon_{2t}}$$

Each equation can be written separately:

$$y_{1t} = c_1 + a_{11} y_{1t-1} + a_{12} y_{2t-1} + \varepsilon_{1t}$$

$$y_{2t} = c_2 + a_{21} y_{1t-1} + a_{22} y_{2t-1} + \varepsilon_{2t}$$

4.3.3 Testing Vector Autoregression Analysis Model Stability Condition:-

The constancy of an estimated Vector Autoregression (VAR) model can be assessed by examining the reverse roots of the AR (AutoRegressive) characteristic polynomial. If all the characteristic roots of the system fall within the unit circle, fulfilling the requirement for consistency, it confirms that the series are stationary. This verification also indicates the appropriateness of the mathematical form utilized in the study.

4.3.4 Impulse Response Funtion (IRF):-

According to Ghozali & Latan (2012), the Impulse Response Function (IRF) analyzes the effects of a shock, or an invention, on a variable within a system of multiple variables over a specified period. IRF helps in understanding the dynamic reaction of each variable to a standard deviation of innovation. It measures the direction of movement of each variable resulting from changes in other variables. This model is instrumental in predicting the patterns of shocks or effects among variables.

4.3.5 Forecast Error Variance Decomposition (FEVD):-

As per Rusiadi, Subiantoro, & Hidayat (2014), Variance Decomposition assesses the variation in a variable resulting from its own fluctuations and shocks from other variables. Anticipating an error Variance Decomposition (FEVD) is utilized to ascertain the relative significance of different shocks on a particular variable and other related variables. The Cholesky decomposition method is employed to identify FEVD. This analysis is aimed at understanding the influence or contribution among interconnected variables.

4.4 Causality Tests (Granger Causality Test and Toda-Yamamoto Causality Test):

4.4.1 Granger Causality Test (Short-Term):-

Granger Causality (GC) was initially developed in econometrics to explore causal connections between multiple time series (Granger, 1969). In this study, we apply GC to a pair of variables. To establish that one variable, let's say X, Granger-causes another variable, say Y, means that by utilizing previous values of both X and Y, we can make better predictions about future values of Y than by relying solely on past observations of Y. Essentially, past data from variable X offers valuable predictive information about Y, beyond what can be gleaned from Y's own past observations. Consider a bivariate time series represented by the dynamic relationship:

$$Y_t = \varphi_0 + \sum_{j=1}^{n} \alpha_j Y_{t-j} + \sum_{j=1}^{n} \beta_j X_{t-j} + \varepsilon_{1t} \qquad (12)$$

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$$\mathbf{X_t} = \lambda_0 + \sum_{j=1}^{n} \boldsymbol{\delta_j X_{t-j}} + \sum_{j=1}^{n} \boldsymbol{\omega_j Y_{t-j}} + \boldsymbol{\varepsilon_{2t}} \quad (13)$$

If $\beta = (\beta_1, \dots \beta_n)^T$ is not the zero vector $(0, .. 0)^T$ and $\omega = (\omega_1, \dots \omega n)^T$ is the zero vector $(0,..0)^T$, then X is said to Granger cause Y. If ω isn't a zero vector while β is a zero vector, it implies that Y Granger-causes X. Conversely, if neither β nor ω is a zero vector, it suggests a mutual relationship between X and Y, signifying feedback between the two variables. However, when both β and ω are zero vectors, Granger causality is absent. These terms denote the white noise innovation at each time instance 't', assumed to be independently and identically distributed following a bivariate normal distribution. The terms $\varphi_0$and λ_0 represent intercepts for each equation.

4.4.2 Toda-Yamamoto Causality Test (Long-Term):-

The Granger Causality test, while versatile and widely used, does have its limitations. Firstlyexecuting a Granger-Causality analysis with a pair of variables without taking into account the influence of other variables may lead to potential model specification biases. Gujarati (1995) highlighted this sensitivity to model specification and lag numbers, emphasizing that omitted relevant variables could significantly alter the results, making the empirical evidence fragile.

Secondly, time series data often exhibit non-stationarity, leading to the issue of spurious regression (Maddala, 2001). Gujarati (2006) also noted that when variables are integrated, the F-test procedure becomes invalid due to the non-standard distribution of test statistics. Although individual coefficients can still be tested for significance using t-statistics, the joint testing of Granger Causality using F-statistics becomes problematic. Enders (2004) demonstrated that under specific conditions, F-statistics could be used to test first-difference VAR when a two-variable VAR has a two-period delay duration along with an irregular factor.. Further drawbacks among these assessments gave been elaborated in Toda and Phillips (1994).

Toda and Yamamoto (1995) proposed an alternative method that involves estimating an augmented VAR, ensuring the asymptotic distribution of the Wald statistic, providing an interesting and straightforward approach to address these limitations. (An asymptotic χ^2-distribution), given that the testing protocol is resilient to the process's integration and combining features. We use a bivariate VAR (m + d_{max}) comprised of bitcoin return and investor sentiment index, following Yamada (1998);

$$X_t = \omega + \sum_{i=1}^{m} \theta_i X_{t-i} + \sum_{i=m+1}^{m+d_{max}} \theta_i X_{t-i} + \sum_{i=1}^{m} \delta_i Y_{t-i} + \sum_{i=m+1}^{m+d_{max}} \delta_i Y_{t-i} + v_{1t} \quad (14)$$

$$Y_t = \psi + \sum_{i=1}^{m} \varphi_i Y_{t-i} + \sum_{i=m+1}^{m+d_{max}} \varphi_i Y_{t-i} + \sum_{i=1}^{m} \beta_i X_{t-i} + \sum_{i=m+1}^{m+d_{max}} \beta_i X_{t-i} + v_{2t} \quad (15)$$

Where X= investor sentiment index and Y=bitcoin return, and ω, θ's, δ's, ψ, φ's and β's are parameters of the model. d_{max} is the maximum order of integration suspected to occur in the system; $\nu_{1t} \sim N(0, \Sigma_{v1})$ and $\nu_{2t} \sim N(0, \Sigma_{v2})$ are the residuals of the model and Σ_{v1} and Σ_{v2} the covariance matrices of ν_{1t} and ν_{2t} , respectively. The null of non-causality from bitcoin return to investor sentiment index can be expressed as H_0: $\delta_i = 0, \forall\ i = 1, 2, \dots, m$.

The implementation of the procedure involves two crucial steps conducted in VAR model estimation and analysis. The first action comprises determining the lag length (m), while the second step entails selecting the maximum order of integration (d_{max}) for the variables in the system. Various measures such as the Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), Final Prediction Error (FPE), and Hannan-Quinn (HQ) Information Criterion are commonly employed to ascertain the suitable lag order of the VAR. These criteria aid in choosing the most appropriate model structure by considering factors like model complexity and goodness of fit.

Following hypothesis was created for testing using the previously mentioned techniques:

- **H1**: There is a quantitatively relevant beneficial result of the Egyptian investor sentiment on the return of each bitcoin.

Figure 2 displays the primary empirical framework that is employed for testing the hypothesis of this research, as shown below:

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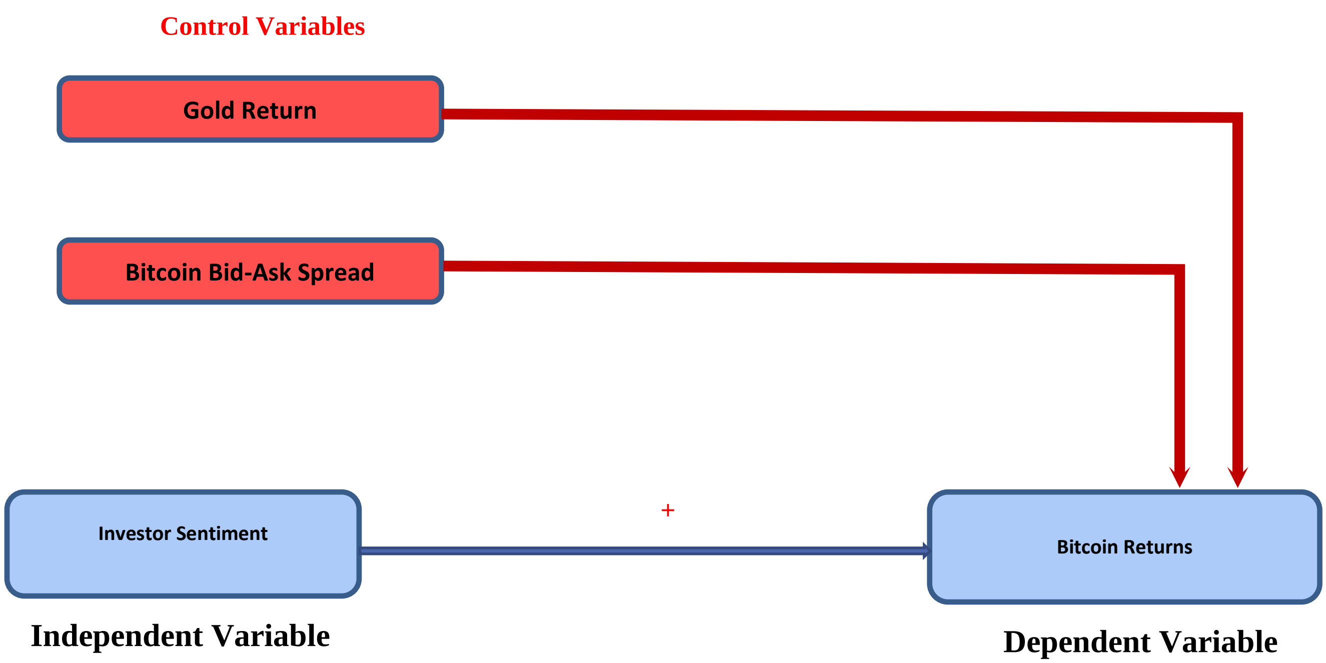

Figure 2. The General Empirical Model

5. Results and Discussion

5.1 Factor (1st. Principal Component) Analysis for Constructing an Improved Investor Sentiment Index:

The table indicates that the Bartlett test and KMO are considered appropriate for this study. 3 below:

Table 3: KMO and Bartlett's Test to Assess the Factorability of the Data

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.505
Bartlett's Test of Sphericity	**Approx. Chi-Square**	17.278
	df	10
	Sig.	.068

In this context, the table indicates that Bartlett's test of sphericity displays significance with a value of .068, falling below the 10% significance level. Furthermore, the initial primary component reports. For 50.5% of the variance observed in the adjusted variables. Moreover, Table 4 illustrates the outcome of the initial principal component matrix derived from the four enhanced proxies representing investor sentiment:

Table 4: First Principal Component Matrix
Component Matrix[a]

ΔVWDt	.468
Mutual Funds Flows	.693
Retail Trades (Buy-Sell Imbalance) Index	-.116
Risk Appetite Index	-.750
Trading Volume	.076

Extraction Method: Principal Component Analysis.
a. 1 components extracted.

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Thus, the equation that ensues can be used to build an enhanced investor sentiment index based on the primary component that is first in the matrix in the previous table 4:

Investor Sentiment Index = 0 .468 ΔVWD_t

+ 0 .693 Mutual Funds Flows
- 0.116 Retail Trades (Buy-Sell Imbalance) Index
- 0.750Risk Appetite Index
+ 0.076 Trading Volume

5.2 KPSS Unit Root Test for Time-Series Adjustments:

According to the findings presented in Table (5), the null hypothesis of stationarity remains unrefuted for all the series examined. For instance, in the case of Bitcoin Return, the test statistic is 0.508867, lower than the critical value at the 1% significance level of 0.739000. This pattern persists across the other stationary variables.

Table 5: Unit Root (KPSS) Test at Level
(Before Differencing)

Series to be Tested	1% Critical Value	KPSS Statistic
Dependent Variable (Bitcoin Return)	0.739000	0.508867
Independent Variable (Investor Sentiment Index)	0.739000	0.146088
Control Variables:		
Bitcoin Bid-Ask Spread	0.739000	0.471269
Gold Return	0.739000	0.144755

5.3. Statistical Description of Research Variables and Correlation Matrix:

Examining the descriptive statistics in Panel a of Table 6, the dependent variable, bitcoin return, shows a maximum of 4.7%, a minimum of -0.39%, a mean of 0.19%, a median of 0.08%, and a standard deviation of 0.59%. The independent variables representing the investor sentiment index range between 80.5 and 75.67, with a mean of -17.06, a median of -74.19, and a standard deviation of 72.6. Regarding the control variables, the bitcoin bid-ask spread has a maximum of 17485.2, a minimum of -20420.5, a mean of 374.1, a median of 1.4, and a standard deviation of 3207.8. Lastly, the gold return shows a maximum of 12.292%, a minimum of -12.154%, a mean of 0.352%, a median of 0.097%, and a standard deviation of 4.601%.

Table 6: Describing Research Variables
Panel A: Descriptive Statistics

	Bitcoin Return	Investor Sentiment Index	Bitcoin Bid-Ask Spread	Gold Return
Mean	0.18720	-17.06307	374.12741	0.352
Median	0.07817	-74.19183	1.4	0.097
Standard Deviation	0.59106	72.56986	3207.7699	4. 601
Minimum	-0.38878	-80.52134	-20420.5	-12.154
Maximum	4.70276	75.67466	17485.2	12.292

Panel A displays the study variable statistical data. The sentiment among investors indicator is the variable that is independent and under investigation. The dependent variable examined is the bitcoin return. The control variables examined are bitcoin bid-ask spread and gold return.

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Table 7: Describing Research Variables
Panel B: Correlations Matrix

	Bitcoin Return	***Investor Sentiment Index***	***Bitcoin Bid-Ask Spread***	***Gold Return***
Bitcoin Return	1			
Investor Sentiment Index	-0.0049	1		
Bitcoin Bid-Ask Spread	-0.0014	0.0422	1	
Gold Return	-0.04386	-0.0238	0.0298	1

The relationship between the study variables is displayed in Panel B. This study looks at the investor sentiment indicator as a distinct factor. The dependent variable examined is the bitcoin return. The control variables examined are bitcoin bid-ask spread and gold return.

Panel B of Table 7 demonstrates the Correlations between variables occurring simultaneously between the factors that the analysis employed. Notably, the correlations between each variable are all below 0.80, indicating an absence of multicollinearity between variables (Gujarat, 2003). There exists a negative relationship between the dependent variable (bitcoin return) and the independent variable (investor sentiment index). Furthermore, there is a negative correlation between the Bitcoin bid-ask spread and its return. Additionally, a positive relationship is observed between gold return and bitcoin bid-ask spread. Moreover, a positive correlation is identified between bitcoin bid-ask spread and the investor sentiment index. Lastly, a negative correlation exists between gold return and both bitcoin return and the investor sentiment index. Despite these results possibly conflicting with existing theory and literature, it is important to note that this solely presents a description of the raw data used in this research.

5.4 Method Selection for the Time-Series Data Analysis:

Since all the variables of interest are stationary, the vector autoregressive (VAR) model can provide unbiased estimates.

5.4.1 Vector Autoregressive (VAR) Model Estimation and Analysis:

5.4.1.1 Optimum Number of Lags Order Selection:-

According to VAR lag order selection criteria as demonstrated in table 8, only lag order of six satisfies one criterion (namely, sequential modified LR test statistic (5% level)). The rest lag orders do not satisfy any criterion. Thus, we decided to use a lag order of six for our model estimation.

Table 8: VAR Lag Order Selection Criteria

Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
1	-1803.364	21.27291	34727920	28.71440	29.16230	28.89638
2	-1793.014	19.23418	37989127	28.80337	29.60959	29.13093
3	-1783.839	16.47127	42381419	28.91085	30.07540	29.38399
4	-1775.710	14.08215	48146399	29.03480	30.55767	29.65352
5	-1750.815	41.55648	42096520	28.89473	30.77592	29.65903
6	**-1732.040**	**30.15886***	**40643061**	**28.85102**	**31.09054**	**29.76091**
7	-1723.250	13.56461	46078066	28.96457	31.56241	30.02004
8	-1710.469	18.92110	49254996	29.01525	31.97142	30.21631

The asterisk (*) denotes the lag order chosen by the criterion. LR represents the sequential modified LR test statistic, with each test conducted at a 5% significance level. FPE refers to the Final Prediction Error. AIC stands for the Akaike Information Criterion. SC indicates the Schwarz Information Criterion. Lastly, HQ represents the Hannan-Quinn Information Criterion.

5.4.1.2. Vector Autoregression Analysis Estimation:-

The following table 9 demonstrates VAR & Least Squares (LS) Estimates:

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Table 9: VAR & Least Squares (LS) Estimates

Lags	**VAR Estimates**	**Least Squares (LS) Estimates**		
	Bitcoin Return	**C**	**Coefficient**	**Prob.**
Bitcoin Return (-1)	0.144354 -0.09689 [1.48992]	**C(1)**	0.144354	0.1370
Bitcoin Return (-2)	0.120849 -0.09932 [1.21676]	**C(2)**	0.120849	0.2244
Bitcoin Return (-3)	0.004584 -0.09877 [0.04641]	**C(3)**	0.004584	0.9630
Bitcoin Return (-4)	-0.03068 -0.10114 [-0.30330]	**C(4)**	-0.030675	0.7618
Bitcoin Return (-5)	-0.12684 -0.09968 [-1.27246]	**C(5)**	-0.126843	0.2039
Bitcoin Return (-6)	0.088981 -0.09593 [0.92753]	**C(6)**	0.088981	0.3542
Investor Sentiment Index (-1)	0.001974 -0.00082 [2.39755]	**C(7)**	0.001974	0.0169
Investor Sentiment Index (-2)	0.000235 -0.00083 [0.28440]	**C(8)**	0.000235	0.7762
Investor Sentiment Index (-3)	-0.00128 -0.00083 [-1.53986]	**C(9)**	-0.001277	0.1244
Investor Sentiment Index (-4)	-0.0004 -0.00084 [-0.47265]	**C(10)**	-0.000399	0.6367
Investor Sentiment Index (-5)	-2.24E-06 -0.00084 [-0.00268]	**C(11)**	-2.24E-06	0.9979
Investor Sentiment Index (-6)	0.001245 -0.00082 [1.51062]	**C(12)**	0.001245	0.1316
Bitcoin Bid-Ask Spread (-1)	-1.68E-05 -2.10E-05 [-0.78731]	**C(13)**	-1.68E-05	0.4315

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Bitcoin Bid-Ask Spread (-2)	5.32E-06 -2.50E-05 [0.21680]	**C(14)**	5.32E-06	0.8285
Bitcoin Bid-Ask Spread (-3)	9.56E-06 -2.50E-05 [0.37758]	**C(15)**	9.56E-06	0.7059
Bitcoin Bid-Ask Spread (-4)	-2.04E-05 -2.60E-05 [-0.79158]	**C(16)**	-2.04E-05	0.4291
Bitcoin Bid-Ask Spread (-5)	-5.01E-06 -2.60E-05 [-0.19348]	**C(17)**	-5.01E-06	0.8467
Bitcoin Bid-Ask Spread (-6)	-1.32E-05 -2.70E-05 [-0.49277]	**C(18)**	-1.32E-05	0.6224
Gold Return (-1)	-0.23274 -1.21527 [-0.19151]	**C(19)**	-0.232740	0.8482
Gold Return (-2)	-0.1732 -1.19742 [-0.14464]	**C(20)**	-0.173195	0.8851
Gold Return (-3)	0.859839 -1.20765 [0.71199]	**C(21)**	0.859839	0.4769
Gold Return (-4)	1.338114 -1.18767 [1.12668]	**C(22)**	1.338114	0.2605
Gold Return (-5)	-1.6096 -1.19606 [-1.34575]	**C(23)**	-1.609599	0.1791
Gold Return (-6)	-1.09301 -1.21959 [-0.89621]	**C(24)**	-1.093013	0.3707
C	0.187003 -0.07509 [2.49054]			
R^2	0.185185			

From the above table (8), we can conclude that there is a positive (0.001974) significant (0.0169 that is less than 5%) effect of the investor sentiment index with -1 order lag upon bitcoin return. This means that a strengthening of investor confidence by 1% results in an increase in bitcoin return by 0.001974 in the next period. Thus, when Egyptian investors become optimistic (bull), there is an increase in bitcoin return. In addition, R^2 equals 18.5185%, which means that our independent variable (investor sentiment index) in hand with the two used control variables (bitcoin bid-ask spread and gold return) explains only 18.5185% of the change in our dependent variable (bitcoin return). This weak explanatory power of our used VAR model can be attributed to the non-existence of other variables that may affect bitcoin return, but we did not use in it.

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5.4.1.3 Testing Vector Autoregression Analysis Model Stability Condition:-

The drawn inverted root of the AR distinctive polynomial of the calculated Vector Autoregression (VAR) is depicted in Figure 3. It is observable that all the characteristic roots of the system stay within the unit circle, meeting the stability condition required for the model. This confirmation indicates that the series is stationary, validating the appropriate mathematical form utilized in this study. Therefore, the VAR analysis can advance based on these stable conditions.

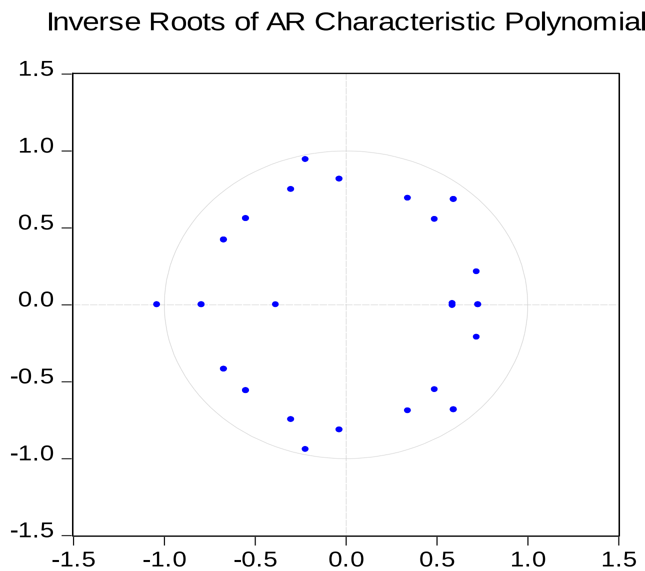

Figure 3. Inverse roots of AR characteristic polynomial of the estimated Vector Autoregression

5.4.1.4 Impulse Response Function (IRF):-

The conclusion drawn from the response to one standard deviation from the returns suggests a reversal of influence. Every variation from the mean of the initial beneficial variable is observed to transform into a negative effect and vice versa in the medium and long term.

Table 10: Summary of Impulse Response Function (Bitcoin Return)

Term	Short (1 Period)	Medium (5 Periods)	Long (10 Periods)
Bitcoin Return	+	-	-
Investor Sentiment Index	+	+	+
Bitcoin Bid-Ask Spread	+	-	+
Gold Return	+	+	+

The analysis from table 10, summarizing the Impulse Response Function (IRF) for bitcoin return, reveals several observations. In the short term, bitcoin return showed a positive response to all variables considered in the study. In the medium term, there was a negative response observed in relation to itself and the bitcoin bid-ask spread, while a positive response was noted in connection with the investor sentiment index and gold return. Looking at the long term, bitcoin return exhibited a negative response in relation to itself, but a positive response in association with the investor sentiment index, bitcoin bid-ask spread, and gold return.

Moreover, from the investor sentiment index, it was observed that each standard deviation of the original positive variable changed, transitioning from positive to negative and vice versa in both the medium and long terms.

5.4.1.5 Forecast Error Variance Decomposition (FEVD):-

Variance Decomposition is a method used to gauge the percentage contribution of each variable in the short-term, medium-term, and long-term scenarios. It serves as a valuable tool for policymaking aimed at controlling these variables. Employing the variance decomposition method in EViews yielded the subsequent outcomes showcased in table 11:

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Table 11: Summary of Variance Decomposition (Bitcoin Return)

Term	Short (1 Period)	Medium (5 Periods)	Long (10 Periods)
Standard Error (SE)	0.595299	0.641650	0.661796
Bitcoin Return	100.0000%	90.99550%	87.88629%
Investor Sentiment Index	0.000000%	6.541183%	6.873011%
Bitcoin Bid-Ask Spread	0.000000%	1.316294%	2.033439%
Gold Return	0.000000%	1.147020%	3.207258%

From the data presented in Table 11, several key observations can be made. In the short term (period 1), the entirety of the forecasted variance error, constituting 100%, is attributed to the bitcoin return itself. Other variables show no response in this initial period; their response becomes noticeable only in the subsequent period.

In the medium term (period 5), approximately 90.99550% of the estimated variance error is accounted for by the Bitcoin return. Among the additional variables influencing bitcoin returns, the investor sentiment index holds a proportionate influence of about 6.541183%, followed by the bitcoin bid-ask spread at 1.316294%, with the gold return exerting the least influence at 1.147020%.

Examining the long term (period 10), the bitcoin return itself explains roughly 87.88629% of the estimated variance error. Similarly, the investor sentiment index displays a notable impact on bitcoin returns, contributing approximately 6.873011%. Following this, the gold return contributes around 3.207258%, while the bitcoin bid-ask spread demonstrates the least impact, accounting for 2.033439% of the variance error.

Additionally, the Standard Error (SE) values for the bitcoin return expectation indicate an increase from 59.53% in period 1 to 66.18% in period 10. This increase suggests a lack of assurance in past period expectations for independent variables within our model.

5.5 Causality Tests (Granger Causality Test and Toda-Yamamoto Causality Test):

5.5.1 Granger Causality Test (Short-Term):-

From table 12, we conclude that there is only short-term impact in one way from investor sentiment index to bitcoin return. In other words, the two null hypotheses of no impact of this test are rejected for the impact of bitcoin return upon investor sentiment index at 5% significance level. This is because the value 0.0207 is less than 5%. Moreover, the reverse is true for the impact of investor sentiment index on bitcoin return. This simply strength the multiple regression analysis results.

Table (12): Granger Causality Test

There is no Impact	Significance Level
Investor Sentiment Index	
From it to Bitcoin Return	0.0207
From Bitcoin Return to it	0.3322

5.5.2 Toda-Yamamoto Causality Test (Long-Term):-

From Table (13), we conclude that there are long-term bidirectional effects between bitcoin return and investor sentiment index. In other words, the two null hypotheses of no impact of this test are rejected at 10% significance level. This is because the values 0.0867 and 0.0654are less than 10%.

Table (13): Toda-Yamamoto Causality Test

There is no Impact	Significance Level
Investor Sentiment Index	
From it to Bitcoin Return	0.0867
From Bitcoin Return to it	0.0654

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6. Conclusion

Bitcoin currency imposed a new reality on the international investment scene. Despite its modernity compared to other currencies, it was able to compete with these ancient currencies strongly and even spread and expanded in the market to the point of shaking the thrones of financial institutions and international and central banks. So, this study tried to research the impact of investor sentiment on it, and reached the following results: The VAR model estimation and analysis reveal a noteworthy positive and significant impact of the investor sentiment index, specifically with a lag of -1 order, on bitcoin returns.; Upon examining the effects of a single standard deviation change in the investor sentiment index, it is evident that this change causes an alteration in influence. Originally, positive variables tend to switch to negative and vice versa, notably observed in the medium and long terms. As per the variance decomposition analysis, the short-term outcome determines that the entire estimated variance error (100%) is explained solely by the Bitcoin return itself. However, in both the medium and long terms, the investor sentiment indicator emerges as the variable that exerts the most influence on bitcoin returns beyond its own impact. Depending upon causality tests, there is only short-term impact in one way from investor sentiment index to bitcoin return applying the Granger causality test. In addition, there are long-term bidirectional effects between bitcoin return and investor sentiment index using Toda-Yamamoto causality test. Bitcoin still needs to be studied given its subtle technical dimensions, as well as its riskier character. Therefore, one of the most important pillars that must be available in Bitcoin is that global governments put in place sufficient safeguards to maintain the credibility of the real financial value of Bitcoin. In addition, besides all the previous, we recommend setting the foundations, regulations, and instructions that regulate the process globally.

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