Determinants of Ethereum Return: Insights from Bitcoin, Investor Sentiment, and Financial Markets

Zhouyun Zhao[1,a,*]

[1]Mentor College, 40 Forest Ave, Mississauga, ON L5G 1L1, Canada
a. junozhao8@gmail.com
**corresponding author*

Abstract: The study explores the spillover effect on Ethereum – one of the leading cryptocurrencies – stemming from key variables in the domains of cryptocurrencies, investor sentiment, and traditional financial markets. This paper is the first to analyze the influence of such dominant representatives from diverse, external fields on cryptocurrency. We select bitcoin, the Fear and Greed index, the Standard and Poor's 500 index and the United States Dollar to Euro Exchange Rate as representatives to investigate the spillover effect on Ethereum. Utilizing linear regression models and vector autoregressive (VAR) models, we find strong correlations between Ethereum's return and that of Bitcoin's, along with investor sentiment. However, the influence of financial market variables on Ethereum are found to be virtually static and negligible. This research offers valuable insights to those seeking to forecast or manipulate crypto market movement through analyzing the complex interplay between these variables and Ethereum.

Keywords: Ethereum, Bitcoin, Financial market, Sentiment, VAR

1. Introduction

In recent years, cryptocurrencies have become widely accepted due to their efficient yet transparent payment systems, which are independent from the control of political bodies. Despite their recent contraction, they had a peak market value of over $2 trillion and they remain as one of the most prominent markets with a value at over $1 trillion dollars [1]. More notably, there are over 12,000 different forms of currencies that are actively traded by the 420 million crypto users worldwide [2]. As one of the most analyzed sensations in the modern age, cryptocurrencies have consistently demonstrated their unstable price fluctuations, as seen through the instance of Ethereum. From October of 2021 to December of 2022, Ethereum's price plummeted from a stunning $3001.13 to merely $1295.77. In this study, Ethereum is analyzed to explore the influences financial influences of its new decentralized, open blockchain system. Additionally, Ethereum, as the world's second most valuable and most traded cryptocurrency behind Bitcoin, is a prominent aspect of the present economy. Recently, studies have explored diverse aspects of Ethereum: including examinations regarding its blockchain technology, factors affecting its prices, its sustainability, its liquidity, its transaction dynamics, and its price movements [3-8].

Nowadays, Ethereum is often viewed as the leading account in the industry, but it remains prone to outer influences, and its price is predicted to be affected by numerous factors stemming from other markets [9-10]. Similar to how the crypto market is susceptible to the external conditions, the use and

© 2023 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

adoption of cryptocurrencies often impact the universal economy [11]. Their broad influences across different markets are mostly due to their high levels of volatility: high degrees of instability and unpredictable price changes [12]. For example, if the crypto market experiences a sudden contraction, investors are likely to react to this risk by selling their assets in other financial markets, leading to a temporary sell off. As a result, apparent changes in areas such as standard financial perspectives, consumer investment behavior, and the popularity of traditional currencies are caused by cryptocurrencies, and this impact can be categorized under one phenomenon – the spillover effect.

As one of the most significant concepts in analyzing cross-market relations, the spillover effect is widely explored in the fields of finance and economics. Especially in the crypto-industry, models such as the vector autoregression (VAR) model are developed through extensive research to accurately examine the effects factors may have during various times of uncertainty. Özdemir utilizes three main methods – EGARCH model, DCC-GARCH model, and wavelet-based methods – to analyze the return and volatility spillover of eight main cryptocurrencies during times of uncertainties (including Bitcoin, Ethereum, Litecoin, and Lumens) [13]. Utilizing the models mentioned above, he found that sudden and uncontrolled increases in the demand of cryptocurrency will cause a significant decline in financial returns due to their low intrinsic value, leading to a dramatic drop in prices. Furthermore, there are several papers emphasizing the spillover effects between cryptocurrencies and currencies during specific risk occasions. Hsu studied the relationship between major cryptocurrencies such as Bitcoin, Ethereum, and Tether and the exchange rate of traditional current markets are analyzed during influential global events: United States and China trade war, the Russian and Ukraine war, and the COVID-19 pandemic [14]. It is observed that under such instances, the cryptocurrencies are not correlated to exchange rates, and they prove as valid options of asset diversification; however, their capabilities as diversifiers may vary depending on the nature of the event, and exceptional investor caution is required. In the study by Zhang and Ding, the comprehensive influences of risks on the crypto market are covered, and it is discovered that the major cryptocurrencies are more sustainable in uncertainties, especially in the extremes of short- and long-term scenarios: mediums like Bitcoin tend to perform well in periods of economic expansion, while smaller currencies are more progressing in the medium term after periods of recession [15]. Their study further intensifies existing knowledge on features of cryptocurrencies that differ in market price, and how they react to different forms of risks.

Moving on, cryptocurrencies are known to be influenced largely by monetary policies, but have little impact upon popular, traditional streams, such as the traditional currency and gold markets [16]. Elsayed and Sousa investigates the interconnectedness between the spillovers of international monetary policies and the crypto market through the use of a time varying parameter vector autoregression (TVP-VAR) model [17]. It was determined that there was an apparent relationship between the two variables. More specifically, when central banks implement large-scale, peculiar monetary policies, the returns of cryptocurrencies and the spillovers of monetary policies were significantly high. Similar to Shu-Han Hsu et al., this study also believes that digital mediums of exchange are a sustainable source of asset diversification, especially when monetary policies are poorly coordinated [17]. Trabelsi explores the relationship between cryptocurrency and widely traded markets, including traditional currencies, stocks, gold, and Brent oil [18]. Using a spillover index, he found that there is little spillover effect between cryptocurrency and these common asset classes, meaning that it is not well integrated into the global market. However, this also suggests that cryptocurrencies are an independent class of financial instrument, and that they pose virtually no risk to other more traditional markets.

The third stream of articles display the spillover effect between cryptocurrencies, through concepts such as volatility spillover, return spillover, behavioral investing. Nikolaos investigates the instances of herding behavior and the impact of Bitcoin within the crypto market [19]. The findings state that

Bitcoin remains undoubtedly the most influential cryptocurrency, in the sense that it is the most common giver and receiver of spillover impacts, and that other cryptocurrencies, such as Ethereum, Litecoin, and Ripple, are tightly related to its effects. It is also noted that there is a high possibility for sustainable spillover behavior in the cryptocurrency market, enabling portfolio managers to mitigate risk by forming diversified portfolios. Additionally, the previous statement is further confirmed by researching the connectedness between Bitcoin and ten alternate coins, and it is suggested that there are surprising instances of spillover in the crypto market [20]. Also, it confirms that the impact of Bitcoin price movements on altcoin prices is extremely hard to predict, making it near impossible for investors to find a reliable indicator of alternate coin performance. This implies that investors should be more cautious and skeptical towards pump-and-dump schemes, and that proper research should be conducted prior to investing in altcoins.

Another stream of articles compares the different impacts of diverse spillover effects on cryptocurrencies. First, as previously mentioned, the main source of spillover is within the market, as leading cryptocurrencies have astounding effects on one another [21]. This takes the form of both unilateral and bilateral influences, as seen through the cases of Bitcoin-Ether, Bitcoin-Litecoin, and Ether-Litecoin relationships. However, stock markets and other financial markets are said to be significant variables that may affect the value of cryptocurrencies [22]. Although cryptocurrencies seem to have a slight influence on the US stock when the uncertainty rate is abnormal, its usual effect is said to be static. Also, cryptocurrencies are intertwined with some of the largest global economies [23]. For instance, cryptocurrencies are shown to have a noticeable impact on China's financial markets, but the counterstatement is false. The variables present within China's economy and markets seem to have very minimal effects on the return of cryptocurrencies. The spillover effects of cryptocurrency and other digital mediums such as non-fungible tokens (NFTs) on Ethereum have also been specifically analyzed in various papers. Ante discovered that there was no significant impact from NFTs to Ethereum, but Ethereum's price shocks affected the active number of NFTs [24]. In Sabalionis's study, it was established that cryptocurrencies, including Bitcoin and Ethereum, exhibit substantial mutual influence on their respective returns [10]. This finding is corroborated by Katsiampa, as previously noted [21]. Nevertheless, the impact of conventional market variables, particularly within the realms of financial markets and macroeconomics, on the returns of Ethereum remains unexplored. This creates a noteworthy research gap that presents an opportunity for further investigation, promising valuable insights into this relatively uncharted territory.

To further advance the existing literature on the spillover effects of cryptocurrencies, this paper aims to delve into the primary sectors influencing Ethereum. The objective is to provide valuable insights for investors, enabling them to employ effective methods in estimating market volatility, and for policymakers, facilitating the implementation of robust regulations to mitigate market risks. Specifically, this study will examine the correlations between macroeconomic indicators, stock market performance, crypto market dynamics, and investor sentiment-related variables in relation to Ethereum returns. Representative daily data from each of these categories will be compared and analyzed. To ensure a comprehensive examination of variables, this research will leverage data from Bitcoin, the Fear and Greed index, the Standard and Poor's 500 (S&P 500) index, and the United States Dollar to Euro (US to EU) Exchange Rate.

The rest of the study is structured as follows: Section 3 discusses the methodology, Section 4 presents the variables and data characteristics, Section 5 displays the empirical results, and Section 6 concludes the paper with implications on investments and policies.

2. Methodology

When assessing the correlation of representative data from varying categories, econometric techniques are employed to showcase explicit and statistically significant results. This research used

DOI: 10.54254/2754-1169/65/20231627

the linear regression and the basic VAR model to analyze the spillover thoroughly and adequately between Ethereum and other cryptocurrencies, investor sentiment, and traditional financial markets. After constructing the VAR model, the Granger causality test was employed to infer causal relationships among variables and further validate the final results.

In the regression equations below, represents the return of Ethereum at a point in time (t), R^{BTC} is the return of Bitcoin, $R^{F/G}$ is the return of the Fear and Greed index, R^{SP500} is the return of the S&P 500 index, and $R^{US/EU}$ is the return of the United States Dollar to Euro Exchange Rate. Also, whereas ${R^{ETH}}_{t-1}$ and ${R^{ETH}}_{t-2}$ represent Ethereum's lagged return. As assumed, α_0 represents the intercept or constant term of the model, while ε_t represents the residual term at time t, explaining the variations unaccounted for by the other values. A similar equation inspiring the formation of this formula is referenced in Nguyen [25].

$$\mathrm{R^{ETH}}_t = \alpha_0 + \alpha_1 \mathrm{R^{BTC}}_{t-1} + \alpha_2 \mathrm{R^{F/G}}_{t-1} + \alpha_3 \mathrm{R^{SP500}}_{t-1} + \alpha_4 \mathrm{R^{US/EU}}_{t-1} + \alpha_5 \mathrm{R^{ETH}}_{t-1} + \alpha_6 \mathrm{R^{ETH}}_{t-2} + \varepsilon_t \tag{1}$$

The regression function was used to summarize the overall effect of the independent variables (Bitcoin, Fear and Greed index, S&P 500 index, and US to EU Exchange Rate) on Ethereum overtime. This clearly demonstrates the linear, unilateral relationship between the different variables and Ethereum, with the resulting coefficients representing their degrees of influence.

In the general basic VAR equation below (with lag 2 and step 8), $\begin{pmatrix} BTC_{Return_t} \\ ETH_{Return_t} \\ F \mid G_{Return_t} \\ SP500_{Return_t} \\ US \mid EU_{Return_t} \end{pmatrix}$ represents the model created by the testing variables' return and Ethereum's Return at a point in time (t). Specifically, Bitcoin's return is symbolized by BTC_{Return}, Ethereum's return is symbolized by ETH_{Return}, Fear and Greed index's return is symbolized by $F|G_{Return}$, S&P 500 index's return is symbolized by $SP500_{Return}$, and US to EU exchange rate's return is symbolized by $US|EU_{Return}$. The coefficients A_1 and A_2 correspond with the influences of the vector autoregression of external variables' return and Ethereum return in lag 1 (shown through t-1) and lag 2 (shown through t-2), respectively. Once again, a_0 represents the intercept of the model, and e_t represents the residual term at time t: with e_1 representing the standard error of Bitcoin, e_2 representing that of Ethereum, e_3 representing that of Fear and Greed index, e_4 representing that of S&P 500 index, and e_5 representing that of US to EU exchange rate. We follow the structure of VAR model as in Blau et al., in which they examine the relationship between Bitcoin and inflation [26]. The basic VAR function is shown as below:

$$\begin{pmatrix} BTC_{Return_t} \\ ETH_{Return_t} \\ F|G_{Return_t} \\ SP500_{Return_t} \\ US|EU_{Return_t} \end{pmatrix} = \mathrm{a}_0 + \mathrm{A}_1 \begin{pmatrix} BTC_{Return_{t-1}} \\ ETH_{Return_{t-1}} \\ F|G_{Return_{t-1}} \\ SP500_{Return_{t-1}} \\ US|EU_{Return_{t-1}} \end{pmatrix} + \mathrm{A}_2 \begin{pmatrix} BTC_{Return_{t-2}} \\ ETH_{Return_{t-2}} \\ F|G_{Return_{t-2}} \\ SP500_{Return_{t-2}} \\ US|EU_{Return_{t-2}} \end{pmatrix} + \begin{pmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \\ e_5 \end{pmatrix} \tag{2}$$

The VAR model was used to analyze the degree by which different variables affect each other, showing the two-way, bilateral relationship between various market representatives and Ethereum. Through analyzing the fluctuations within the models produced by this function, the variables' spillover effects will be apparent. This allows us to make valid conclusions on not only different

DOI: 10.54254/2754-1169/65/20231627

variables' influences over Ethereum, but vice versa. Also, this allows us to identify various relationships between other variables.

3. Data

Throughout the study, leading, comprehensive data sources of each category of interest are employed to summarize their impacts on Ethereum, with Bitcoin representing the cryptocurrencies, the Fear and Greed index representing the core investor sentiment, the S&P 500 index representing the stock market, and the US to EU Exchange Rate representing global macroeconomic variables. The prices of Etheurem are downloaded through CoinMarketCap, those of Bitcoin are obtained through Yahoo! Finance, the values of Fear and Greed index are retrieved through CNN, the values of S&P 500 index are found through S&P Dow Jones Indices, and the exchange rate between USD and Euros is attained through the Wall Street Journal. To ensure the stationary of data in statistical models, the returns of each of the variables above are calculated. All of the data lasted from May 28, 2018, to March 31, 2023, and were collected based on daily intervals. Since the variables S&P 500 index and US to EU Exchange Rate are unrecorded on Saturdays and Sundays, those data points are cleared in order to ensure validity within final results and consistency between data variables. In the end, there were 1265 different data points employed for each of the variables, allowing for well-founded and reasonable conclusions.

Beginning with a brief statistical summary, basic statistical characteristics of each variable can be found in Table 1. This provides an estimate for the skewness range of the different sources, as well as information regarding the overall distribution of data – such as their central tendency, spread, and shape. In this specific instance, the summary would help spot any outliers within the variables, highlighting significant dates that resulted in large alterations in returns.

Table 1: Descriptive statistics for variables.

Variable	Obs	Mean	Std. Dev.	Min.	Max.
ETH_Return	1265	0.0010601	0.0504714	-0.4213278	0.2615157
BTC_Return	1265	0.0012352	0.0385351	-0.3659244	0.187677
F/G_Return	1265	0.0228125	0.2689057	-0.7555556	5.6
SP500_Return	1265	0.0004203	0.0137109	-0.1198405	0.0938277
US_EU_Return	1265	-0.0000385	0.0047157	-0.0181818	0.0355636

Moving on, the Augmented Dickey-Fuller (ADF) test is used to confirm the stationary characteristics of the variables and to ensure that they are appropriate to be represented in the regression and basic VAR models. Unit root tests conclude that all variables are stationary. Specifically, this is done through testing the null hypothesis that a unit root is present within the time-series data, indicating non-stationarity. The unit root tests of each variable can be found in Table 2.

Table 2: Augmented Dickey-Fuller test and p-value of variables.

Variable	Test Statistic	1%	5%	10%	P-Value
ETH_Return	-30.858	-3.430	-2.860	-2.570	0
BTC_Return	-29.428	-3.430	-2.860	-2.570	0
F/G_Return	-31.952	-3.430	-2.860	-2.570	0
SP500_Return	-41.218	-3.430	-2.860	-2.570	0
US_EU_Return	-32.542	-3.430	-2.860	-2.570	0

DOI: 10.54254/2754-1169/65/20231627

The overall trends of Ethereum are showcased in Figure 1. In Figure 2, the returns of external data, including that of Bitcoin, Fear and Greed index, S&P 500 index, and US to EU Exchange Rate, are showcased in the same manner. As shown through the graphs, all of the variables' returns are relatively stationary, with occasional spikes. Overall, they maintain a consistent pattern, with returns that are typically quite steady. Once again, this confirms their suitability to be adapted into regression and VAR models.

The pairwise correlations are examined to get a basic understanding of the data's relationships with each other. This is done through comparing the different correlation coefficients, with the larger absolute values quantifying larger degrees of linear association, and the sign representing positive or negative correlations. At first glance, Bitcoin and the Fear and Greed Index seem to have the largest correlations with Ethereum, which was expected, considering their proximity in multiple aspects (which will be discussed later) with the cryptocurrency. The correlation coefficients between each of the variables are displayed in Table 3.

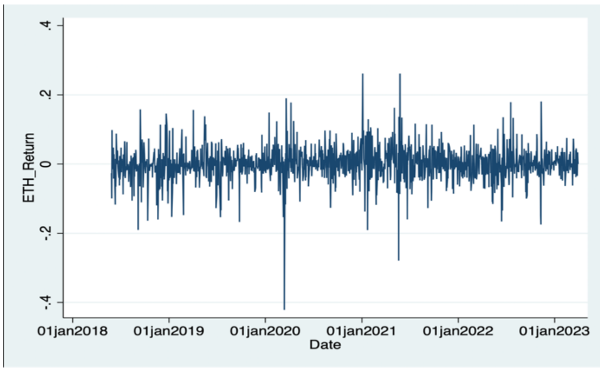

Figure 1: The return of Ethereum over 2018-2023.

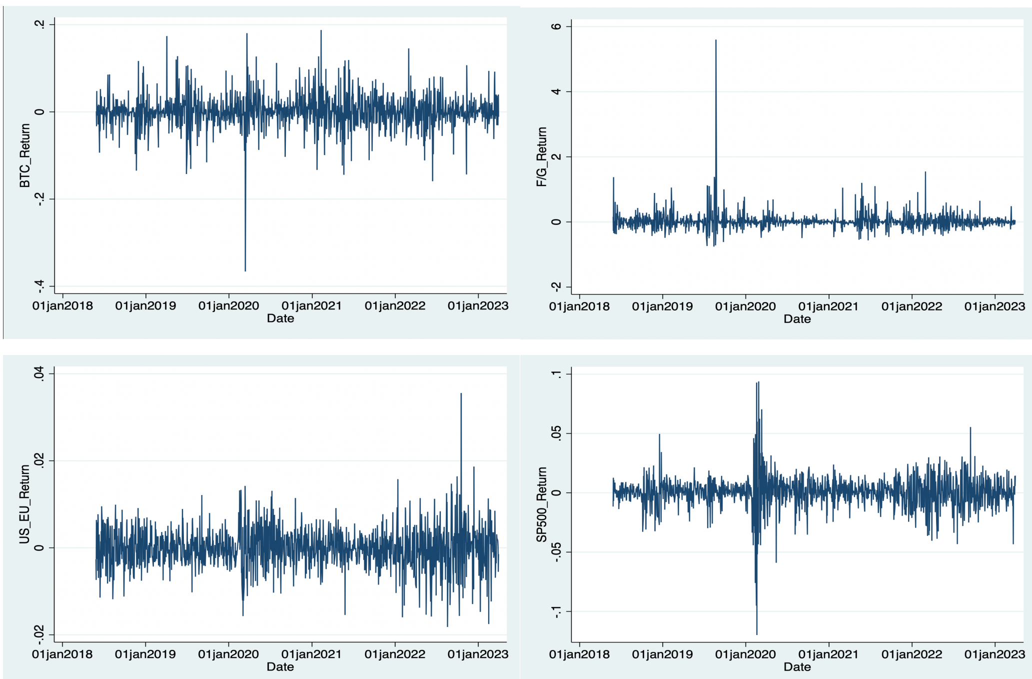

Figure 2: The returns of Bitcoin, Fear and Greed index, S&P 500 index, and US to EU Exchange Rate over 2018-2023.

DOI: 10.54254/2754-1169/65/20231627

Table 3: Correlation matrix.

Variable	ETH_Return	BTC_Return	F/G_Return	SP500_Return	US_EU_Return
ETH_Return	1.0000				
BTC_Return	0.8341	1.0000			
F/G_Return	0.4202	0.4373	1.0000		
SP500_Return	-0.0483	-0.0561	-0.0042	1.0000	
US_EU_Return	-0.0101	-0.0221	-0.0102	-0.0225	1.0000

To summarize, all of the data employed are in the appropriate time-series format, stationary, and have linear associations with Ethereum, making them ready to be adapted into the regression and basic VAR models.

4. Results

To explore the direct spillover effect of different variables on Ethereum, we employ ordinary least square (OLS) method to estimate linear regression models. To showcase the individual impacts of each variable, separate regression models were first constructed. Through analyzing the regression coefficient and statistical significance of the data, valid and reliable conclusions can be made. The Table 4 columns (1)-(4) show the estimation results of separate regression models. They reveal the independent effects of each variable. Column (5) presents estimation result of a comprehensive model with all variables.

Starting off, the impact of Bitcoin – the world's most valuable and most traded cryptocurrency – on Ethereum is demonstrated in Table 4 column (1). Through the regression coefficient of 1.092 and the statistically significant result (a p-value of less than 0.05), it can be assumed that Bitcoin's return holds major positive influences over that of Ethereum's. Next, the regression on Fear and Greed index, the metric evaluating investor sentiment across online platforms and trading centers, and Ethereum is shown in Table 4 column (2). Although the regression coefficient is quite low (0.079), the result is shown to have a positive correlation while being statistically significant (a p-value of less than 0.05), hinting that the Fear and Greed index holds considerable impacts over Ethereum's return. Moreover, the influence of the S&P 500 index, the key measure of economic trends occurring within the stock market, on Ethereum is analyzed through Table 4 column (3). The regression coefficient of -0.178 signals that there are weak, negative correlations between the return of S&P 500 index and that of Ethereum; however, the result is not statistically significant since the p-value is greater than 0.1. Lastly, the impact of the US to EU Exchange Rate, the macroeconomic variable measuring the values of two of the world's most prominent currencies, on Ethereum is demonstrated through Table 4 column (4). The double starred regression coefficient -0.108 indicates that there is a weak, negative correlation between the return of the US to EU Exchange Rate and that of Ethereum. This data is statistically significant and holds a p-value of less than 0.05. However, it is important to note that there is a significant standard error, suggesting that the value may fluctuate dramatically.

Here, in Table 4 column (5), a collective regression including all of the variables and Ethereum's return is displayed. As seen through the columns, when the comprehensive regression results are shown, the regression coefficients and statistical significance of the variables changed. Although most of the variables remained roughly the same, the US to EU Exchange Rate differs significantly, switching from a weak, negative, and statistically significant influence to a weak, positive, and non-statistically variable. This is mainly due to the multicollinearity of variables, their confounding effects, as well as the interactions between each of the variables. Despite this, the comprehensive regression model allows us to view the variables' effects on a real-world basis: when relevant factors from various domains that may affect Ethereum are considered.

Table 4: Correlation matrix.

	(1)	(2)	(3)	(4)	(5)
BTC_Return	1.092 **				1.053**
	(0.020)				(0.023)
F/G_Return		0.079 **			0.013**
		(0.005)			(0.003)
SP500_Return			-0.178		-0.010
			(0.103)		(0.057)
US_EU_Return				-0.108**	0.088
				(0.301)	(0.165)
Intercept	-0.000	-0.001	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Obs	1265	1265	1265	1265	1265

Standard error is in parentheses. * $p < 0.1$, ** $p < 0.05$

To begin, both Bitcoin and the Fear and Greed index remain statistically significant, which is to be expected due to their close relationship with Ethereum. On one hand, Bitcoin, the cryptocurrency with the largest trading volume, acts as a reliable indicator of the overall economic trend of the crypto market. On the other hand, the Fear and Greed index represents overall investor sentiment across diverse platforms, taking into account their confidence and fearfulness in different periods of time. As predicted, both of these factors play significant roles in influencing Ethereum, and with positive coefficients, they demonstrate positive, linear relationships with Ethereum's return. With Bitcoin's significantly larger coefficient of 1.053, it can be speculated that it has a stronger correlation with Ethereum, which is probable due to it being an asset of similar nature in the same field. Contrastingly, although the Fear and Greed index thoroughly evaluates consumer behavior, it considers sentiments from different fields – such as stock markets and other financial markets. As a result, the return of Bitcoin is concluded to be closely related to that of Ethereum, holding a strong, positive linear relationship with each other. As previously mentioned, it was found that all of the pairs of cryptocurrencies showed outstanding unilateral influences on each other, validating the results found through the regression model [21]. Also, Lin et al. found a strong correlation between investor sentiment and cryptocurrency return [27]. Therefore, when analyzing cryptocurrency trends, it is crucial to first consider the influence of crypto market movements and sentiment contagion.

Contrastingly, the S&P 500 index and US to EU Exchange Rate are statistically insignificant and have extraordinarily large standard errors. This implies that the correlation between these variables and Ethereum's return is surprisingly low, or even negligible. As both of these variables are representative figures in their domains, the results of this study can be generalized, suggesting that most factors in financial markets and macroeconomics hold trivial influences on Ethereum's return. As displayed by Khalfaoui, as well as Cao and Xie, both financial market and macroeconomic variables tend to play negligible roles when affecting crypto market trends [22-23]. Compared to the previous variables mentioned, the S&P 500 index and the US to EU Exchange Rate are of much less significance when looking to forecast upcoming movements regarding cryptocurrencies' values.

However, Ethereum's previous returns may have notable effect on its current return, as predicted through the regression formula shown in Section 3. Therefore, Table 5 was constructed to analyze the influence of Ethereum's lagged returns through an autoregression model, with column 1 representing the coefficient of Ethereum's return in lag 1, column 2 representing the coefficient of Ethereum's return in lag 2, and column 3 representing the predicted result with both lagged returns.

Table 5: Ethereum's Regression with Lagged Returns.

	(1)	(2)	(3)
RETHt−1	-0.043		-0.039
	(0.034)		(0.037)
RETHt−2		0.001	0.023
		(0.002)	(0.039)
Intercept	0.001	0.000	0.000
	(0.002)	(0.002)	(0.002)
Obs	1012	759	759

Standard error is in parentheses. * $p < 0.05$, ** $p < 0.01$

After conducting the autoregression with Ethereum, it can be observed that Ethereum's previous returns do not hold remarkable impact on its current or future return. As shown through the table, neither of the lag coefficients are statistically significant, with their p-values falling outside of the conventional range of 0.5. This explains that there are other more prominent factors that are not present within this analysis. In conclusion, the lagged coefficients play trivial roles when it comes to affecting Ethereum's return.

Moving on, the basic VAR model is utilized to showcase the bilateral impact between variables, further showcasing the variables' influences on each other. Through the VAR models, the effect of Ethereum on other variables can be observed via simulated shocks, which is instrumental to the results of this paper. For instance, this allows us to observe Ethereum's spillover effect on Bitcoin, instead of just Bitcoin's spillover effect on Ethereum. Through Figure 3, the basic VAR models composed of all of the discussed variables are showcased, displaying various astounding results.

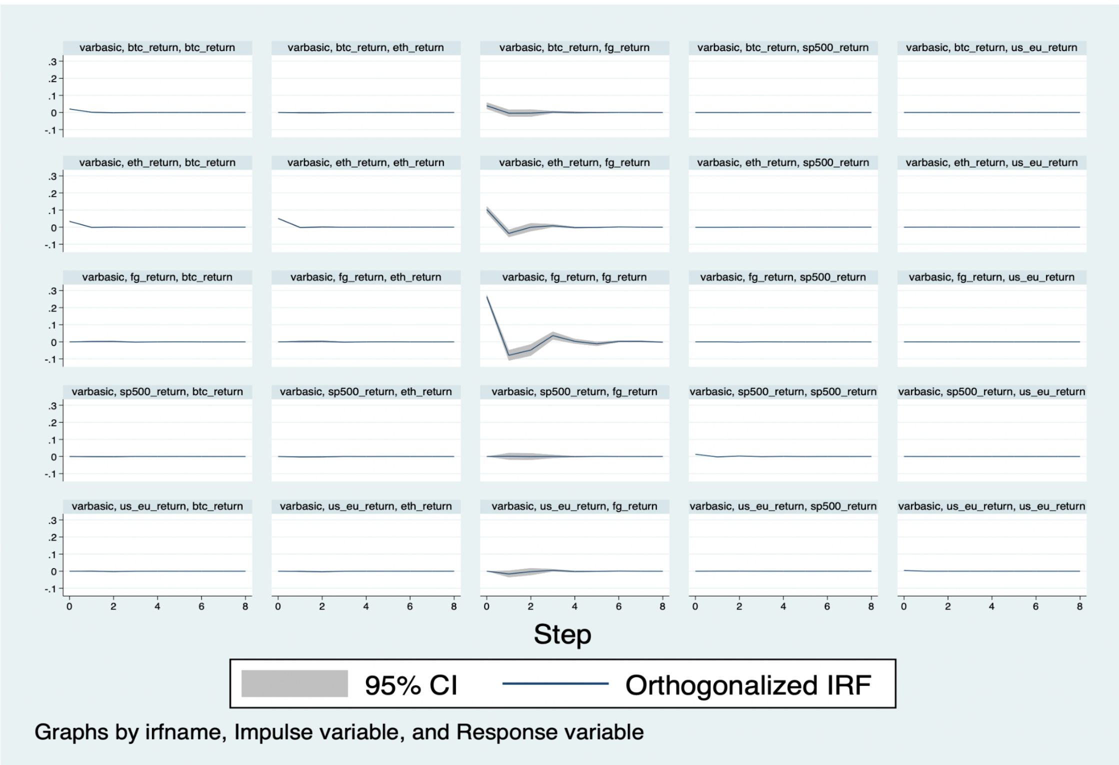

Figure 3: Impose Response Function of VAR.

As shown from Figure 3 row 1, Bitcoin is set as the response variable, it can be concluded that Ethereum's return also has a notable influence over that of Bitcoin's. As two of the largest and most valuable cryptocurrencies, both Ethereum and Bitcoin's returns are representative of the current state of the crypto market. Therefore, this conclusion is logical, as changes in one of the currencies' returns will undoubtedly impact that of the other. Additionally, Bitcoin and Ethereum seem to hold major influences over the Fear and Greed index. As shown through the graphs where the Fear and Greed index is set as the response variable, shocks to both Ethereum and Bitcoin seem to hold major influences over its return. This is expected, since drastic changes in both the return of Bitcoin and Ethereum will result in large changes in investment sentiment, as they are premier crypto-based variables recognized by investors all across the globe. Once again, these results can be justified by the reputable papers of Katsiampa et al. and Lin et al., thoroughly demonstrating the outstanding spillover effect resulting from alternative cryptocurrencies and investor emotions [21,28]. In terms of the financial markets and macroeconomics representatives of the S&P 500 index and the US to EU Exchange Rate, they seem to be unaffected by the other variables. As shown through the graphs, when the variables were set as response variables, shocks in any of the other variables do not seem to affect their return. However, they do seem to have a notable spillover effect on the Fear and Greed index, since the latter is a direct reflection of investor sentiment across all significant markets. To re-emphasize, these financial market and macroeconomic oriented variables seem to be static and negligible when it comes to affecting Ethereum's return, as supported by Khalfaoui and Cao and Xie [22-23].

5. Conclusion

This paper successfully achieves its objective by reinforcing the spillover impact of Bitcoin, investor sentiment, and traditional financial markets on Ethereum. The analysis reveals that cryptocurrencies, particularly Bitcoin, exert the most substantial influence on Ethereum's returns. Additionally, investor sentiment-related variables, exemplified by the Fear and Greed index, exhibit noteworthy impacts on Ethereum. Both factors demonstrate statistically significant, positive, linear relationships with Ethereum, with Bitcoin appearing to exert a more pronounced influence. Conversely, Ethereum appears to have discernible effects on both Bitcoin and the Fear and Greed index, highlighting the dynamic and interconnected nature of these relationships. However, the financial market variable – the S&P 500 index – and the macroeconomic, currency exchange variable – US to EU Exchange Rate – seem to be both unaffecting to Ethereum's return and unaffected by shocks in Ethereum's return. This is primarily shown through the regression model, demonstrating that both the variables' regression coefficients have exceptionally large standard errors. To add on, these variables are not considered as statistically significant. As a result, their impact on Ethereum is concluded to be negligible. Also, these variables seem to be unaffected by Ethereum, as them acting as response variables present virtually no reaction to shocks in Ethereum's return. In fact, the only noticeable shock they induced was to the Fear and Greed index, a variable aimed to reflect investor sentiment in various significant markets.

The findings of this paper hold relevance for investors engaging in markets represented by variables across cryptocurrency, financial markets, and macroeconomics. When attempting to predict the trends in the returns of these variables, it is crucial for investors to analyze factors exerting significant influence. In the context of Ethereum's return, a preliminary analysis of the trends in Bitcoin and the Fear and Greed index is imperative. Notably, both variables exhibit positive, linear relationships with Ethereum, suggesting a proportional relationship in their returns. Conversely, investors may overlook trends associated with financial market and macroeconomic variables when deciding on Ethereum investments, as their impacts are statistically insignificant and practically negligible, as demonstrated by cases such as the S&P 500 index and the US to EU Exchange Rate.

DOI: 10.54254/2754-1169/65/20231627

Furthermore, the implications of the findings extend bidirectionally. As revealed through basic VAR models, Ethereum significantly influences Bitcoin. Consequently, when investors aim to forecast future trends in Bitcoin, historical data on Ethereum's return becomes a valuable starting point.

The paper's insights are also beneficial for policymakers focused on implementing economic regulations. Aligning with the aforementioned considerations, regulations can be targeted at one variable to mitigate market risk for another. For example, restricting Ethereum's volatility by reducing its return might prompt policymakers to initially limit the returns of other cryptocurrencies. This, in turn, could devalue the overall crypto market and subsequently lower Ethereum's value. Overall, this paper not only offers various implications but also serves as a catalyst for future studies, as the analysis of spillover effects between these significant categories is virtually limitless. Future research could incorporate more representative data from diverse categories to establish more in-depth relationships between variables from different fields. For now, the identified directions influencing Ethereum's returns provide valuable insights that can already be applied across various domains.

References

[1] *CoinMarketCap. (2023, March). Cryptocurrency Prices, Charts and Market Capitalizations. coinmarketcap.com/.*

[2] *Kline, Matthew. (2021, February)"How Many Cryptocurrencies Are There? The Complete Guide." The Motley Fool, https://www.fool.com/investing/stock-market/market-sectors/financials/cryptocurrency-stocks/how-many-cryptocurrencies-are-there/.*

[3] *Vujičić, D., Jagodić, D., & Ranđić, S. (2018, March). Blockchain technology, bitcoin, and Ethereum: A brief overview. In 2018 17th international symposium infoteh-jahorina (infoteh) (pp. 1-6). IEEE.*

[4] *Angela, O., & Sun, Y. (2020, August). Factors affecting cryptocurrency prices: Evidence from ethereum. In 2020 International Conference on Information Management and Technology (ICIMTech) (pp. 318-323). IEEE.*

[5] *De Vries, A. (2023). Cryptocurrencies on the road to sustainability: Ethereum paving the way for Bitcoin. Patterns, 4(1).*

[6] *Theiri, S., Nekhili, R., & Sultan, J. (2023). Cryptocurrency liquidity during the Russia–Ukraine war: the case of Bitcoin and Ethereum. The Journal of Risk Finance, 24(1), 59-71.*

[7] *Zanelatto Gavião Mascarenhas, J., Ziviani, A., Wehmuth, K., & Vieira, A. B. (2020). On the transaction dynamics of the Ethereum-based cryptocurrency. Journal of Complex Networks, 8(4), cnaa042.*

[8] *Novianda, N., Munawir, M., & Fauziana, L. (2022). ETHEREUM CRYPTOCURRENCY PRICE MOVEMENT PREDICTION SYSTEM USING TRIPLE EXPONENTIAL SMOOTHING METHOD. International Journal of Social Science, Educational, Economics, Agriculture Research and Technology, 2(1), 921-939.*

[9] *Ciaian, P., Rajcaniova, M., & Kancs, D. A. (2016). The economics of BitCoin price formation. Applied economics, 48(19), 1799-1815.*

[10] *Sabalionis, A., Wang, W., & Park, H. (2021). What affects the price movements in Bitcoin and Ethereum?. The Manchester School, 89(1), 102-127.*

[11] *Moratis, G. (2021). Quantifying the spillover effect in the cryptocurrency market. Finance Research Letters, 38, 101534.*

[12] *Ahmed, M. Y., Sarkodie, S. A., & Leirvik, T. (2023). Mutual coupling between stock market and cryptocurrencies. Heliyon, 9(5).*

[13] *Özdemir, O. (2022). Cue the volatility spillover in the cryptocurrency markets during the COVID-19 pandemic: evidence from DCC-GARCH and wavelet analysis. Financial Innovation, 8(1), 1-38.*

[14] *Hsu, S. H. (2022). Investigating the co-volatility spillover effects between cryptocurrencies and currencies at different natures of risk events. Journal of Risk and Financial Management, 15(9), 372.*

[15] *Zhang, X., & Ding, Z. (2021). Multiscale systemic risk and its spillover effects in the cryptocurrency market. Complexity, 2021, 1-22.*

[16] *Hsu, S. H., Sheu, C., & Yoon, J. (2021). Risk spillovers between cryptocurrencies and traditional currencies and gold under different global economic conditions. The North American Journal of Economics and Finance, 57, 101443.*

[17] *Elsayed, A. H., & Sousa, R. M. (2022). International monetary policy and cryptocurrency markets: dynamic and spillover effects. The European Journal of Finance, 1-21.*

[18] *Trabelsi, N. (2018). Are there any volatility spill-over effects among cryptocurrencies and widely traded asset classes?. Journal of Risk and Financial Management, 11(4), 66.*

[19] Kyriazis, N. A. (2019). A survey on empirical findings about spillovers in cryptocurrency markets. Journal of Risk and Financial Management, 12(4), 170.
[20] Balcilar, M., & Ozdemir, H. (2023). On the Risk Spillover from Bitcoin to Altcoins: The Fear of Missing Out and Pump-and-Dump Scheme Effects. Journal of Risk and Financial Management, 16(1), 41.
[21] Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. Finance Research Letters, 29, 68-74.
[22] Khalfaoui, R., Jabeur, S. B., & Dogan, B. (2022). The spillover effects and connectedness among green commodities, Bitcoins, and US stock markets: Evidence from the quantile VAR network. Journal of environmental management, 306, 114493.
[23] Cao, G., & Xie, W. (2022). Asymmetric dynamic spillover effect between cryptocurrency and China's financial market: Evidence from TVP-VAR based connectedness approach. Finance Research Letters, 49, 103070.
[24] Ante, L. (2022). The non-fungible token (NFT) market and its relationship with Bitcoin and Ethereum. FinTech, 1(3), 216-224.
[25] Nguyen, K. Q. (2022). The correlation between the stock market and Bitcoin during COVID-19 and other uncertainty periods. Finance research letters, 46, 102284.
[26] Blau, B. M., Griffith, T. G., & Whitby, R. J. (2021). Inflation and Bitcoin: A descriptive time-series analysis. Economics Letters, 203, 109848.
[27] Lin, X., Meng, Y., & Zhu, H. (2023). How connected is the crypto market risk to investor sentiment?. Finance Research Letters, 56, 104177.