Exploring the Ethereum Merge: Pearson Correlation, Granger Causality, and Wavelet Coherence Analysis of the Lead-Lag Relationship Between Ethereum, Bitcoin, Twitter Sentiment and Twitter Uncertainty

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Post hoc ergo propter hoc

Abstract

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Mathieu Giacometti

In the realm of cryptocurrencies, the environmental impact of proof-of-work (POW) mining has long been a contentious issue, primarily due to its substantial energy consumption. This paper explores the transition from POW to proof-of-stake (POS) in Ethereum, known as "The Merge," which drastically reduced energy consumption and enhanced scalability and security. Leveraging a vast dataset of over 1.6 million tweets and specific hashtags, this study constructs a Twitter cryptocurrency sentiment index. Along with the Twitter-based Uncertainty Index constructed by Baker et al., 2021, this study delves into the lead-lag relationship between Ethereum, Bitcoin and the two aforementioned indexes using Pearson correlation, Granger causality, and wavelet analysis. We found that Bitcoin and Ethereum exhibit a lead-lag relationship, that the influence of social media sentiment on cryptocurrency prices appeared not to change post-merge and that Bitcoin and Ethereum remained relatively stable and less susceptible to the effects of the merge. Furthermore, the study develops a lead-lag momentum trading strategy, highlighting a robust relationship between Ethereum and Bitcoin prices, offering lucrative trading opportunities. This research contributes to a deeper understanding of cryptocurrency market dynamics and their interconnectedness with social media sentiment.

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Introduction

Cryptocurrencies have long faced criticism due to their environmental impact, primarily attributed to the mining protocol known as proof-of-work (POW). This consensus mechanism relies on graphic processing units (GPUs) to decode blockchain blocks and validate transactions. Unfortunately, this process consumes significant amounts of electricity, which often originates from non-green sources such as coal. Consequently, the environmental cost associated with this method is substantial.

The majority of cryptocurrencies currently adhere to the POW protocol. However, an alternative approach called proof-of-stake (POS) offers an eco-friendlier solution. In the POS protocol, validators are selected based on the number of coins they hold and have staked. When a transaction needs validation, a random validator is chosen to perform the task of using their own GPU. Unlike POW, there is no competition among validators, resulting in a drastic reduction of energy costs by approximately 99.95%.

Addressing the energy consumption of cryptocurrencies and blockchain technology is crucial for their widespread adoption in the long run. By transitioning to a more sustainable consensus mechanism like POS, we can mitigate the environmental concerns associated with these technologies.

The biggest cryptocurrency by market capitalization is Bitcoin. It was created by Satoshi Nakamoto in 2008 (Nakamoto, 2008). Its main purpose is to serve as a currency and as a store of value. The second-largest cryptocurrency by market capitalization is Ethereum. It was founded by Vitalik Buterin and the first transaction happened July 30, 2015. It also serves as a currency and store of value but also has further applications such as smart contracts[1] and decentralized applications. The first are like traditional contracts but are stored on the blockchain and will be executed if the right predefined conditions are satisfied. The latter permits the combination of smart contracts and a “frontend user interface”[2]. Their four main characteristics are that they

1 https://ethereum.org/en/smart-contracts/
2 https://ethereum.org/en/developers/docs/dapps/

are decentralized, deterministic, Turing complete and isolated. The backend code runs "on a decentralized peer-to-peer network"[3].

Until September 15, 2022, both Bitcoin and Ethereum were using POW protocols. However, the creators of Ethereum decided to change the protocol onward from that date from POW to POS. This date is called "The Merge". According to the Ethereum.org website, "the merge reduced Ethereum's energy consumption by approximately 99.95%"[4]. Additional reasons for the merge are scalability and security reasons. The current goal of the merge was not to reduce gas fees, but rather to permit a higher number of transactions per second. The change enabled better infrastructure to address this issue, by enabling the transition, not yet completed, from Proto-Danksharding to Danksharding. They "Both aim to make transactions on Layer 2[5] as cheap as possible"[6]. Layer 2s are also known as rollups. It is estimated that as of now, Layer 2 is approximately 3 to 8 times cheaper than layer one and that the end goal would be that transactions cost less than 0.001$[7].Concerning security, the upgrade increased both network and physical security. The first is related to coordinated attacks. If the network is attacked, only the staked coins are at play and the protocol ensures that the coins will be automatically destroyed. For the latter, stakers are no longer required to own a great amount of expensive hardware to validate transactions.

Pertaining to investor implications, a protocol change can significantly impact demand from investors. Positive changes that enhance security, utility, and adoption tend to attract more interest and drive-up demand. However, if the change introduces risks or uncertainties, investor confidence might waver, leading to reduced demand. Investor sentiment, network effects and real-world use cases all play crucial roles in determining investor implications.

This provided grounds to examine if there is a difference between the pricing of Bitcoin and Ethereum from a pre-merge perspective and the post-merge. We expected that Bitcoin will continue to lead Ethereum as was shown (Qiao et al., 2020) and historically, Bitcoin has shown market leadership which led to greater institutional interest. This led the cryptocurrency to have

3 Idem
4 https://ethereum.org/en/roadmap/merge/
5 "A layer 2 is a separate blockchain that extends Ethereum and inherits the security guarantees of Ethereum." https://ethereum.org/en/layer-2/
6 https://ethereum.org/en/roadmap/danksharding/
7 https://ethereum.org/en/roadmap/scaling/

the biggest market capitalization. Thus, we investigated if there is price co-movement and lead-lag relationship using Pearson correlation, Granger causality and wavelet coherence analysis between Ethereum and Bitcoin. We found that the lead-lag dynamics between Bitcoin and Ethereum exhibited evolving patterns, with the pre-merge period demonstrating some degree of synchronization, while post-merge, the short-term nature of their relationship became more apparent. This shift in dynamics underscores the impact of Ethereum's network upgrade on its price relationship with Bitcoin, highlighting the growing influence of investor sentiment in shaping cryptocurrency markets. These findings contributed to a deeper understanding of the cryptocurrency market's dynamics.

Twitter proved to be a valuable resource for predicting cryptocurrency prices, as it offers real-time information flow, providing timely insights into market sentiment, news, and important announcements that can significantly impact prices. Additionally, our sentiment analysis has the capability to comprehend shifts in sentiment associated with alterations in environmental impact caused by protocol changes. By analyzing the sentiment expressed in tweets, traders can assess how people perceive and respond to various events in the cryptocurrency market. Moreover, Twitter serves as a platform where influential figures share their opinions, which can strongly influence market sentiment.

We sought to go deeper into the subject of Twitter’s effect on Bitcoin and Ethereum prices because of various studies such as (Shen et al., 2019; Bin Mohd Sabri et al., 2022; Öztürk & Bilgiç, 2022) explored the effect of Twitter on Bitcoin. We expanded the literature on the subject as no such study had yet been conducted observing the pre-and post-merge effects of investor sentiment on Bitcoin and Ethereum. Engaging in community discussions on Twitter enabled traders to gain a deeper understanding of market dynamics and identify emerging trends. Considering these advantages, we developed a cryptocurrency sentiment index based on a dataset of 1,611,165 tweets. We utilized specific hashtags such as #ETH, #ETHEREUM, #BTC, and #BITCOIN to curate the relevant tweets for our analysis. Moreover, we used the Twitter global Uncertainty index developed by Baker et al. (2021) for a similar use. We found that changes in sentiment on Twitter could impact the prices of both Bitcoin and Ethereum.

Furthermore, to investigate the practical implications of our findings, we devised a lead-lag correlation momentum trading strategy using our Pearson, Granger causality, and wavelet approximation results. We tested this strategy on various scenarios: Bitcoin lagging Ethereum, Twitter Uncertainty Index lagging Bitcoin, Twitter Sentiment Index lagging Bitcoin, Ethereum lagging Bitcoin, Twitter Uncertainty Index lagging Ethereum, and Twitter Sentiment Index lagging Ethereum. Our results showed that the strategy that stood out with the highest net trading profit was when Ethereum lagged Bitcoin by 13 days, boasting a Pearson correlation coefficient of 0.89. This strategy resulted in a remarkable net trading profit of $445,826.75 from 280 buy transactions, showcasing a strong lead-lag relationship between Ethereum and Bitcoin, indicating significant potential for profitable trading in the cryptocurrency market. Similarly, when the Twitter Uncertainty Index lagged Bitcoin by 7 days, it resulted in a net trading profit of $70,833.07 from 765 buy transactions, with a P-value of 0.05. These findings demonstrated the potential for implementing lead-lag correlation strategies based on statistically significant relationships, offering valuable opportunities in the cryptocurrency market.

Section 2 will be the literature review, section 3 the hypothesis, section 4 will be about data, section 5 will be methodology, section 6 will be the results and section 7 will be the conclusion.

2. Literature Review

2.1 Analysis relationship

Numerous studies extensively examined the factors that influenced Bitcoin's price, employing various methodologies to identify key predictors and their relative impact.

A series of studies explored the dynamics of Bitcoin price movements and their underlying factors. In the notable study of Cheah et al. (2022), they conducted a study spanning from October 2011 to January 2019. They employed a predictive regression model and uncovered valuable predictors of Bitcoin returns, including time-series momentum, economic policy uncertainty, and financial uncertainty variables. Time-series momentum was defined as the excess daily return of Bitcoin over the previous 12 days, while economic policy uncertainty and financial uncertainty variables were derived from the works of (Moskowitz et al., 2012) and (Baker et al., 2016), respectively. Their "findings suggest that time-series momentum, economic policy uncertainty, and financial uncertainty variables are useful predictors of Bitcoin returns"

(Cheah et al., 2022). Adding to those factors are the findings of Liu, Y., Tsyvinski, A., & Wu, X. (2022) that “cryptocurrency market, size, and momentum—capture the cross-sectional expected cryptocurrency returns for a long-short strategy”.

A prominent study, Sabalionis et al. (2021) took a different approach by utilizing the Engle and Kroner (1995) VAR-GARCH-BEKK model. Their study was based on data collected from July 2017 to February 2018, aiming to explore the influence of Google search interest, the number of tweets, and active addresses on the blockchain on the prices of both Bitcoin and Ethereum over time. Their findings highlighted the significance of Metcalfe's law, a concept that measures network value based on user numbers, in explaining the impact of Google searches and tweets on Bitcoin and Ethereum prices.

Ahmed (2022) contributed to this body of research by employing extreme bound analysis (EBA) to investigate various factors affecting Bitcoin price movements. These factors included the number of transactions, the number of Bitcoins mined, hash rate, trading volume, realized volatility of Bitcoin prices, Wikipedia views, S&P indexes, and the economic policy uncertainty index. The results of this analysis pointed to several robust determinants of Bitcoin price movements, including the number of units in circulation, transaction volume, daily views of Bitcoin's Wikipedia page, and the U.S. economic policy uncertainty index.

An alternative approach involved utilizing wavelet coherence to assess the existence of a lead-lag relationship between two variables. A detailed explanation of this method was provided in the methodology section of this paper. Employing the technique and the Morlet wavelet, Kristoufek (2015) established that standard fundamental factors such as trade usage, money supply, and price levels played a significant role in Bitcoin prices over the long term.

The same Morlet wavelet was employed by Sun & Xu (2018) to analyze the weekly frequency market indices of Japan, Singapore, Hong Kong, and China spanning the years 2000 to 2013. Their research uncovered a long-term relationship between these markets. Furthermore, Omane-Adjepong & Alagidede (2019), utilizing the maximum overlap discrete wavelet transform, observed that Bitcoin and Ethereum were the two most influential cryptocurrencies among the top seven coins by market capitalization. This finding is aligned with the conclusions drawn by

Qiao et al. (2020), who, through wavelet analysis, identified Bitcoin as the leading variable for most cryptocurrencies at low frequencies.

In the study titled "Volatility Spillover in Cryptocurrency Markets: Some Evidence from GARCH and Wavelet Analysis" by Kumar & Anandarao (2019), the authors delved into the volatility spillover between Bitcoin and Ethereum within the cryptocurrency markets. Their findings indicated a negative correlation between Bitcoin and Ethereum during market turbulence, signifying investor panic and a shift from Bitcoin to Ethereum. This correlation was particularly pronounced in the short term and gained significance after 2017. The study also revealed that volatility spillover was moderate and primarily confined to the short term, suggesting the presence of both short-term traders and long-term investors in the cryptocurrency markets.

In conclusion, the study of lead-lag relationships in finance and economics has utilized various methodologies such as lagged correlations, Granger Causality, and wavelet analysis. These approaches have revealed insights into the cross-correlation between variables, temporal emergence of lead-lag phenomena, and long-term relationships. Specifically, studies have examined lead-lag relationships in foreign exchange markets, stock markets, and the Bitcoin market, uncovering connections between search trends, returns, volume changes, and fundamental factors. These findings emphasize the importance of employing diverse methodologies to understand the dynamics and interdependencies within different markets and economic systems.

2.2 Sentiment Index and Natural Language Processing

In recent years, there was a significant focus on researching the impact of sentiment analysis on Bitcoin prices. Various sources were explored as proxies for investor sentiment, including news articles, forum posts, social media platforms such as Twitter and Reddit, and even Google search trends. This literature review aimed to provide an overview of the existing literature on sentiment analysis and Bitcoin prices, highlighting the methodologies employed and the insights gained from these studies.

In current research, numerous studies provide insights into the cryptocurrency landscape, its associations with economic indicators, and sentiment on social media platforms. Guégan & Renault (2021) undertook an investigation into Bitcoin sentiment, leveraging a dataset of 988,622 messages from StockTwits exchanged between 2017 and 2019. Through meticulous analysis, they unveiled the predictive potential of sentiment indicators, particularly within short intervals of up to 15 minutes. However, this predictive power appeared to wane beyond the 15-minute threshold, a finding substantiated by multivariate regressions and Granger causality tests. The study underscored the nuanced temporal connection between sentiment prevailing on social networks like StockTwits and the swift fluctuations characterizing the cryptocurrency market.

Building upon this foundational work, Bouteska et al. (2022) advanced the exploration of sentiment analysis by focusing on the daily sentiment expressed within StockTwits messages exclusively related to cryptocurrencies. The authors probed sentiment trends across the spectrum of 532 crypto tickers supported by the platform. Employing the lexicon-based methodology established by Chen et al. (2019), they harnessed StockTwits' public API to access messages, converting them into unigrams and bigrams for sentiment analysis. The innovation here was the incorporation of user-tagged sentiment, enriching the depth of insights into cryptocurrency sentiment dynamics. By synergizing lexicon-based and user-tagged indicators, Bouteska et al. offered a comprehensive understanding of how sentiment fluctuated in the context of cryptocurrencies.

Another facet of the sentiment-cryptocurrency nexus was investigated by Kraaijeveld & De Smedt (2020). The authors undertook a comprehensive analysis of the relationship between Twitter Sentiment index and the returns of prominent cryptocurrencies—Bitcoin, Bitcoin Cash, and Litecoin. Employing a domain-specific sentiment analysis technique and bilateral Granger-causality tests, their study demonstrated the predictive potential of Twitter Sentiment index in influencing the price movements of these cryptocurrencies. Of particular interest was their identification of automated "bot" accounts, adding depth to the understanding of sentiment's reach and impact within the cryptocurrency discourse.

Collectively, these studies contributed to a holistic comprehension of the interplay between sentiment analysis and cryptocurrency performance. They revealed the temporal nuances of sentiment's predictive power, its intricate relationship with market dynamics, and the varying roles it assumed across different facets of the cryptocurrency landscape.

In the realm of contemporary research, several intriguing studies shed light on various aspects of the cryptocurrency landscape and its interactions with broader economic indicators and sentiment from social media platforms.

Sharif et al. (2020) explored intricate interconnections and spillover effects among green economy indices, select black cryptocurrencies, and clean cryptocurrencies across the U.S., Euro, and Asian markets. They used the innovative quantile spillover index methodology introduced by Ando et al. (2018) to analyze daily data from November 9, 2017, to April 4, 2022. The empirical findings revealed a stronger link between green economy indices and clean cryptocurrencies compared to their associations with questionable cryptocurrencies. Green economic indexes tended to receive more attention, while outcomes for cryptocurrencies varied across quantiles, variables, and time periods. The primary objective of this study was to comprehensively examine spillover implications among green economic indicators, clean and less savoury cryptocurrencies, in the specific contexts of the U.S., Europe, and Asia economies.

Shifting our focus to another significant study, Tong et al. (2022) analyzed the area of causal connections between cryptocurrencies and investor attention. Employing the transfer entropy methodology, this research unlocked fresh insights in this domain. The research outcomes revealed that Google exhibited a heightened level of significant bidirectional information transfer as compared to Twitter. Intriguingly, the number of cryptocurrencies displaying noteworthy one-directional information flow from Twitter to cryptocurrency returns mirrored that originating from Google. Furthermore, the research delved deeper by highlighting the substantial impact of tail events on the dynamics of information transfer.

The presented texts on sentiment analysis and its impact on Bitcoin prices highlight a range of findings, some of which seem to be in contradiction with each other. On one hand, studies like Guégan & Renault (2021) and Kraaijeveld & De Smedt (2020) suggest that sentiment analysis, particularly from sources like StockTwits and Twitter, can have predictive potential on short-term price movements of cryptocurrencies, especially within certain time intervals. This implies that sentiment can play a role in influencing market dynamics. On the other hand, the study by Sharif et al. (2020) suggests a more complex interaction, where the relationship between economic indicators and different types of cryptocurrencies varies. Additionally, the findings of Suardi et al. (2022) imply that sentiment dispersion in times of market uncertainty can increase investor return volatility, which seems to contradict the predictive power highlighted by other studies. Furthermore, Critien et al. (2022) showcase the potential of sentiment analysis combined with neural network models in predicting Bitcoin price changes, a result that seems at odds with the nuanced temporal dynamics noted in some earlier studies. These contrasting findings emphasize the intricate and multifaceted nature of the relationship between sentiment analysis and cryptocurrency performance, reflecting the challenges of establishing consistent patterns across different contexts and methodologies.

Traditionally, economics assumed that market agents always acted in the most rational way. However, behavioral economics challenges this assumption by considering that agents are often irrational. Behavioral economics influences the use of sentiment analysis in investment strategies, aiming to understand the irrational influence of market psychology on prices. Recent advancements in natural language processing (NLP) and machine learning have made it more accessible to decode investor sentiment using these tools. However, with a multitude of approaches and models to choose from, it can be challenging to determine the most suitable one.

In their comprehensive review, Dang et al. (2020) discussed the three main approaches to sentiment analysis: lexicon-based techniques, machine-learning-based techniques, and hybrid approaches. Lexicon-based techniques involved probabilistic approaches that determined the placement of words in a sentence based on a given model. For example, the N-gram model, used by Salas-Zárate et al. (2017) in their sentiment analysis of tweets about diabetes, achieved a precision of 81.93%, a recall of 81.13%, and an F1 measure of 81.24%.

Machine-learning-based techniques, as described by Dang et al. (2020), could be further divided into traditional models and deep learning models. Traditional models encompassed classifiers such as naïve Bayes, maximum entropy, and support vector machines. On the other hand, deep learning models included variations of convolutional neural networks, deep neural networks, recurrent neural networks, and the Long Short-Term Memory (LSTM) model.

The hybrid approach combined different techniques to achieve more accurate results in natural language processing and sentiment analysis. Two prominent approaches in this category were Term Frequency-Inverse Document Frequency (TF-IDF) and Word2Vec. TF-IDF assigned importance to words based on their frequency in a document compared to others, aiding in classification. Word2Vec, on the other hand, learned word embeddings from large datasets, treating each word as a unique vector signature.

Another noteworthy model, not previously mentioned, was Valence Aware Dictionary for sEntiment Reasoning (VADER), as used by Chiny et al. (2021). VADER utilized a sentiment lexicon with positive and negative labels for lexical features, enabling the evaluation of words within a range of -4 to 4 based on their semantic context. Being pre-trained, VADER was readily available for research purposes, free of charge.

It was crucial to consider the context of the data when training sentiment analysis models. The language used in classical literature differed significantly from that of tweets, which were often constrained by a character limit of 280. Abbreviations and slang were common in the latter, necessitating modifications in natural language processing. Several studies, including those by (Hasan et al., 2018; Nasir et al., 2019; Neethu & Rajasree, 2013; Salas-Zárate et al., 2017), explored the connection, if any, between sentiment analysis and stock prediction, using various algorithms and techniques.

One recent breakthrough in deep learning for natural language processing was Bidirectional Encoder Representations from Transformers (BERT). BERT was a transformer-based architecture that utilized attention mechanisms to learn contextual relations between words (Devlin et al., 2019). It achieved state-of-the-art results in various NLP tasks, including question answering and sentiment analysis. In the domain of cryptocurrencies, Raheman et al. (2022) studied the correlation between different sentiment metrics and price movements of Bitcoin, finding that one specific variation of BERT outperformed others and demonstrated practical interpretability and value. They examined a total of 21 models based on BERT, facing challenges such as sarcasm, idioms, negations, and non-textual data.

Liu et al. (2019) presented significant improvements to BERT, surpassing the original model's performance on multiple benchmark datasets. They proposed modifications to the pre-training procedure, including longer training, dynamic masking, and larger batch sizes, which contributed to enhancing results. Additionally, Barbieri et al. (2020) introduced TweetEval, an evaluation framework for English language tweets that covered various purposes, such as sentiment analysis, emotion recognition, offensive language detection, hate speech detection, stance prediction, emoji prediction, and irony detection. This framework built upon the work of SentEval (Conneau & Kiela, 2018), GLUE (Wang et al., 2019), and SuperGLUE (Wang et al., 2020).

Considering the evidence, ROBERTA stood out as the most effective model for sentiment analysis. It consistently outperformed other models, such as TF-IDF, VADER, WORD2VEC, SVM, and K-Means. Based on the research conducted by Barbieri et al. (2020) on tweets in the English language, ROBERTA was currently the best pre-trained model available. Unfortunately, due to limited access to a substantial volume of tweets and restricted computing capabilities, creating and training a custom model was not feasible.

In conclusion, the studies presented underlined the complex interplay between sentiment analysis and cryptocurrency performance. While sentiment analysis offered insights into short-term price trends and market dynamics, its predictive power was nuanced and context dependent. These investigations highlighted the importance of choosing suitable techniques, with recent advancements like BERT and ROBERTA proving effective. Contradictory findings across studies underscored the intricate nature of this relationship. As technology evolved, the connection between sentiment analysis and cryptocurrencies remained a captivating and influential research domain.

2.3 Trading Strategy

In recent years, the cryptocurrency market garnered significant attention from researchers who sought to unravel its intricacies. This focus led to a diverse range of studies aimed at understanding the efficiency and profitability of trading opportunities within the cryptocurrency markets. This text delved into a collection of key studies that shed light on the predominant methodologies employed in this field, with a particular emphasis on the role of technical and sentiment analysis in predicting cryptocurrency price movements. These studies offered valuable insights into the evolving landscape of cryptocurrency research and its implications for market analysis and trading strategies.

In Kyriazis (2019)`s study titled "A survey on efficiency and profitable trading opportunities in cryptocurrency markets," the focus was on examining the efficiency and profitability of trading opportunities within cryptocurrency markets. The study's findings revealed that 66% of the research work centered around technical analysis, indicating its significant influence in this field. In contrast, only 23% of the studies were based on fundamental analysis, while 11% utilized general analysis approaches. These findings underscored the dominance of technical analysis and offered valuable insights into the research methodologies employed for studying stock prediction.

Another noteworthy study conducted by Garcia & Schweitzer (2015) involved the development of an algorithmic trading strategy that combined economic and social signals. Their specific focus was on whether social media sentiment could predict financial returns within the Bitcoin ecosystem. Using a vector autoregressive (VAR) model with a one-time lag and employing Granger causality, they identified significant variables to incorporate into their strategy. The study yielded four distinct strategies: Valence (emotional valence), polarization (opinion polarization), Combined, and FXVOLUME. Surprisingly, the first three strategies outperformed random trading, indicating that sentiment analysis could effectively predict Bitcoin price movements.

Taking a different approach, Suardi et al. (2022) delved into the relationship between sentiment dispersion, market uncertainty, and cryptocurrency investors' behaviour. Their findings illustrated that as sentiment dispersion increased during periods of heightened market uncertainty, investor return volatility also rose. The study's exploration of investor attention (IA) revealed that while IA could predict Bitcoin trading volume, its ability to forecast returns and volatility exhibited variability. Notably, the researchers developed an IA-induced trading strategy that outperformed a passive buy-and-hold approach in a specific year, highlighting the potential, albeit limited, of sentiment as a trading parameter.

In a similar vein, when enhancing a technical analysis trading strategy, Erog (2022) discovered that the utilization of wavelet transform effectively filtered out extraneous noise, thereby resulting in a higher likelihood of generating profitable trades within a pairs trading strategy.

3.Hypotheses

Proof-of-work (POW) and proof-of-stake (POS) are two consensus mechanisms employed in blockchain networks. POW entails miners competing against one another, leading to significant energy consumption. On the other hand, POS selects validators based on the amount of cryptocurrency they hold, resulting in reduced energy usage. POS offers a more sustainable solution compared to POW, effectively addressing environmental concerns without compromising the security or decentralization of the network. The decision to adopt either POW or POS depends on the specific goals and requirements of the network.

Regarding environmental considerations, Ethereum has made the decision to transition from a POW protocol to a POS mechanism on September 15, 2022. The POW approach heavily relies on energy-intensive mining using graphics cards, although it offers substantial rewards to miners. In contrast, the POS protocol randomly selects stakers to validate transactions and distributes rewards through a lottery-like system. Moreover, validators must already possess Ethereum to stake them, which introduces certain limitations on access to staking.

POW consensus mechanisms are known for their high energy consumption and reliance on specialized hardware, such as powerful mining rigs, to solve complex computational puzzles. Consequently, miners incur significant operational costs, which can lead to higher transaction fees for users. In contrast, POS consensus mechanisms require less energy and do not depend on expensive mining equipment.

POW consensus mechanisms function through a competitive process where multiple miners utilize computational power, resulting in a substantial energy footprint. The computational work required to solve puzzles in POW leads to high energy demands. Conversely, POS consensus mechanisms consume significantly less energy by selecting validators based on the amount of cryptocurrency they hold and are willing to "stake" as collateral. This eliminates the need for extensive computational calculations and improves energy efficiency.

When it comes to security against 51% attacks, POW consensus mechanisms are generally regarded as more resistant. This is because such attacks require an attacker to control a majority of the network's computational power, which can be difficult and costly to achieve. The computational power is distributed among multiple miners, enhancing network security and decentralization. In contrast, POS consensus mechanisms typically necessitate an attacker to possess a majority of the cryptocurrency supply, which is generally more expensive and less feasible. This approach also contributes to the security and decentralization of the network.

In POW consensus mechanisms, miners are rewarded with newly minted coins and transaction fees for their role in securing the network. This creates incentives for miners and investors who mine or hold these cryptocurrencies, as they can potentially benefit from the appreciation in token value. Conversely, POS consensus mechanisms involve validators earning transaction fees as rewards for staking their tokens. By staking their tokens, validators contribute to the security and integrity of the network while also receiving rewards.

Thus, we believed that interest would go down as it will not be mineable. This leads us to the following hypothesis:

Hypothesis 1a: There will be a difference between the lead-lag relationship pre-and post-merge on the 15th of September 2022 for Ethereum as the loss of the mining community will impact Ethereum's price.

Urquhart (2022) showed that throughout time, Ethereum investors “HODL”[8] longer and that the average time held is 1 to 3 years from 2018 onward. Thus, having a great number of active addresses was shown to impact the price of Bitcoin and Ethereum (Sabalionis et al., 2021). This will greatly diminish the number of active addresses associated with miners as they will look to change mining operations to another POW cryptocurrency. A corollary is the following hypothesis 1b.

Hypothesis 1b: The impact of investor sentiment will be greater post merge as the importance of mining is eliminated regarding Ethereum.

There should be no impact on Bitcoin’s price as in a study conducted by (Wendl et al., 2023), more than 50 pertinent papers were examined, covering topics such as scalability, throughput, cost reduction, and energy efficiency. While it is challenging to ascertain the exact number of Bitcoin miners, it is possible to analyze the rate at which Bitcoin mining equipment becomes obsolete. According to De Vries (2021) , it takes approximately 1.29 years for new equipment to become outdated, thereby impeding mining accessibility for Bitcoin. Additionally, Makarov & Schoar (2021) discovered that in the case of Bitcoin, the top 10% of miners control 90% of the mining capacity, with a mere 0.1% (approximately 50 miners) commanding close to 50% of the total capacity.

Hypothesis 2: We expected that the merge will not impact the price of Bitcoin due to it being the most influential cryptocurrency and is not receiving spillover effects.

4.Data

The Ethereum and Bitcoin time series were obtained using CoinMarketCap's application programming interface (API) and Python. For Ethereum, the first available trading day was August 7, 2015. As mentioned earlier, the merge occurred on September 15, 2022, giving us 2,596 trading days before the merge. To maintain comparability, we had the same dataset length for

[8] “Hold on for dear life”

Bitcoin, even though it started trading earlier. For the post-merge analysis, we utilized six months of trading data from September 15, 2022, to March 15, 2023, resulting in 181 trading days. In total, we have 2777 daily price data points.

Our analysis follows the approach commonly adopted in prior studies, as surveyed by Bariviera & Merediz-Solà (2021). We use the daily closing prices for both coins. Since cryptocurrencies trade continuously, 24 hours a day and 7 days a week, we rely on the closing price provided by CoinMarketCap. Therefore, the closing price on the day of the merge, September 15, 2022, is included in the post-merge datasets.

In time series analysis, a stationary time series exhibits constant statistical properties over time, while a non-stationary time series displays varying statistical properties, such as trends or seasonality. Stationary series are easier to analyze, while non-stationary series require preprocessing techniques to become stationary. To assess stationarity, we conducted Augmented Dickey-Fuller (ADF) tests on each time series. As shown in Table 1, the results reveal that both the Bitcoin and Ethereum closing price series have p-values of 0.44, suggesting that we cannot reject the null hypothesis and concluding that both series are non-stationary. Conversely, for the Twitter Sentiment Index and Twitter Uncertainty Index time series, the p-values were less than 0.05, allowing us to reject the null hypothesis and conclude that these series do not exhibit a unit root, indicating stationarity.

To make the Bitcoin and Ethereum series stationary, we used the returns, and the ADF test confirms the stationarity of the return series for both Bitcoin and Ethereum. It's important to note that due to the methodology used for calculating returns, one data point is omitted at the series' outset. As a result, our dataset comprises a total of 2776 returns, with 2595 returns in the pre-merge dataset and 181 returns in the post-merge dataset. As seen in Table 1, we observed the following differences between the pre and post Bitcoin and Ethereum datasets. Notably, that both series hit their peak value before the merge and that the standard deviation is higher pre-merge. Furthermore, the kurtosis post-merge is negative and close to 0 compared to the positive and high values observed post-merge. In Table 2, we observed, for the descriptive statistics of the returns of Ethereum and Bitcoin, that like the price time series, that both maximum values were observed during the pre-merge period. Additionally, both kurtoses were higher pre-merge, with Ethereum having the highest difference between pre and post merge. Only the Ethereum pre-merge return has a positive skewness.

--Insert Table 1 about here--

--Insert Figure 1 about here—

--Insert Table 2 about here--

In their respective studies, Cheah et al. (2022) and Ahmed (2022) found that the Economic Policy Uncertainty by Baker et al. (2016) is one of many determinants of the price of Bitcoin. As of our knowledge, other studies such as (French,2021; Wu et al.,2021; Aharon et al.,2022) have used the Twitter-based Uncertainty Indices Baker et al. (2021)[9] to examine Cryptocurrency prices. Our unique contributions compared to the previous papers are our dataset range, our pre-post merge comparison and economically testing our results in a trading strategy. We extracted the data directly from their website at: https://www.policyuncertainty.com/twitter_uncert.html. They provide various TEU indices such as the TEU-ENG "consists of the total number of daily English-language tweets containing both Uncertainty[10] terms as well as Economy terms[11]", TEU-USA that are geographically based tweets based on users in the United States, TEU-WGT but is a "weighted variant" of the TEU-USA and "to control for changes in Twitter usage intensity over time, our TEU-SCA index scales the number of tweets each day by the number of tweets on that day that contain the word 'have'". We chose to use the TEU-ENG as it is more global and matched our methodology for tweet extraction regarding crypto sentiment.

Finally, we developed a Twitter Sentiment index index using the Python programming language and the Tweepy V2.0 API. We obtained academic access to Twitter's database to retrieve historical tweets. Our focus was on tweets related to cryptocurrencies, particularly those

[9] The reader can access a wide range of Economic Policy Uncertainty Indices by visiting the website:

[10] "The Uncertainty terms are as follows: 'uncertain', 'uncertainly', 'uncertainties', 'uncertainty'."

[11] " Keywords related to the economy are the following: 'economic', 'economical', 'economically', 'economics', 'economies', 'economist', 'economists', 'economy'."

with the hashtags #ETH, #ETHEREUM, #BTC, and #BITCOIN. To ensure data quality, we filtered for English language tweets and excluded retweets. Since not all tweets containing the specified hashtags were relevant to the crypto world, we conducted a manual inspection of random samples. Based on this inspection, we removed tweets containing specific strings such as "ETH ZURICH," "Not ease for Sonia," "ETH BRAZIL Firmin," "Trucking," and "Looking for a #Class #A CDL Drivers-BT." After this cleansing process, our pre-merge data set comprised 1,397,220 unique tweets. Following the merge, the post-merge data set contained 213,945 unique tweets. This resulted in a total of 1,611,165 unique tweets used for analysis. We must mention that during tweet extraction, for some unknow reason, the API gave an error message for the 10-02-2018 date. Thus, we could not extract tweets for that date. Consequently, for the creation of the Twitter Sentiment Index, we used the previous day value given by RoBERTa to fill in our dataset. Regarding tweet accessibility, it's essential to highlight that as of February 9, 2023, Twitter discontinued free access to both the v2 and v1.1 APIs. Instead, they are introducing a paid basic tier, resulting in restricted accessibility.

--Insert Table 3 about here—

In Table 3, we observed that, for both indices, the maximum value occurred pre-merge. Contrary to the Twitter Uncertainty Index, our index has negative skewness across all observed periods. Additionally, variance is higher pre-merge than post. The Twitter Uncertainty Index contains more striking differences pre and post merge such as the Skewness, Kurtosis and the quantile distribution of the dataset suggesting more uncertainty post-merge.

We worked with a total of four primary time series: Bitcoin prices, Ethereum prices, the Twitter Sentiment Index, and the Twitter Uncertainty Index. To enable seamless comparisons before and after the merge, we categorized these time series into pre-merge and post-merge, resulting in a total of 12-time series.

5.Methodology

5.1 Cross-correlation

Our goal to use Cross-correlation was to identify the presence and strength of any linear relationship or similarity between the two series, as well as the time lag between them. Using this, we aimed to research the lead-lag relationship between our datasets, examine if we reject or not our hypothesis and, if the results prove conclusive, develop a trading algorithm based on the results.

Thus, we tested various lags of up to 14 days in between the various time series using the build in Corr function from the Pandas library that uses the Pearson correlation test. This is expressed in the following formulae:

$$\boldsymbol{r} = \frac{\sum(\boldsymbol{x_i} - \overline{\boldsymbol{x}})(\boldsymbol{y_i} - \overline{\boldsymbol{y}})}{\sqrt{\sum(\boldsymbol{x_i} - \overline{\boldsymbol{x}})^2(\boldsymbol{y_i} - \overline{\boldsymbol{y}})^2}}$$

Where $\boldsymbol{x_i}$ is the value of the x variable on day i, $\boldsymbol{y_i}$ is the value of the y variable on day I, $\overline{\boldsymbol{x}}$ is the arithmetic average of the x variable, $\overline{\boldsymbol{y}}$ is the arithmetic average of the y variable and r is the correlation coefficient situated between 0 and 1. To calculate the lagged correlation, we adjusted for either x or y, the i indice by changing it to i-1, i-2 until i-14 to represent the lagged correlation of 14 days.

Cross-correlation alone fails to establish causality within time-series data, thus we employed Granger causality.

5.2 Granger causality

As previously highlighted, our Bitcoin and Ethereum price series exhibited non-stationarity, prompting us to employ their return series. Granger causality serves the purpose of assessing whether previous values in one time series can effectively predict future values in another. Our primary objective is twofold: firstly, to determine if we can reject this notion, and secondly, to discern whether there is a compelling reason to utilize this method in the development of a trading strategy based on our findings. This motivated us to use the following bivariate VAR(P) system for Granger Causality:

$$\boldsymbol{X_t = \gamma_1 + \sum_{i=1}^{P} a_{1i} X_{t-i} + \sum_{j=1}^{P} b_{1j} Y_{t-j} + \varepsilon_{1t}}$$

$$\boldsymbol{Y_t = \gamma_2 + \sum_{i=1}^{P} a_{2i} X_{t-i} + \sum_{j=1}^{P} b_{2j} Y_{t-j} + \varepsilon_{2t}}$$

Within this context, $\boldsymbol{\gamma_1}$and $\boldsymbol{\gamma_2}$ are constants, while a and b represent estimated coefficients. The parameter 'P' denotes the optimal lag length determined using the Akaike Information Criterion (AIC), and $\boldsymbol{\varepsilon_{1t}}$ and $\boldsymbol{\varepsilon_{2t}}$ denote the residuals obtained from the VAR model. We employed Python with the statsmodels.tsa.api library to construct the optimal VAR (Vector Autoregressive) models for each pair of time series in our analysis. Our initial step involved determining the optimal lag order, considering up to 10 lags, using the Akaike Information Criterion (AIC). However, to prevent code errors, we established a rule that if the best lag order turned out to be 0, it would be automatically set to 1.

Following this, we utilized the .test_causality function, employing a Wald test with a significance level of 5%, to compute critical values for assessing causality between the time series. Our estimation of VAR models commenced from the 50th date in our dataset and continued until the end, ensuring compatibility with the selected 10-lag order.

To assess the autocorrelation in the residuals of each optimal VAR model, we conducted a Ljung-Box test. Given the substantial number of more than 38,178 VAR models estimated per time series, it was impractical to review each individual test result. To address this challenge, we systematically noted lags in the residuals where the P-value was greater than 0.05, followed by a P-value less than 0.05 in the subsequent lag. This approach allowed us to identify the point at which autocorrelation was present.

For a more intuitive understanding of the results, we created visual graphs depicting the identified lags, providing a clear representation of the ultimate lag order at which autocorrelation ceased to be a significant factor.

As Granger causality tests linear causality between time series, we opted to also test causality using a non-linear analysis which is wavelet analysis.

5.3 Wavelet Analysis

A wavelet is a mathematical function used to analyze signals with time and frequency variations. We employed the PyWavelets Python library (Lee et al., 2019) to perform wavelet analysis, specifically the continuous wavelet transform (CWT). The CWT captures both time and frequency characteristics, helping us identify localized spillover effects between variables. This approach reveals the transmission of shocks or information and detects relationships that may be missed by other methods. PyWavelets provides a reliable implementation of the CWT, enhancing the accuracy of our analysis.

Continuous Wavelet transform:

$$\boldsymbol{x_w(a,b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} X(t)\bar{\psi}\left(\frac{t-b}{a}\right) dt}$$

Where: a is the scaling parameter (1/frequency) and “b” is the shifting parameter. $\boldsymbol{\bar{\psi}(t)}$ is the mother wavelet. Wavelets can be categorized into different families based on their shape. These families can be further divided into discrete and continuous wavelet families. The main distinction between these families lies in the values of the scaling parameters.

In continuous wavelet transform (CWT), the scaling parameters can theoretically take infinite values. However, this can pose practical challenges in analysis. To address this, the discrete wavelet transform (DWT) is commonly used. In DWT, the scaling parameter 'a' is replaced by 2−j, where 'j' is known as the scaling parameter. The shifting parameter 'b' is then made proportional to 'a', specifically b = k*2−j. In DWT, 'k' serves as the proportionality constant, taking on the role of the shifting parameter. By discretizing the scaling parameters in DWT, wavelet analysis becomes more practical and computationally feasible. This is why DWT is widely utilized in practice, allowing for efficient and effective analysis of signals using wavelets.

Discrete Wavelet transform:

$$x_w(a,b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} X(t)\bar{\psi}\left(\frac{t-b}{a}\right) dt$$

$$\psi_{j,k}(t) = \sqrt{2^j}\psi(2^j t - k)$$

This brings us to the concept of wavelet decomposition and recomposition. Decomposition involves separating the signal into approximation coefficients (A_N) for high-frequency components and detailed coefficients (D_N) for low-frequency components. This separation is achieved using the wavelet function 'ψj,k(t)' for high-frequency and the scaling function 'ϕj,k(t)' for low-frequency. High-frequency components obtained through decomposition can capture discontinuities, ruptures, and singularities present in the original data. On the other hand, low-frequency components characterize the overall structure of the data, helping identify long-term trends. Hence, high-frequency components complement the information provided by low-frequency components. To reconstruct the original signal, the following mathematical representation is used:

$$x(t) = \sum_{k=-\infty}^{\infty} a_{j_0,k}\varphi_{j_0,k}(t) + \sum_{j=-\infty}^{j_0} \sum_{k=-\infty}^{\infty} d_{j,k}\psi_{j,k}(t)$$

Where x(t) would be the reconstructed time series using the A_N and D_N coefficients. The maximum level of wavelet decomposition using the pywt.wavedec[12] function is calculated the following way:

$$\max\_level = \left\lfloor log_2\left(\frac{data\_len}{filter\_len - 1}\right)\right\rfloor$$

We performed a comprehensive analysis on our four time series by utilizing the "pywt.wavedec" function to extract multilevel coefficients. To explore different wavelet families, we took advantage of the wide range of discrete wavelet families available in the Python package, including Biorthogonal, Coiflets, Daubechies, Discrete FIR approximation of Meyer wavelet, Haar, Reverse biorthogonal, and Symlets. To reconstruct the time series, we effectively employed the "pywt.waverec" function.

[12] https://pywavelets.readthedocs.io/en/latest/ref/dwt-discrete-wavelet-transform.html

To assess the accuracy of the reconstructed time series, we employed the root mean square error (RMSE) as a measure of quality. The RMSE played a crucial role in determining the most suitable wavelet for our analysis. For each specific match, we selected the wavelet that minimized the error between the recomposed time series and the original time series. This rigorous minimization process ensured a highly accurate representation of the original data using the selected wavelet.

$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(x_i-\hat{x}_i)^2}{N}}$$

Where x_i is the actual value of the time series at time I and $\hat{x}_i$ is the reconstructed value of the time series.

Subsequently, we adopted a methodology, inspired by the research conducted by Kang et al. (2019), to explore the existence of a lead-lag relationship. To achieve this objective, we employed the Cross wavelet transform on two time series. By utilizing the Cross wavelet transform, our aim was to analyze the time-frequency relationship between the two series and pinpoint regions where they display comparable patterns or coherence. This approach enabled us to evaluate potential lead-lag dynamics between the time series and acquire valuable insights into their temporal dependencies.

To further analyze the data, we employed the Wavelet coherence technique. Wavelet coherence allows us to investigate the relationship between the two time series in the time-frequency domain. By calculating the normalized cross-spectrum between the time series, Wavelet coherence provides a quantitative measure of their coherence at different scales or frequencies. This approach enabled us to identify significant regions where the two series exhibit synchronized or correlated behaviour, thereby facilitating a comprehensive understanding of their interactions and dependencies over time.

Wavelet coherence:

$$R^2(a,b)=\frac{\left|S(C_x^*(a,b)C_y(a,b))\right|^2}{S(|C_x(a,b)|^2)\cdot S(\left|C_y(a,b)\right|^2)}$$

Where: S represents a smoothing operator, and $0 \leq R^2(a, b) \leq 1$.

To delve deeper into the analysis, we incorporated the Wavelet coherence phase difference. Wavelet coherence phase difference not only enables us to explore the time-frequency relationship between the two time series but also provides insights into the phase difference between them. By examining the phase angle associated with the cross-spectrum at different locations and scales, we can quantify the phase difference between the two series. This information contributes to a comprehensive understanding of the temporal dynamics and synchronization patterns exhibited by the time series, allowing us to gain deeper insights into their relationship.

Wavelet coherence phase difference:

$$\phi_{xy}(u,s) = tan^{-1}\left(\frac{\Im\{(S(s^{-1}W^{xy}(u,s))\}}{\Re\{(S(s^{-1}W^{xy}(u,s))\}}\right)$$

Where: $\Im$ is the imaginary and $\Re$ is the real part of the "the smoothed cross-wavelet transform".

We calculated all the previous using the biwavelet[13] library and its wta function in R. Monte Carlo methods of 1000 iterations were used to determine the degree of significance. The results will be shown using phase graphs in the result section. The Mother wavelet used by the wta function is the Morlet Wavelet:

$$\psi(x) = e^{-x^2/2}\, cos(5x)$$

Where: x is the value of the time series.

Wavelet coherence emerges as a robust tool for dissecting complex lead-lag relationships within time series data, offering distinct advantages over traditional methods like Pearson correlation and Granger causality. Its capacity to provide a time-frequency representation of relationships empowers analysts to unveil how associations evolve over time and across different frequencies. This capability proves particularly valuable when confronting non-stationary data, as wavelet coherence can adapt to changing statistical properties. Furthermore, unlike Pearson correlation and Granger causality, it excels at detecting multiple time lags and enables visual interpretation through informative wavelet plots. Moreover, its resistance to noise and outliers and ability to capture bidirectional relationships make it a versatile choice for investigating intricate time-dependent interactions in various domains.

[13] https://cran.r-project.org/web/packages/biwavelet/index.html

5.4 Twitter Sentiment index

The primary aim of creating a Bitcoin and Ethereum crypto sentiment index was to investigate its potential influence on cryptocurrency prices and returns. Furthermore, it strived to capitalize on economic opportunities by employing an effective trading strategy for maximum profitability, leveraging insights obtained from the previously mentioned lead-lag analysis methods.

The Twitter Sentiment index utilized in this study involved the application of a "roBERTa-base model" that had been trained on a vast dataset of approximately 58 million tweets. The model was specifically fine-tuned for sentiment analysis using the TweetEval benchmark, as outlined by Barbieri et al. in 2020. This sentiment analysis model, which is well suited for the English language, was provided by Cardiff University's CardiffNLP, a renowned institution in the field of Natural Language Processing (NLP).

To employ this model effectively, several libraries and tools were employed, including TensorFlow, transformers, SciPy, Special, NumPy, and Pandas. These libraries are widely used in the NLP domain and facilitate various tasks involved in tweet processing and analysis. Prior to inputting the tweets into the roBERTa model, certain modifications were made to the text to enhance the tweet processing. Specifically, references to users and websites were altered. User references, denoted by words starting with "@," were changed to "@user," while words beginning with "http," indicating website links, were transformed to "http." These modifications did not impact the sentiment analysis results but assisted in the overall tweet processing pipeline. Each tweet was then added to a list, creating an entry in the tweet processing database. Tokenization, a process that involves splitting paragraphs and sentences into smaller units for improved interpretation, was subsequently performed on the collected data. The tokenized data was transformed into a tensor, which served as the input format for the roBERTa model. The sentiment analysis provided by the model yielded negative, neutral, and positive scores, each ranging from 0 to 1. To obtain a final sentiment score for each tweet, the negative score was subtracted from the neutral score, and the positive score was added. These calculations resulted in a single sentiment score for each tweet. To generate a daily sentiment time series, the sentiment scores for tweets were averaged on a per-day basis.

In summary, the Bitcoin and Ethereum crypto sentiment index was created to explore its influence on cryptocurrency prices and optimize trading strategies. Using a roBERTa-based sentiment analysis model trained on Twitter data, various NLP tools were employed for efficient data processing. The resulting daily sentiment time series offers valuable insights into the connection between social media sentiment and cryptocurrency markets.

5.5 Trading Strategy

The goal of our trading strategy was to explore any potential economic advantages of our lead-lag analysis results. We devised a lead-lag momentum trading strategy. We facilitated comprehension by employing line charts as powerful visual aids, narrowing our focus to the analysis of two time series at any given point in our exploration.

--Insert Figure 2 here--

In this framework, we explored scenarios where Security 1 asserted its leadership over Security 2, a determination made through either Pearson correlation or Granger causality analysis, within the T-n to T timeframe. Notably, if this period coincided with an upward trajectory in Security 1's price, we conjectured the emergence of a similar price pattern in Security 2, albeit with a discernible time lag in its response to the movements in Security 1's price.

Recognizing the inherent uncertainty shrouding Security 2's future price trajectory from time t to time t+n, we adopted a fundamental assumption: it would closely replicate the observed price pattern in Security 1. This fundamental assumption gave rise to our initial governing rule:

General Strategy: If Security 1 demonstrated leadership over Security 2, and the price of Security 1 rose from T-n to T, we executed the purchase of one unit of Security 2 at time T, accompanied by an automatic sell order for one unit of Security 2 at time T+n.

We present modifications to the buy rule of our basic trading strategy as the holding period and sell rule will remain unchanged, contingent upon whether we applied the methodologies outlined in sections 5.1 and 5.2.

For Section 5.1, we introduced a refined rule:

Buy Rule 1: If Security 1 demonstrated leadership over Security 2, the price of Security 1 rose from T-n to T, and the Pearson correlation P-Value exceeded a specific threshold, we executed the purchase of one unit of Security 2 at time T. The threshold for the Pearson correlation P-Value was determined through rigorous testing, ranging from 0.05 to 0.85 in 0.05 intervals, and with finer intervals of 0.01 above 0.85, driven by the assumption that higher correlations would yield more profitable trading outcomes.

Turning to the Granger causality trading strategy, we introduced a modified version of Rule 1:

Buy Rule 2: If Security 1 demonstrated leadership over Security 2, the price of Security 1 rose from T-n to T, and the Granger causality P-Value is under a specific threshold, we execute the purchase of one unit of Security 2 at time T. The threshold for the Granger Causality P-Value was determined through rigorous testing, ranging from 0.00 to 0.05 in 0.005 intervals.

Given the non-stationary nature of both Bitcoin and Ethereum, we transform the time series into return time series for each asset, ensuring stationarity through an augmented Dickey-Fuller test. Using these Granger P-value results, we tested them on the closing price time series and not the returns as you cannot practically trade using returns, a security must be bought.

In the context of the wavelet-based trading strategy, we used Buy Rule 1 but modified our time series:

We employed decomposing each time series and subsequently reconstructing them. To identify the most suitable wavelet for each asset, we compared the reconstructed time series with the original data, calculating the root mean square error (RMSE). Our findings indicated that the bior 3.5 wavelet performs optimally for Bitcoin and Ethereum, while the bior 3.3 wavelet is most suitable for both the Twitter Uncertainty index and the RoBERTa index.

Within our strategy, we leveraged the Lagged Pearson Correlation Momentum Strategy, making enhancements by incorporating level 1 to 4 decompositions instead of utilizing the original time series for lagged inputs. After a thorough examination of the results, we discerned that these decomposition levels strike an effective balance in capturing the underlying trend of the time series. During the reconstruction process, we deliberately focused on the approximation coefficients, setting all detail coefficients to 0. This strategic adjustment prioritized the information conveyed by the approximation coefficients, amplifying the overall quality of our results. Through this iterative approach, we strived to refine our strategy and elevate our analytical capabilities.

6.Results

This section will be divided into various sub sections for the purpose of clarity and to adequately compare the pre-merge time series with the post-merge time series. In Section 6.1, we present the findings of the lagged cross-correlation analysis. This is followed by the results of the Granger causality test in Section 6.2 and the Wavelet coherence analysis in Section 6.3. Section 6.4 provides a comprehensive summary of our results in relation to our hypotheses, and finally, Section 6.5 offers conclusions based on our trading strategy results.

6.1 Cross-correlation

Examining the Bitcoin lags Ethereum relationship, we discovered that from mid-2016 to mid-2017, a positive and significant (5%) correlation emerged as seen in Figure 3. Subsequently, from 2018 to the end of our dataset, the correlation values oscillated between 0.75 and 0.93. Post-merge, we observed that as the lag increased, the correlation weakened but stayed significant (5%), emphasizing the short-term nature of this relationship as seen in Figure 5.

--Insert Figure 3 here--

For the Bitcoin lags the Twitter Sentiment Index relationship, we noted a slight positive correlation in the first half of 2016, followed by a slight negative trend, with values hovering around -0.3 to -0.4 until the dataset's end and being significant at the 5% level from mid-2017 onward as shown in Figure 5. Interestingly, as the lag increased post-merge, the correlation values tended to become more negative, while closer lags showed positive correlations as demonstrated in Figure 4. The inverse relationship, where the Twitter Sentiment Index lagged Bitcoin, displayed a convergence toward a small positive correlation coefficient of 0.25 was significant from mid-2017 onward at 5% as shown in Figure 5.

--Insert Figure 4 here--

Analyzing Bitcoin's lagging relationship with the Twitter Uncertainty Index, we observed peak positive correlation periods from 2016 to 2018 and from 2020 to mid-2021, coinciding with Bitcoin's all-time high price periods. Bitcoin tended to lag the uncertainty index, and the correlation strength was generally weaker. Additionally, the p-value is mostly significant throughout the dataset apart from a few peaks around 2016, the middle of 2017, 2019 and 2022. Post-merge, the correlation values aligned with the long-term trend. For the inverse relationship, we observed the same results for both the pre-merge and post merge.

Regarding Ethereum lagging with the Twitter Sentiment Index, a small peak around 0.2 in mid-2016 indicated mostly negative Pearson correlation coefficients but significant at the 5% level as shown in Figure 5. During Ethereum's all-time high periods, we observed peak negative correlation with the Twitter Index. Post-merge, we found that the further the lag, the more negative the relationship, while closer lags exhibited positive correlations, mirroring the Bitcoin and Twitter Index findings. Conversely, in the inverse relationship, where our Twitter Index lagged Ethereum, all lags converged to positive values within a narrow range around 0.25.

--Insert Figure 5 here--

Finally, in the Ethereum lags the Twitter Uncertainty Index relationship, we identified a small positive correlation between 2016 and 2017, but subsequent coefficients oscillated around the 0.0 mark, indicating no significant correlation between the Uncertainty Index and Ethereum's price. Post-merge, the results closely paralleled those found in the Bitcoin analysis. For the Twitter Uncertainty Index relationship lags Ethereum, we observed that it mirrored the previous analysis.

--Insert Figure 6 here--

In conclusion, from mid-2016 to mid-2017, there existed a noteworthy positive correlation between Bitcoin and Ethereum. Furthermore, Bitcoin demonstrated a slight negative correlation with the Twitter Index, while it exhibited peak positive correlations with the Twitter Uncertainty Index during specific periods. Conversely, Ethereum mainly displayed negative correlations with the Twitter Sentiment Index. After the merge, the correlations between Bitcoin and Ethereum remained significant but weakened as the lag increased. Additionally, the negative correlation between Bitcoin and the Twitter Index became more pronounced with an increasing lag. Moreover, correlations between Bitcoin and the Twitter Uncertainty Index followed long-term trends, and Ethereum's correlations with the Twitter Sentiment Index became increasingly negative with greater lag. In cases where the Twitter Index lagged, correlations generally converged to positive values within a narrow range around 0.25.

6.2 Granger causality

We tested the same 10 lead-lag relationships as in the correlation results section. For the Bitcoin granger causes Ethereum, our analysis revealed that from the second quarter of 2021 until the end of the dataset, only the 1-day lag demonstrates a 5% level of significance, indicating that Bitcoin returns Granger cause Ethereum returns as shown in Figure 7. Notably, the 3-day and 4-day lags emerge as significant at a 10% level, while all other lags do not reject the null hypothesis that Bitcoin does not Granger cause Ethereum. Post-merge results exhibit abundant autocorrelation among residuals, rendering the findings unreliable. Still, the 1-day and 3-day lags remain significant throughout the entire period.

--Insert Figure 7 here--

In the context of Ethereum Granger causing Bitcoin, only the 0-day and 8 to 9-day lags display significance at the 5% level. This suggests that Ethereum can be valuable for predicting Bitcoin's price movements. Post-merge, autocorrelation among residuals persists, but the 0 and 1-day lags remain significant. For the post-merge period, the 0, 3, and 14-day lags show significance at the 5% level.

--Insert Figure 8 here--

Looking at the relationship for Bitcoin lagging our Twitter Sentiment Index, disregarding the data between 2016 and 2017 due to autocorrelations in the residuals, we observed significance from mid-2019 onward, with lags 3 (5% level), 4 (5% level), and lag 2 (10% level) indicating that Bitcoin's price causes our Twitter index. Additionally, our Twitter Index also Granger causes the price of Bitcoin. This could be attributed to Twitter users' reactionary behavior or efforts to motivate cryptocurrency buyers during the crypto winter of 2018 to almost the end of 2020. Post-merge, only the 3-day lag is significant for Bitcoin Granger causing Twitter, while for the inverse relationship, lags 1 (5% level),, 2 (5% level), and 6-day (10% level) exhibit significance.

--Insert Figure 9 here--

In the relationship between Bitcoin and the Twitter Uncertainty Index, a similar pattern to our constructed index emerges. However, Bitcoin Granger causes the Twitter Uncertainty Index for fewer lags than the inverse relationship, possibly due to differences in data collection methodologies. Post-merge, no lags cause the Twitter Uncertainty index for Bitcoin. For the inverse relationship, the 0 and 9-day lags are significant at a 10% level, and the 1-day lag is significant at a 5% level.

--Insert Figure 10 here--

Our findings indicate that from mid-2019 onward, we cannot reject the null hypothesis regarding Ethereum Granger causing the Twitter Index. This aligns with the upward movement of Ethereum prices starting in mid-2020, suggesting Twitter users' efforts to influence the crypto's performance on the platform. In the contrary relationship, the index Granger causes the price of Ethereum for a wide range of lags, emphasizing the index's role as a prime determinant of Ethereum's price. Post-merge results were not specified.

The relationship between Ethereum and the Twitter Uncertainty Index resembles our own index findings, with the uncertainty index having a more significant "granger" influence than Ethereum's price towards the index. Post-merge, the 0 and 9-day lags are significant, and the 1-day lag is significant at a 10% level.

--Insert Figure 11 here—

--Insert Figure 12 here—

In summary, our analysis shed light on the presence of Granger causality in various cryptocurrency and social media sentiment relationships, offering valuable insights into the interplay between these factors. It's important to note that autocorrelation in residuals and variations in significance levels can impact the reliability of these findings, necessitating caution in their interpretation. However, these findings support our earlier cross-correlation results.

--Insert Figure 13 here--

--Insert Figure 14 here--

6.3 Wavelet coherence

As mentioned earlier, we employed the WTA function from the Biwavelet library in R to generate the graphs showcased in Figures 8 and 9. These graphs, referred to as phase plots, contain several important technical insights. Specifically, arrows symbolize the lead/lag phase relationships. Rightward arrows indicate that x and y are in phase, while leftward arrows signal an anti-phase relationship. A zero-phase difference implies that the two time series move together at a specific scale. In-phase implies they move in the same direction, whereas anti-phase suggests opposite directions. Upward arrows suggest that y leads x by $\pi/2$, and downward arrows indicate that x leads y by π/2. The horizontal axis represents time in years (or months), while the vertical axis represents time scales in days. The coherence, ranging from 0 to 1, is depicted by the bar chart on the right side of the plots, with blue denoting no co-movement (0) and 1 representing complete co-movement.

Regarding the wavelet coherence graphs for the entire sample in Figure 15, our results indicated that Bitcoin and Ethereum were predominantly in phase. This meant that Bitcoin lagged Ethereum, except for the period between 2016 and 2018 for scales up to 64, and from 2018 to 2023, particularly around the 256-day scales. In essence, from 2018 onward, Bitcoin lagged behind Ethereum at shorter time scales of less than 64 days. For Bitcoin and the Twitter Sentiment Index, the time-series displayed low dependence between them, except for a few randomly distributed clusters on the chart. As for Bitcoin and the Twitter Uncertainty Index, the dependence between the time series was such that the Uncertainty Index lagged Bitcoin. However, this was true only from 2019 to 2023, and for scales greater than approximately 300.

In the case of Ethereum and the Twitter Sentiment Index, it was observed that around the time of the merger, both series were in phase, with Ethereum being the leading variable—an unexpected finding. One possible explanation could be that uncertainty in crypto space was influenced by Ethereum's price movement. Similarly, Ethereum and the Twitter Uncertainty Index yielded results like Bitcoin, but with fewer instances of anti-phase. This suggested a smaller lead-lag relationship of the Uncertainty Index in relation to Ethereum's price movement.

--Insert Figure 16 here--

Moving on to the post-merger wavelet coherence analysis as seen in Figure 16, the y-axis of the charts was now limited to a maximum of 62 days for the scale, and the x-axis ranged from the merger date to mid-March. In the case of Bitcoin and Ethereum, both series were nearly in phase for all data points, except for a few clusters, and Bitcoin mostly lagged behind Ethereum. Bitcoin and the Twitter Sentiment Index showed that Bitcoin was in phase in October and November 2022 for scales between 16 and 32 days, with Bitcoin also being the leading variable. Another noticeable cluster was observed in March 2023, where the Twitter Sentiment Index led for scales around 8 days. For Bitcoin and the Twitter Uncertainty Index, there was only a phase alignment between October and November 2022, with the Twitter Sentiment Index leading.

In contrast, Ethereum and the Twitter Sentiment Index exhibited phase alignment between October and November 2002, with Ethereum being the leading variable. Ethereum and the Twitter Uncertainty Index showed no consistent phase alignment, except for sporadic clusters, throughout the entire sample period.

To compare results between Granger Causality and the Wavelet analysis, our study found that Bitcoin often lagged behind Ethereum, with Ethereum influencing Bitcoin's price movements and a complex relationship with our Twitter Sentiment Index and Twitter Uncertainty Index, as supported by both coherence and Granger causality analyses.

6.4 Lead-Lag Synthesis

Examining the Bitcoin to Ethereum relationship over an extensive period, we uncovered intriguing trends. From mid-2016 to mid-2017, a significant positive correlation emerged between Bitcoin and Ethereum, suggesting that these two leading cryptocurrencies moved somewhat in sync during that timeframe. Subsequently, from 2018 through the end of our dataset, the correlation values exhibited a consistent oscillation, hovering between 0.75 and 0.93. This stable positive and significant correlation implied that, over this period, changes in the values of Bitcoin and Ethereum tended to be positively correlated, albeit not perfectly. However, for the post-merge period, we noted that as the time lag between Bitcoin and Ethereum data points increased, the correlation between them weakened significantly. This emphasized the inherently short-term nature of the Bitcoin-Ethereum relationship, indicating that their price movements became less intertwined as the temporal gap expanded. This phenomenon had potential implications for traders and investors seeking to understand the evolving dynamics of the cryptocurrency market.

To compare results between Granger Causality and the Wavelet analysis, the relationship between Bitcoin and Ethereum revealed that Bitcoin often lagged behind Ethereum, as indicated by Wavelet coherence analysis. Granger causality analysis further supported this observation, particularly at a 1-day lag, aligning with the coherence results. In contrast, Ethereum demonstrated its influence on Bitcoin's price movements, especially with no lag, underscoring its potential for predicting Bitcoin's price. Regarding Bitcoin's interactions with the Twitter Sentiment Index, a complex relationship was suggested by coherence results, with Granger causality analysis showing bidirectional causality at different lags. Similarly, the coherence analysis showed a phase relationship between Bitcoin and the Twitter Uncertainty Index, which was substantiated by Granger causality results, indicating that Bitcoin Granger caused fluctuations in the Uncertainty Index. For Ethereum's interactions with sentiment and uncertainty indices, Granger causality results aligned with coherence findings, reflecting Ethereum's influence on these indices, albeit with varying degrees of influence. These findings form the basis for the discussion of our hypotheses:

Hypothesis 1a: This hypothesis suggested that there will be a significant difference in the lead-lag relationship for Ethereum before and after the merge on September 15, 2022. Our three methods of analysis showed that Ethereum and Bitcoin continued to exhibit similar patterns, with Bitcoin lagging behind Ethereum, both before and after the merge. The analysis does not support this hypothesis thus we reject it, indicating that the loss of the mining community, resulting from the merge, did not substantially impact Ethereum's price dynamics concerning lead-lag relationships.

Hypothesis 1b: This hypothesis posited that the influence of investor sentiment would be greater post-merge as the importance of mining diminished for Ethereum. Our three methods of analysis revealed that for cross-correlation no change was observed, for Granger Causality, no change was observed regarding the influence of the indices of Ethereum and for wavelet analysis we arrived at the same conclusion as the two previous methods. The analysis does not align with this hypothesis; thus, we reject it, suggesting that there was no shift in Ethereum's price dynamics post-merge.

Hypothesis 2: This hypothesis suggested that the merge did not significantly impact the price of Bitcoin. Our three methods of analysis showed that Bitcoin's relationship with Ethereum and social media sentiment did not exhibit significant changes post-merge. Our analysis supports this hypothesis thus we do not reject it, indicating that Bitcoin, as the most influential cryptocurrency, remained less susceptible to spillover effects from the merge.

In conclusion, the findings suggest that the merge did not influence the dynamics of Ethereum's price. However, Bitcoin remained relatively stable and less affected by these changes, reinforcing its position as a dominant cryptocurrency in the market. These insights contributed to a deeper understanding of the complex interplay between cryptocurrency prices and external factors like social media sentiment and network upgrades.

6.5 Trading Strategy

In this section, we will be exposing our various trading strategy results. First, we will share our lagged cross-correlation results, secondly our Granger causality results and lastly our discrete wavelet transforms lagged cross-correlation results. Our initial trading amount was 10,000 and we always reinvested the full amount to buy one unit of the leading variable. However, in some cases, the value would go negative, thus incurring in a capital call.

6.5.1 Lagged Cross-Correlation

It is important to note that because the correlation between the cryptocurrencies and the Sentiment index and the Uncertainty index were unconclusive, we decided not to test the trading strategies on them for the correlation strategy as it would have just let the strategy run on "luck". We tested all lags up to 14 for all p-values as indicated in the methodology section. Results for our top 5 best performing strategies are seen in table 4 as the total number of tested combinations based on our metrics was 434.

--Insert Figure 17 here--

Starting with Ethereum that lags Bitcoin, our results show that the best performing strategy is the one where Ethereum lags Bitcoin by 13 days, with a Pearson correlation coefficient of 0.89. This can be shown in Chart 17. The total gain of the strategy was 688,385.03 and the total loss was 242,558.27 for a net trading profit of 445,826.75. The total number of buy transactions was 280 thus resulting in 280 sell orders. What is interesting to note is that there is a small cluster of trades around the end of 2017 that results in a net loss value. Afterwards, the strategy lays dormant until mid-2021, whereas seen on the Net value history chart. It becomes profitable. We conclude that the Trading Strategy shows that economically, there is a lead-lag relationship between Ethereum and Bitcoin for trading purposes.

--Insert Figure 18 here--

Continuing with Bitcoin that lags Ethereum, our results show that the best performing strategy is the one where Ethereum lags Bitcoin by 14 days, with a Pearson correlation coefficient of 0.93. This can be shown in Chart 18. The total gain of the strategy was 45,917.56 and the total loss was 20,316.43 for a net trading profit of 25,601.12. The total number of buy transactions was 361 thus resulting in 361 sell orders. Our results show that more trades occurred and that they happened in 2 clusters. What is interesting is that the strategy proved to always have a positive net value. The reason that it is less profitable than the inverse relationship is that the rule is to buy 1 unit and sell 1 unit, because the price of Ethereum is smaller than the price of Bitcoin. We also found that there is a lot of volatility in the Net value when trades occur in 2022-2023.

6.5.2 Lagged Granger Causality

For the Granger causality, because we cannot trade sentiment indices, we did the following pairs: Ethereum granger causes Bitcoin, Bitcoin granger causes Ethereum, Twitter Sentiment Index granger causes Bitcoin, Twitter Sentiment Index granger causes Ethereum, Twitter uncertainty Index granger causes Bitcoin and Twitter uncertainty Index granger causes Ethereum. Our total number of tested strategies was 140 per combination.

--Insert Figure 19 here--

Commencing with Ethereum Granger causing Bitcoin, our findings indicated that the most effective strategy involved Ethereum trailing Bitcoin by a margin of 10 days, accompanied by a P-value of 0.035. This correlation is visually depicted in Figure 19. The cumulative profit from this strategy amounted to 810,715.24, while the losses incurred were 485,508.34, ultimately yielding a net trading profit of 325,206.89. This strategy comprised a total of 464 buy transactions, leading to an equal number of sell orders.

Moving to the Bitcoin Granger causing Ethereum analysis, our study revealed that the optimal approach entailed Bitcoin lagging Ethereum by a span of 3 days, with a corresponding P-value of 0.040. This observation is graphically represented in Figure 20. The cumulative profit generated through this strategy reached 6,036.24, while the losses amounted to 4,193.36, culminating in a net trading profit of 1,842.86. In total, this strategy involved 64 buy transactions, each followed by a corresponding sell order.

--Insert Figure 20 here--

Turning to Twitter Sentiment Index Granger causing Bitcoin, our analysis indicated that the most successful strategy was characterized by the Twitter Sentiment Index trailing Bitcoin by a duration of 13 days, yielding a P-value of 0.05. This relationship is graphically depicted in Figure 21. The cumulative profit realized from this strategy totaled 282,301.84, with concurrent losses amounting to 158,758.01, resulting in a net trading profit of 123,543.82. This strategy encompassed a total of 113 buy transactions, each resulting in a corresponding sell order.

--Insert Figure 21 here--

When implementing the strategy where Twitter Sentiment Index Granger causes Ethereum, our best strategy contained 11 lags with a P-value of 0.04. The total gain of the strategy was 20097.49 and a total loss of 6224.03 that yields a final net value of 13873.46 as seen in Figure 22. There was a total of 232 transactions.

--Insert Figure 22 here--

In the case of Twitter Uncertainty Index Granger causing Bitcoin, our research unveiled that the most effective strategy involved the Twitter Uncertainty Index lagging Bitcoin by a span of 7 days, accompanied by a P-value of 0.05. This trend is visually depicted in Figure 23. The cumulative profit from this strategy amounted to 553,755.84, while the losses incurred were 482,922.77, ultimately yielding a net trading profit of 70,833.07. This strategy comprised a total of 765 buy transactions, resulting in an equivalent number of sell orders.

--Insert Figure 23 here—

Similarly, when Twitter Uncertainty Index Granger caused Ethereum, the strategy that yielded the best results involved the Index lagging Ethereum by a period of 13 days, with a corresponding P-value of 0.045. This relationship is depicted in Figure 24. The cumulative profit generated through this strategy reached 5,994.36, while the losses amounted to 3,017.99, resulting in a net trading profit of 2,976.37. In total, this strategy involved 173 buy transactions, each followed by a corresponding sell order.

--Insert Figure 24 here—

--Insert Table 4 here—

--Insert Table 5 here—

In conclusion, our analysis of various Granger causality relationships between Ethereum, Bitcoin, and our Twitter Sentiment Index and Twitter Uncertainty index has provided valuable insights into trading strategies. We've observed that in certain scenarios, lagged relationships between these factors can lead to profitable trading strategies, as evidenced by the net trading profits generated. Notably, when Ethereum lagged Bitcoin by 3 days, it resulted in a significant trading profit, whereas Bitcoin lagging Ethereum by 13 days also demonstrated a profitable strategy. Additionally, the Twitter Sentiment Index lagging Bitcoin by 13 days and the Twitter Uncertainty Index lagging Bitcoin by 13 days yielded favorable trading outcomes. The strategy involving Twitter Sentiment Index lagging behind Ethereum by 11 days did produce economically viable trades.

--Insert Table 6 here—

--Insert Table 7 here--

These findings highlighted the potential for leveraging time-based relationships and sentiment indicators in cryptocurrency trading strategies. However, it's important to consider the dynamic nature of these markets and conduct ongoing analysis to adapt to changing conditions and optimize trading strategies for long-term success.

6.5.3 Discrete Wavelet Transform

For the Wavelet Analysis, we only tested it on the correlation algorithms as, the results are better than the Var Granger Trading Strategy. We tested the same number of combinations i.e., 434.

--Insert Figure 24 here—

As shown in Figure 24, we tested whether the decomposition of the time series at various levels could help enhance the trading returns of the Pearson correlation strategy. We tested for both the Ethereum price close lags Bitcoin price close and the inverse relationship.

--Insert Table 8 here--

Concerning the first, the “vanilla” trading strategy yielded a net value of 445,826.76 with 560 trades for a lead-lag of 13 lags. Using the Bior3.5 wavelet for decomposition, we found that at level 3 of decomposition yielded the best results with a net profit value of 440195.02, a total number of trades of 582 for a lead-lag of 13 lags as shown in table 8. Thus, we conclude that the wavelet transform did not enhance our trading returns although the net value is very close from one another.

--Insert Table 9 here--

Turning to the inverse relation, the “vanilla” trading strategy yielded a net value of 25,601.13 with 722 trades for a lead-lag of 14 lags. Using the Bior3.5 wavelet for decomposition, we found that at level 2 of decomposition yielded the best results with a net profit value of 24810.25, a total number of trades of 758 for a lead-lag of 14 lags as show in table 9. Thus, we conclude that the wavelet transform did not enhance our trading returns although the net value is very close to one another.

This concluded that, in our case of Pearson Momentum lead-lag relationship, discrete wavelet decomposition does not enhance returns. This confirms the findings of (Erog, 2022) that wavelet denoising can help generate profitable trades, however, further research would be needed to determine if it can help enhance returns.

For most trading strategies, there was a great number of trades executed post-merge. However, it is difficult to conclude that these are the results of the merge or rather an increase in volatility in both the Ethereum and Bitcoin prices.

7.Conclusion

In conclusion, our comprehensive analysis of the lead-lag relationships between Bitcoin, Ethereum, and our Twitter Sentiment index and the Twitter Uncertainty index has provided valuable insights into the dynamics of the cryptocurrency market, both pre and post the merge event on September 15, 2022.

In the pre-merge period, we observed significant correlations, Granger causality and wavelet analysis relationships between Bitcoin and Ethereum. Concerning these cryptocurrencies and social media sentiment, the connection can be characterized as weak but significant in various time frames. These findings suggest that there existed complex interactions between cryptocurrency prices and external factors, such as investor sentiment and uncertainty.

Furthermore, our trading strategy analysis indicated the potential for profitable trading strategies based on these lead-lag relationships.

However, the post-merge period revealed interesting shifts in these relationships. While Bitcoin and Ethereum continued to exhibit a lead-lag relationship, indicating the resilience of this dynamic even after the merge, as shown by our rejection of our hypothesis 1. Additionally, the influence of social media sentiment on cryptocurrency prices appeared to not change post-merge, emphasizing that the role of investor sentiment as mining dynamics changed did not change which rejected our hypothesis 1b. Notably, Bitcoin remained relatively stable and less susceptible to the effects of the merge, reinforcing its position as a dominant cryptocurrency in the market which confirmed our hypothesis 2.

Our trading strategy analysis offered insights into the potential profitability of leveraging these lead-lag relationships, but it also highlighted the need for caution due to market volatility and changing conditions as most trades occur in a high volatility environment.

In summary, the merge event did not influence the dynamics of Ethereum's price and Bitcoin’s price. These insights contribute to a deeper understanding of the evolving cryptocurrency market and provide valuable information for traders and investors looking to navigate this complex and dynamic landscape. Further research is warranted to explore the ongoing impact of such events and the potential for enhanced trading strategies.

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Figures

Figure 1: Total datasets statistics, the red line indicates the merge date of September 15th, 2022.

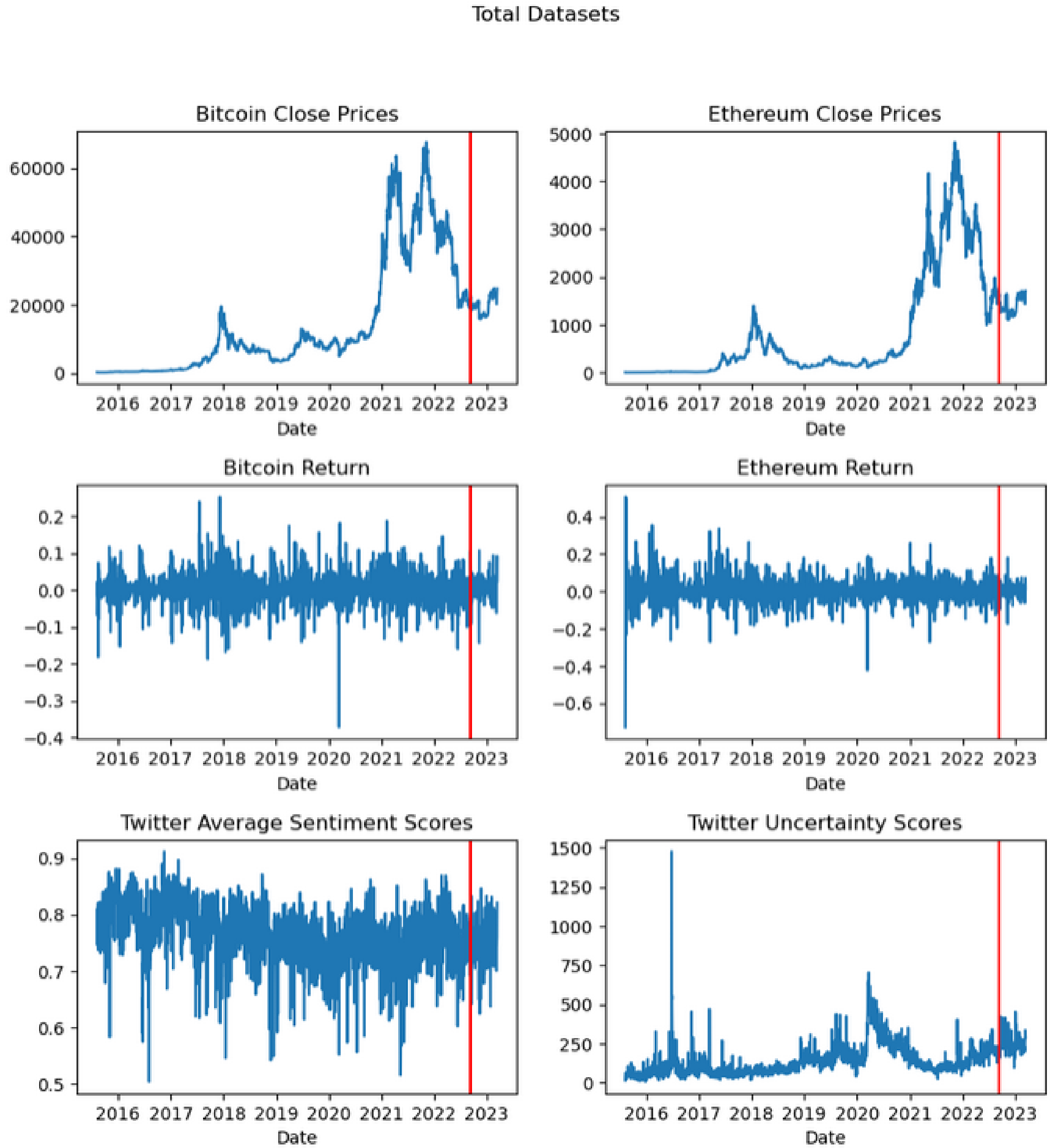


Figure 2

Momentum Trading Strategy simplification where T is the time and n is the number of days.

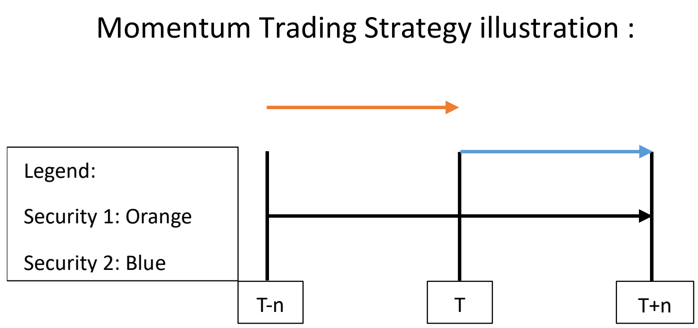


Figure 3:
Pearson Correlation coefficients when one time series lags another for all the combinations of our datasets for the entire sample period. The red line is the merge date.

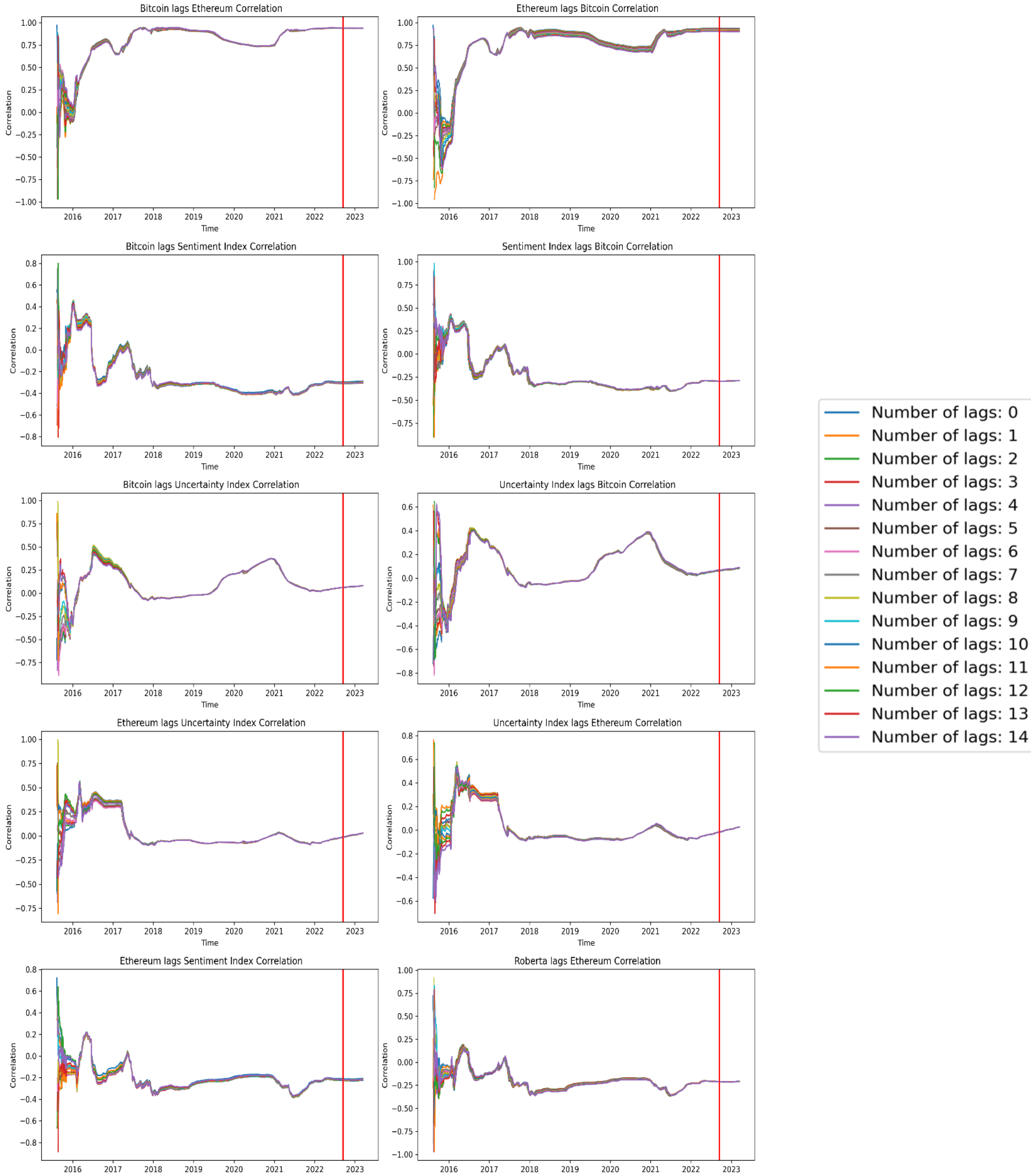


Figure 4:

Pearson Correlation coefficients when one time series lags another for all the combinations of our datasets for the Post-Merge sample period.

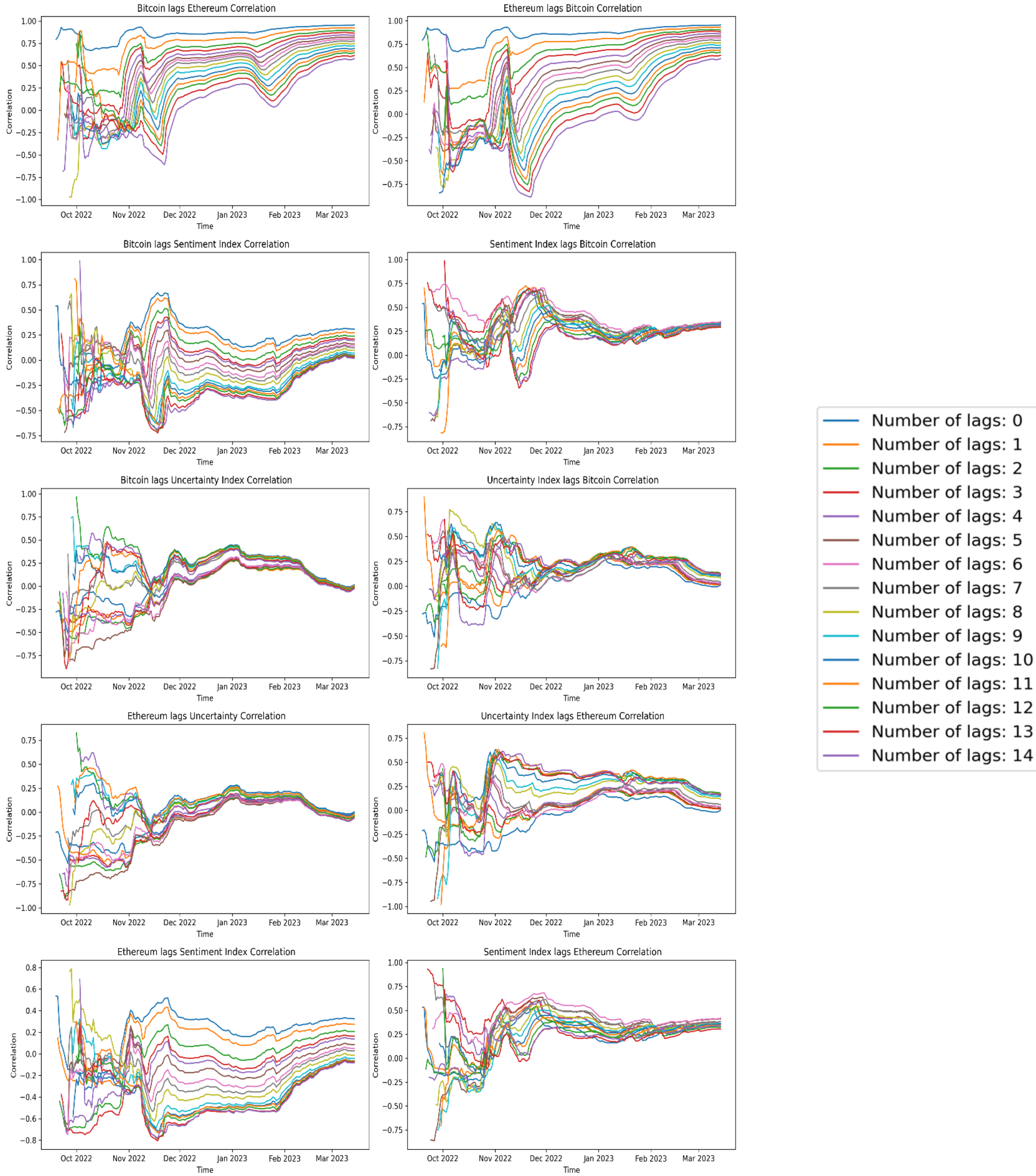


Figure 5

Pearson Correlation coefficients p-values when one time series lags another for all the combinations of our datasets for the entire sample period. The red line is the merge date, the horizontal pointy red line is the 5% level threshold, and the pointy purple line is the 10% level threshold.

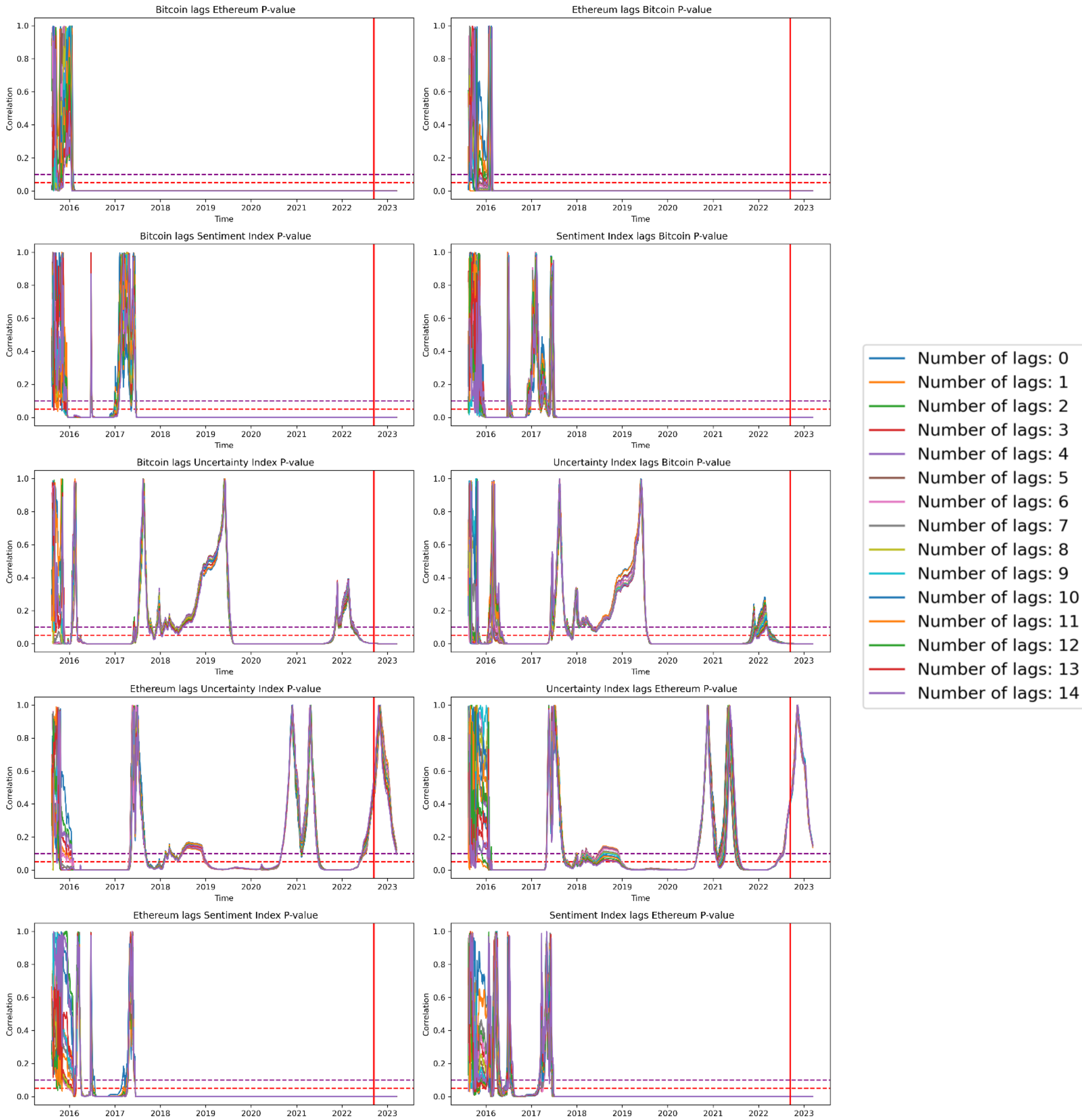


Figure 6:
Pearson Correlation coefficients P-values when one time series lags another for all the combinations of our datasets for the Post-Merge sample period. The red line is the merge date, the horizontal pointy red line is the 5% level threshold, and the pointy purple line is the 10% level threshold.

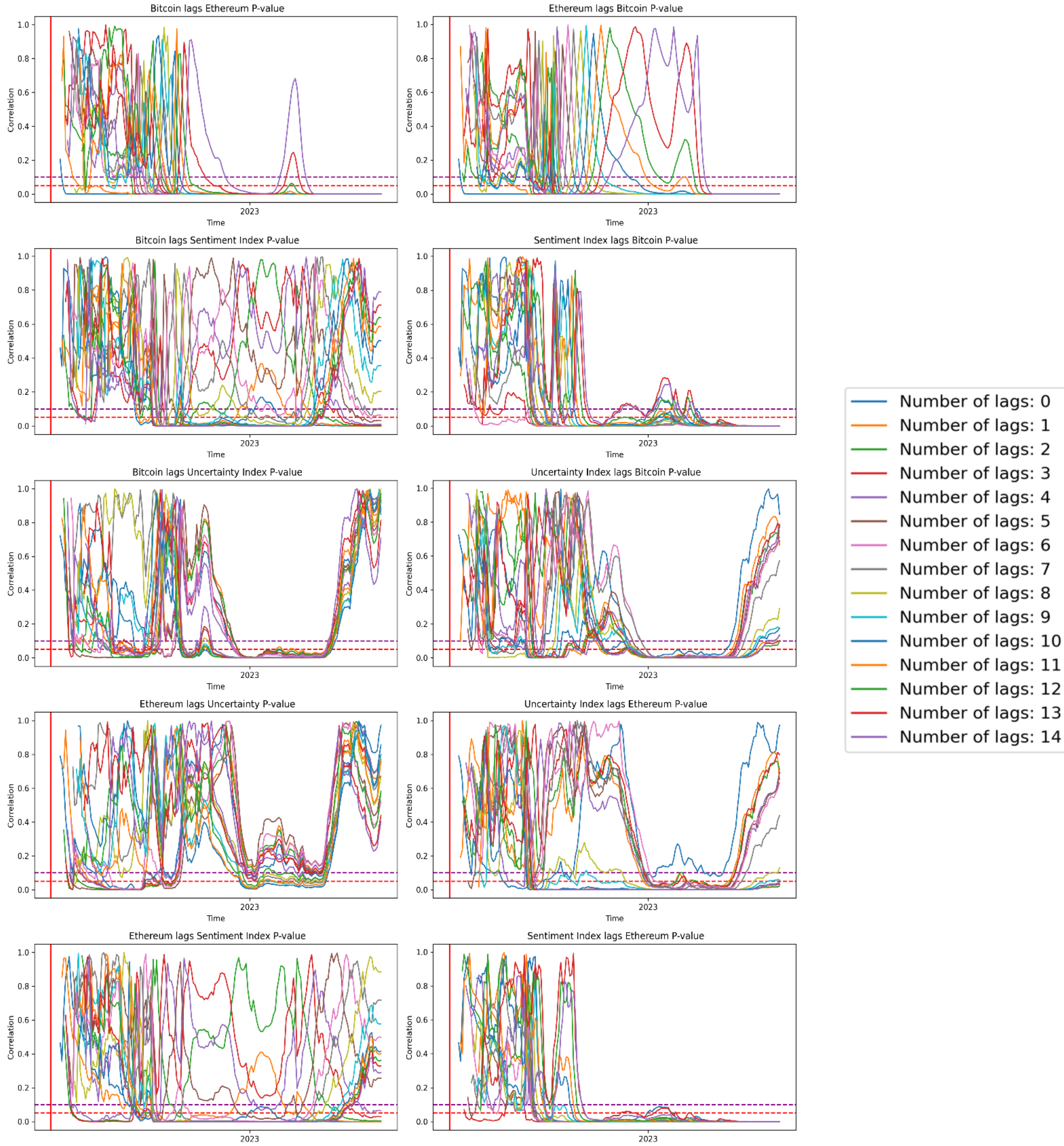


Figure 7 Total sample for lags 0 to 14 for the P-values over time for the Granger Causality tests, the number of VAR model lags and the where the Ljung-Box lag for autocorrelation detection appears. The red line is the merge date, the horizontal pointy red line is the 5% level threshold, and the pointy purple line is the 10% level threshold.

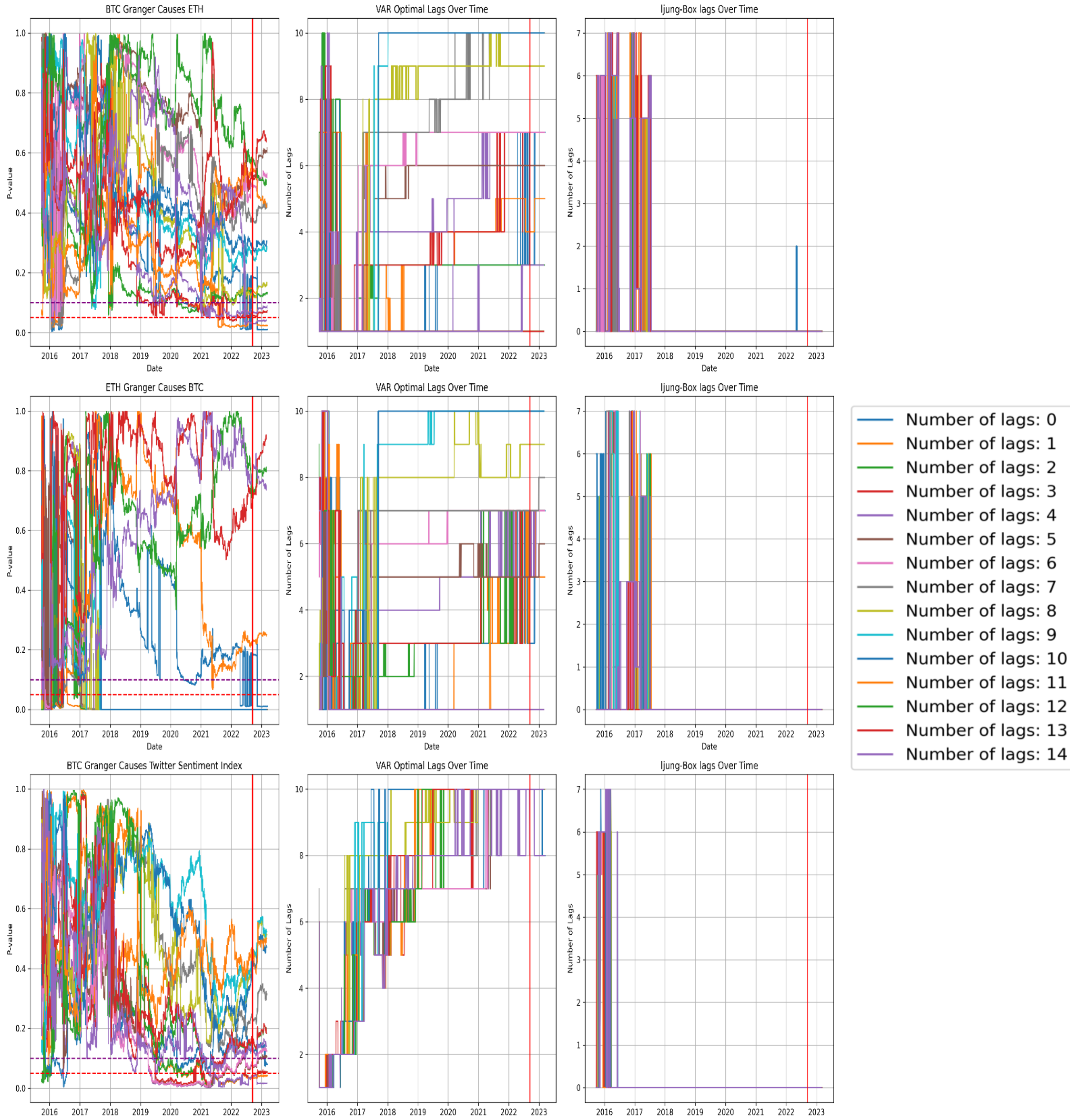


Figure 8 Total sample for lags 0 to 14 for the P-values over time for the Granger Causality tests, the number of VAR model lags and the where the Ljung-Box lag for autocorrelation detection appears. The red line is the merge date, the horizontal pointy red line is the 5% level threshold, and the pointy purple line is the 10% level threshold.

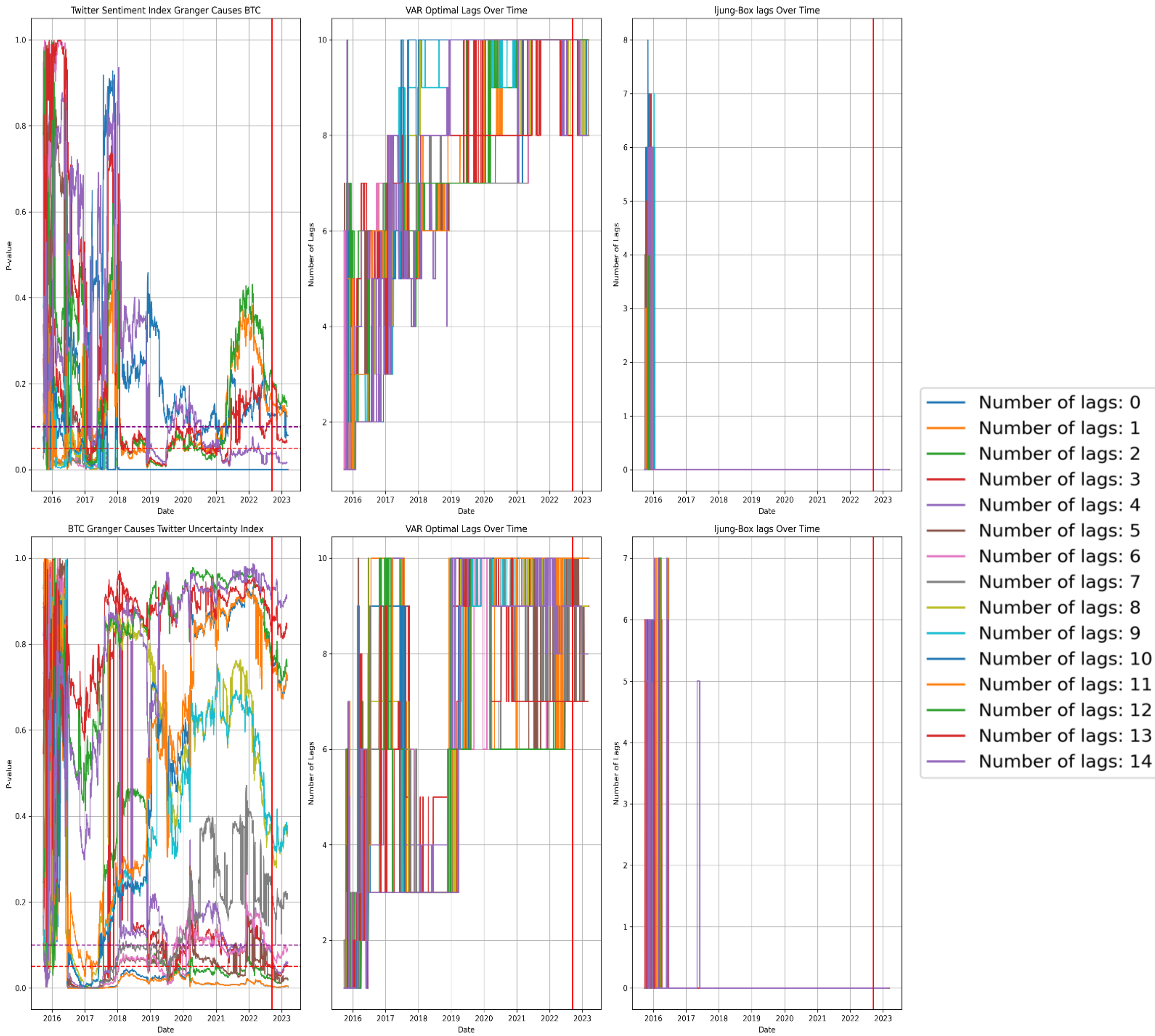


Figure 9 Total sample for lags 0 to 14 for the P-values over time for the Granger Causality tests, the number of VAR model lags and the where the Ljung-Box lag for autocorrelation detection appears. The red line is the merge date, the horizontal pointy red line is the 5% level threshold, and the pointy purple line is the 10% level threshold.

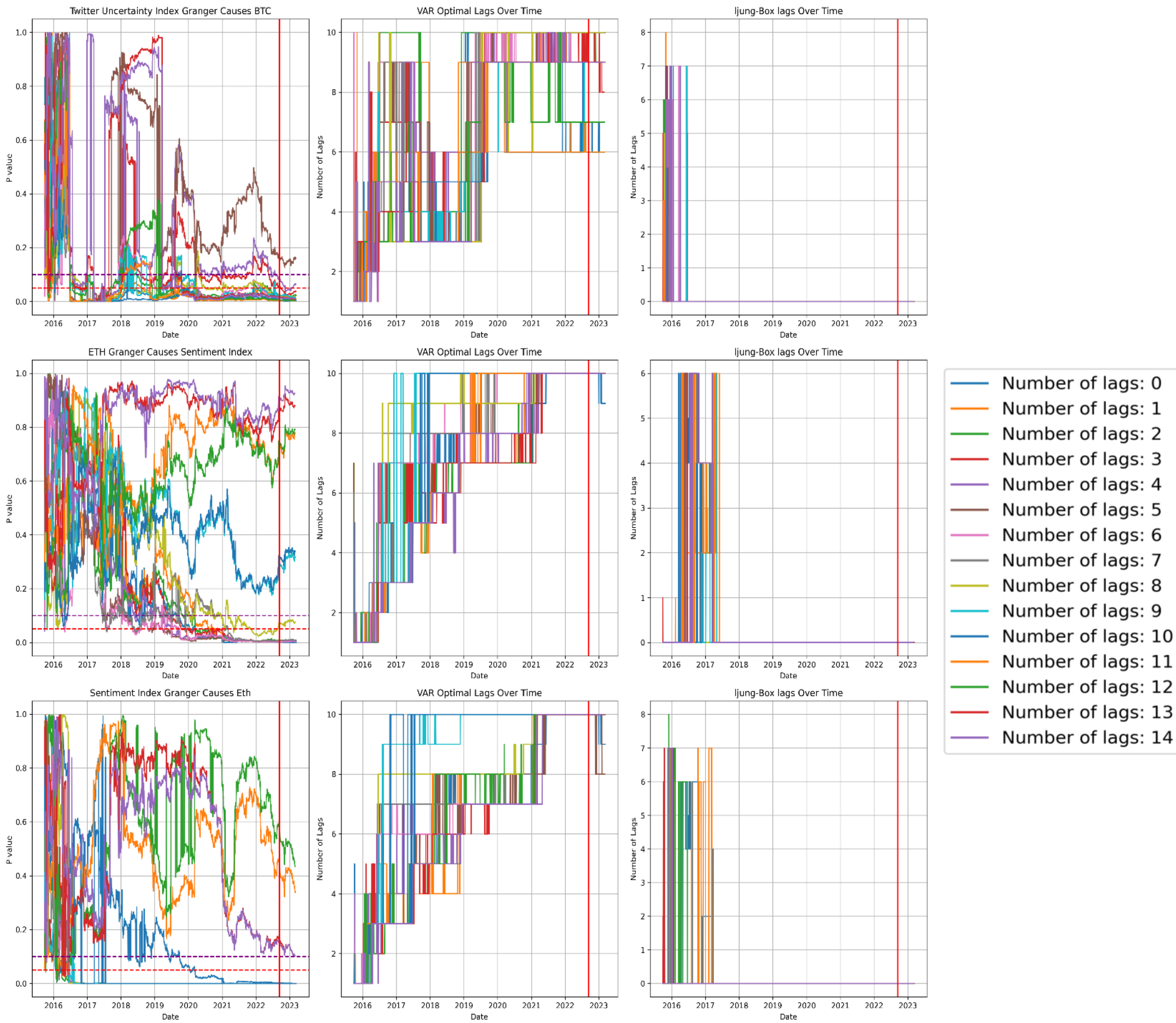


Figure 10 Total sample for lags 0 to 14 for the P-values over time for the Granger Causality tests, the number of VAR model lags and the where the Ljung-Box lag for autocorrelation detection appears. The red line is the merge date, the horizontal pointy red line is the 5% level threshold, and the pointy purple line is the 10% level threshold.

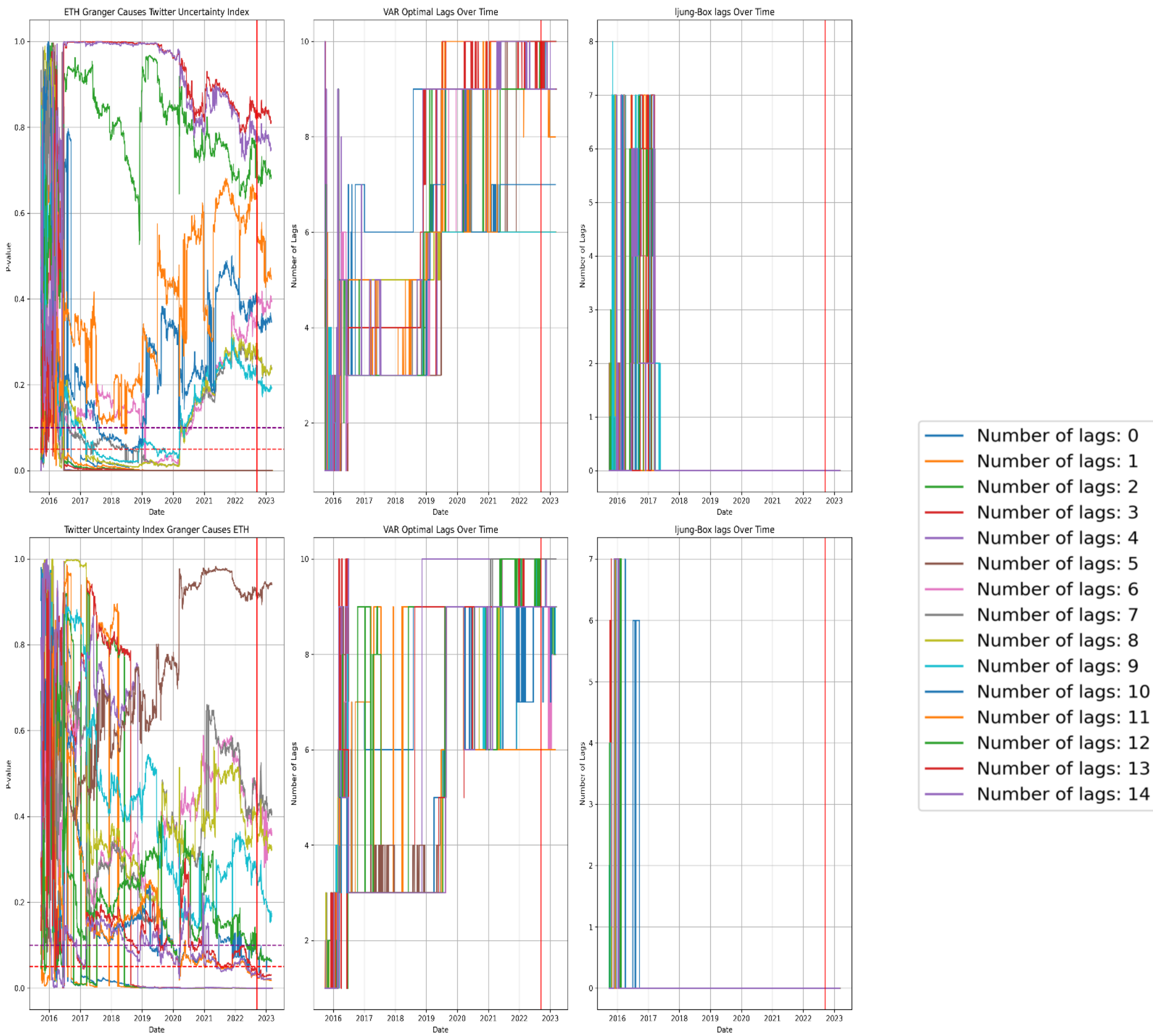


Figure 11 Post merge sample for lags 0 to 14 for the P-values over time for the Granger Causality tests, the number of VAR model lags and the where the Ljung-Box lag for autocorrelation detection appears. The red line is the merge date, the horizontal pointy red line is the 5% level threshold, and the pointy purple line is the 10% level threshold.

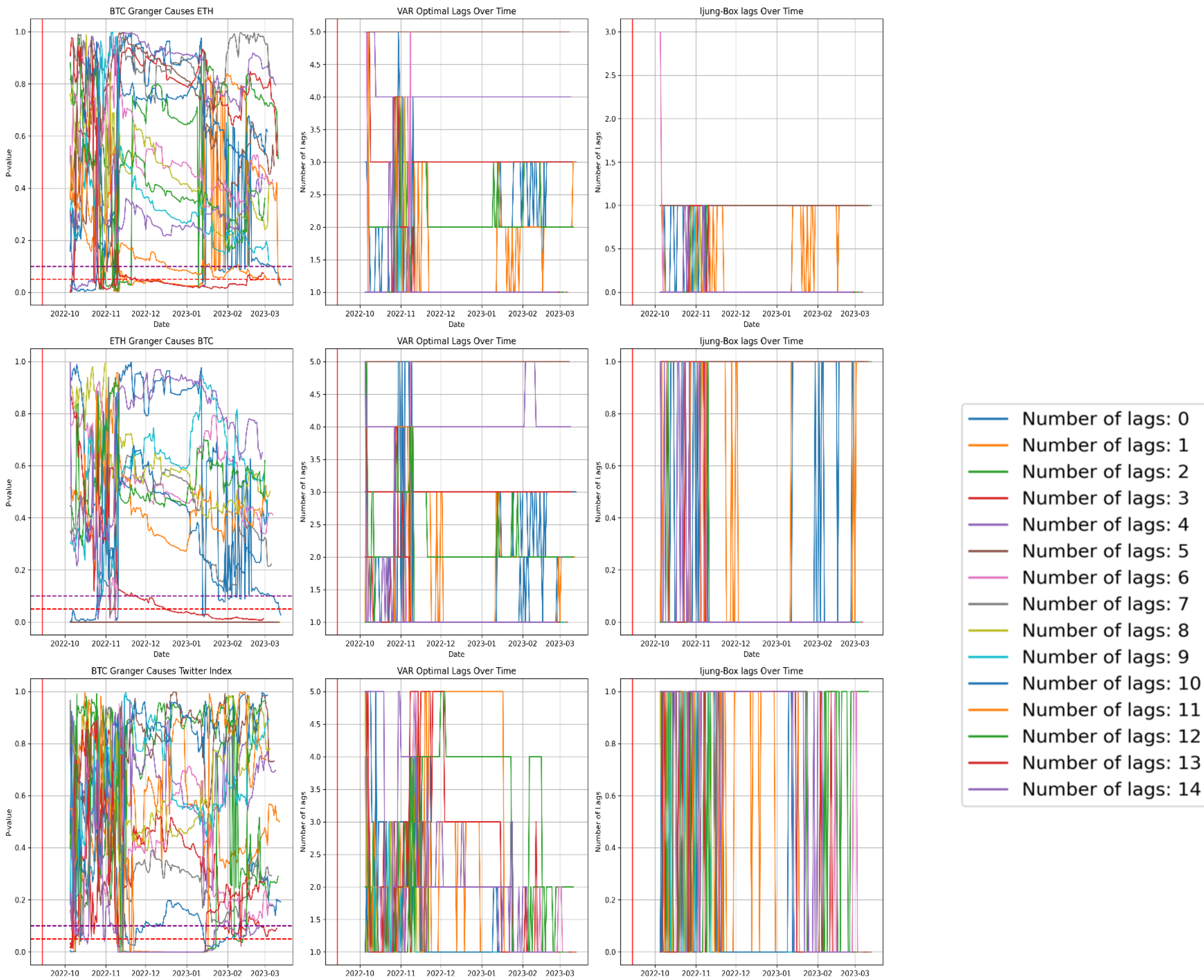


Figure 12 Post merge sample for lags 0 to 14 for the P-values over time for the Granger Causality tests, the number of VAR model lags and the where the Ljung-Box lag for autocorrelation detection appears. The red line is the merge date, the horizontal pointy red line is the 5% level threshold, and the pointy purple line is the 10% level threshold.

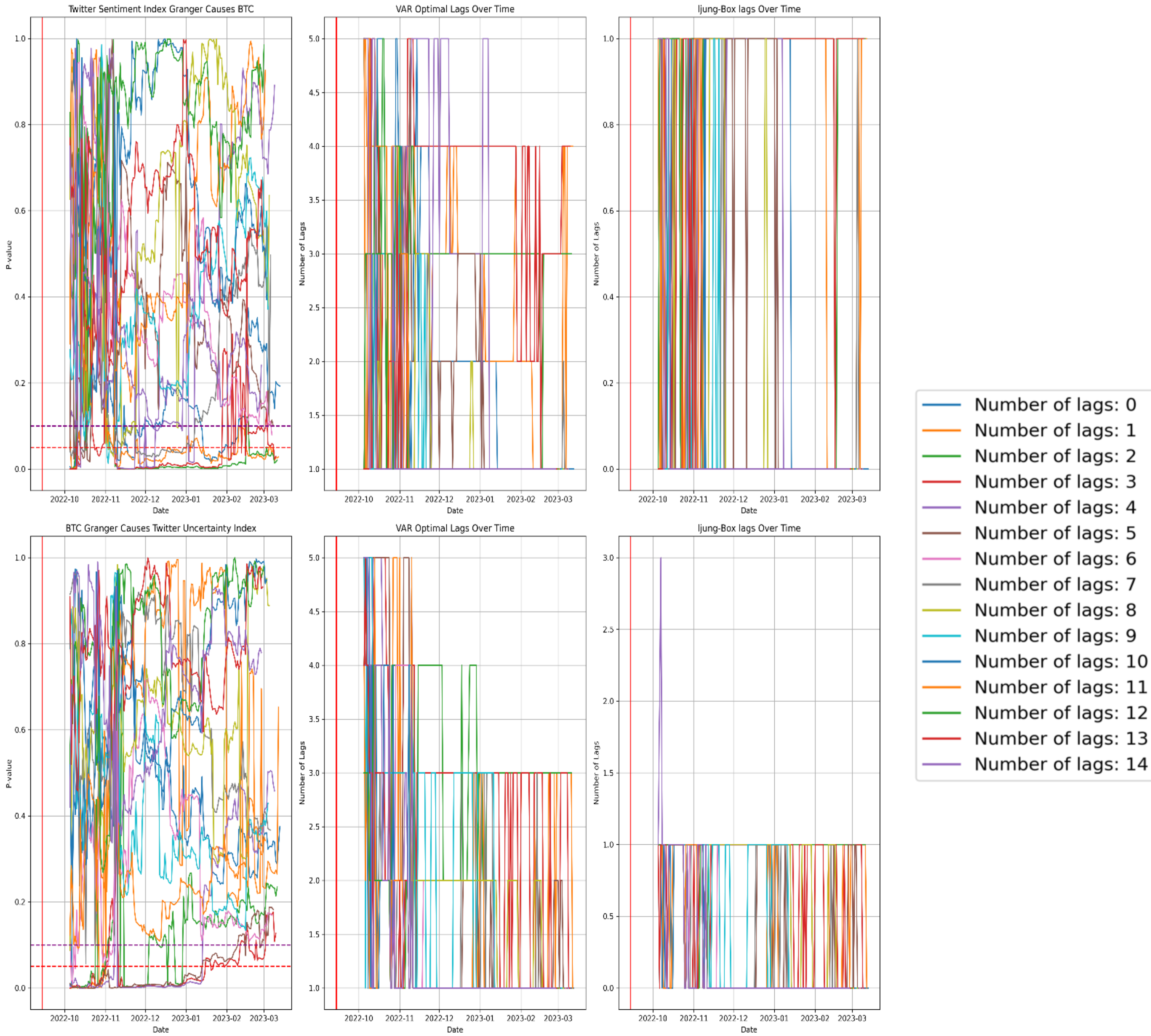


Figure 13 Post merge sample for lags 0 to 14 for the P-values over time for the Granger Causality tests, the number of VAR model lags and the where the Ljung-Box lag for autocorrelation detection appears. The red line is the merge date, the horizontal pointy red line is the 5% level threshold, and the pointy purple line is the 10% level threshold.

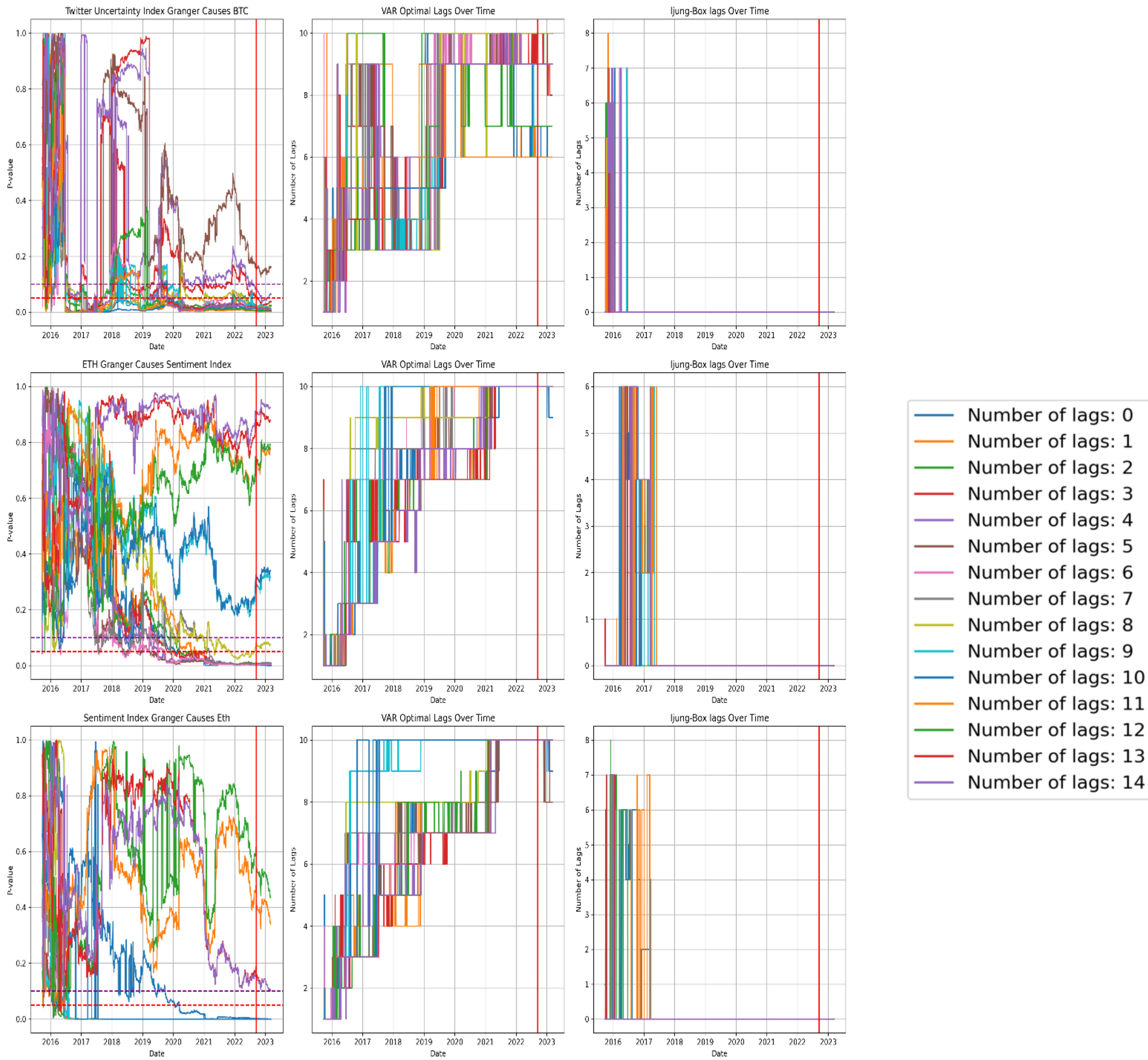


Figure 14 Post merge sample for lags 0 to 14 for the P-values over time for the Granger Causality tests, the number of VAR model lags and the where the Ljung-Box lag for autocorrelation detection appears. The red line is the merge date, the horizontal pointy red line is the 5% level threshold, and the pointy purple line is the 10% level threshold.

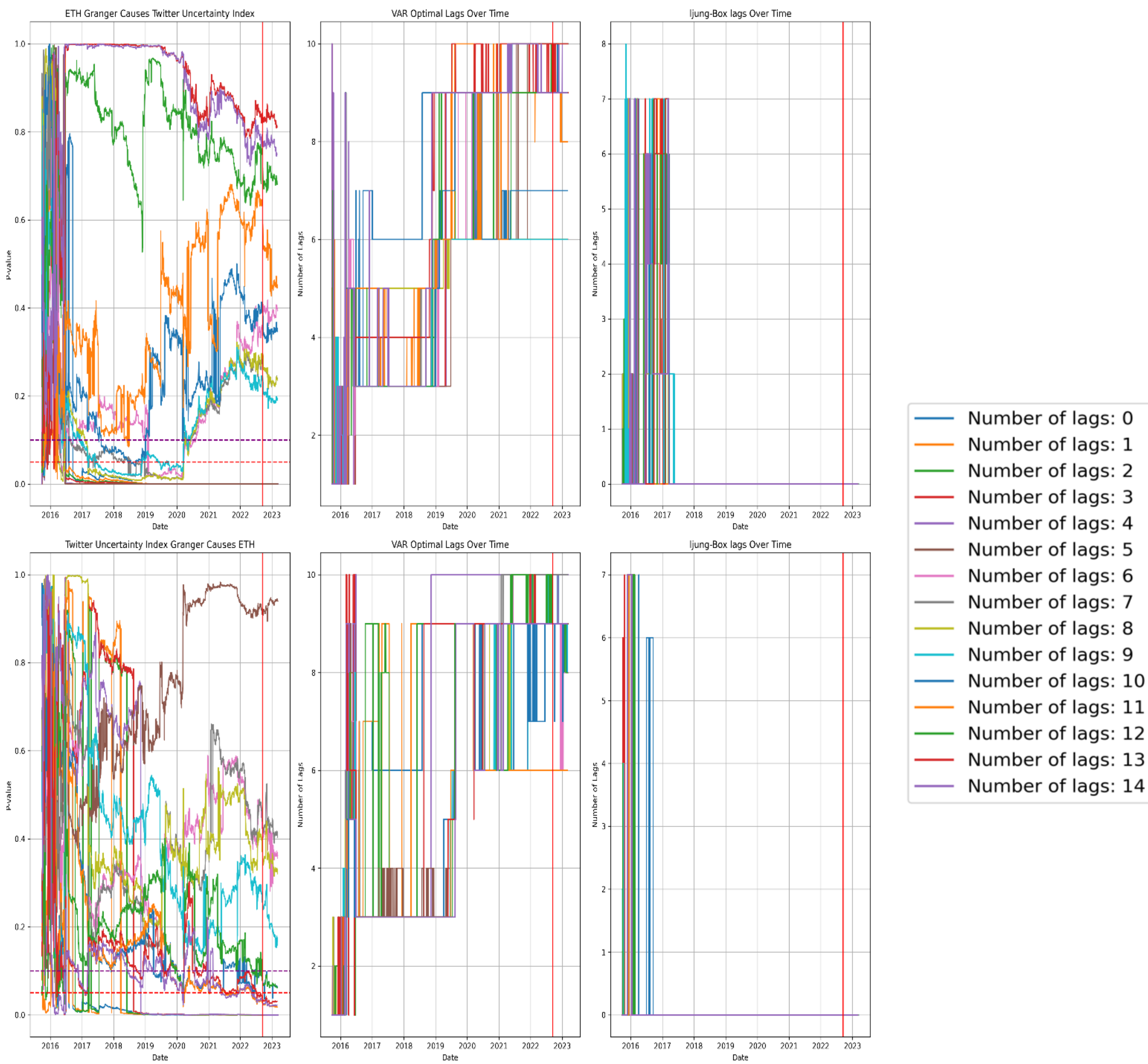


Figure 15 Wavelet Coherence Total sample Phase plots. Arrows symbolize the lead/lag phase relationships. Rightward arrows indicate that x and y are in phase, while leftward arrows signal an anti-phase relationship. A zero-phase difference implies that the two time series move together at a specific scale. In-phase implies they move in the same direction, whereas anti-phase suggests opposite directions. Upward arrows suggest that y leads x by π/2, and downward arrows indicate that x leads y by π/2. The horizontal axis represents time in years (or months), while the vertical axis represents time scales in days. The coherence, ranging from 0 to 1, is depicted by the bar chart on the right side of the plots, with blue denoting no co-movement (0) and 1 representing complete co-movement.

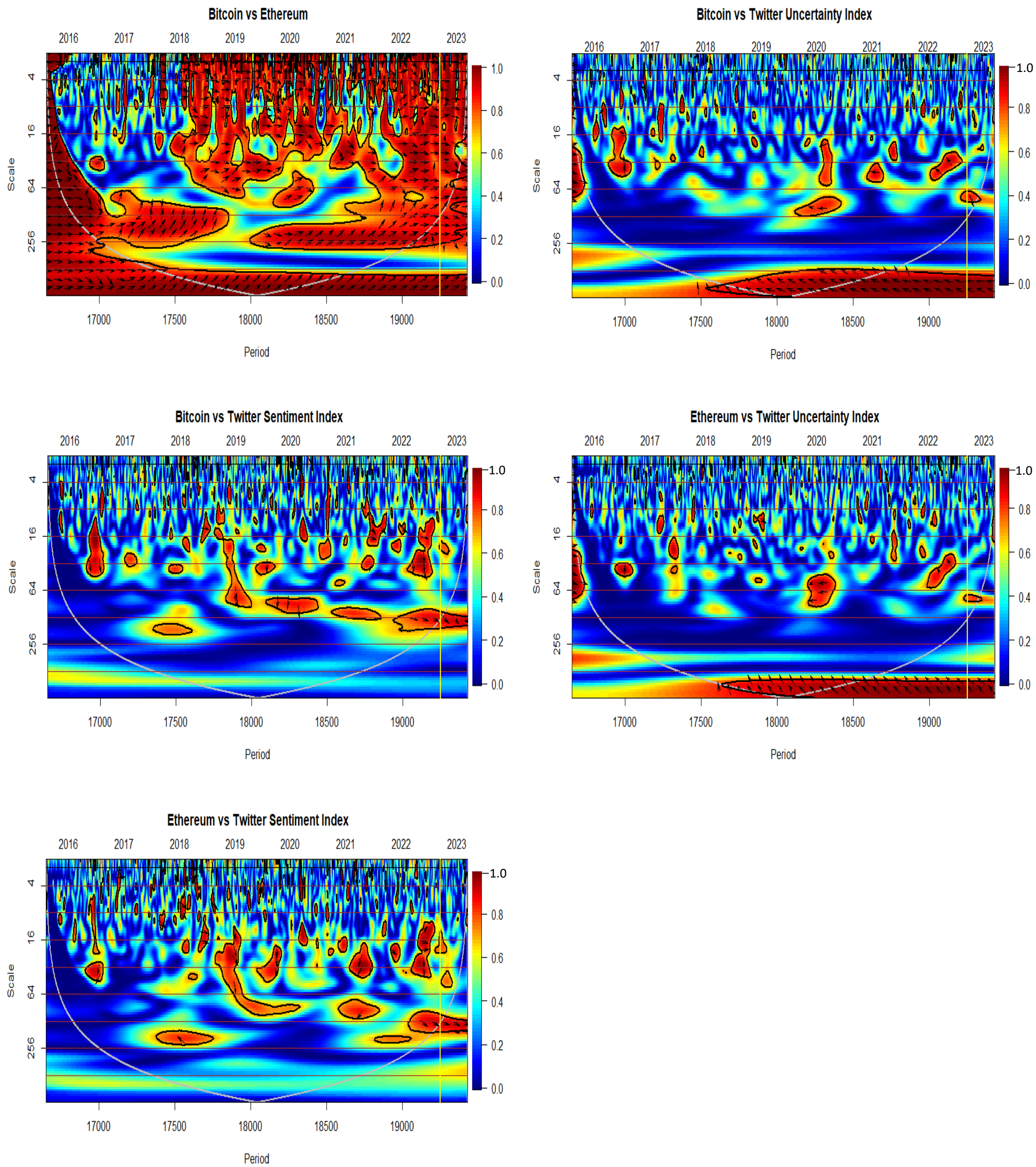


Figure 16 Wavelet Coherence Post-merge Phase plots. Arrows symbolize the lead/lag phase relationships. Rightward arrows indicate that x and y are in phase, while leftward arrows signal an anti-phase relationship. A zero-phase difference implies that the two time series move together at a specific scale. In-phase implies they move in the same direction, whereas anti-phase suggests opposite directions. Upward arrows suggest that y leads x by π/2, and downward arrows indicate that x leads y by π/2. The horizontal axis represents time in years (or months), while the vertical axis represents time scales in days. The coherence, ranging from 0 to 1, is depicted by the bar chart on the right side of the plots, with blue denoting no co-movement (0) and 1 representing complete co-movement.

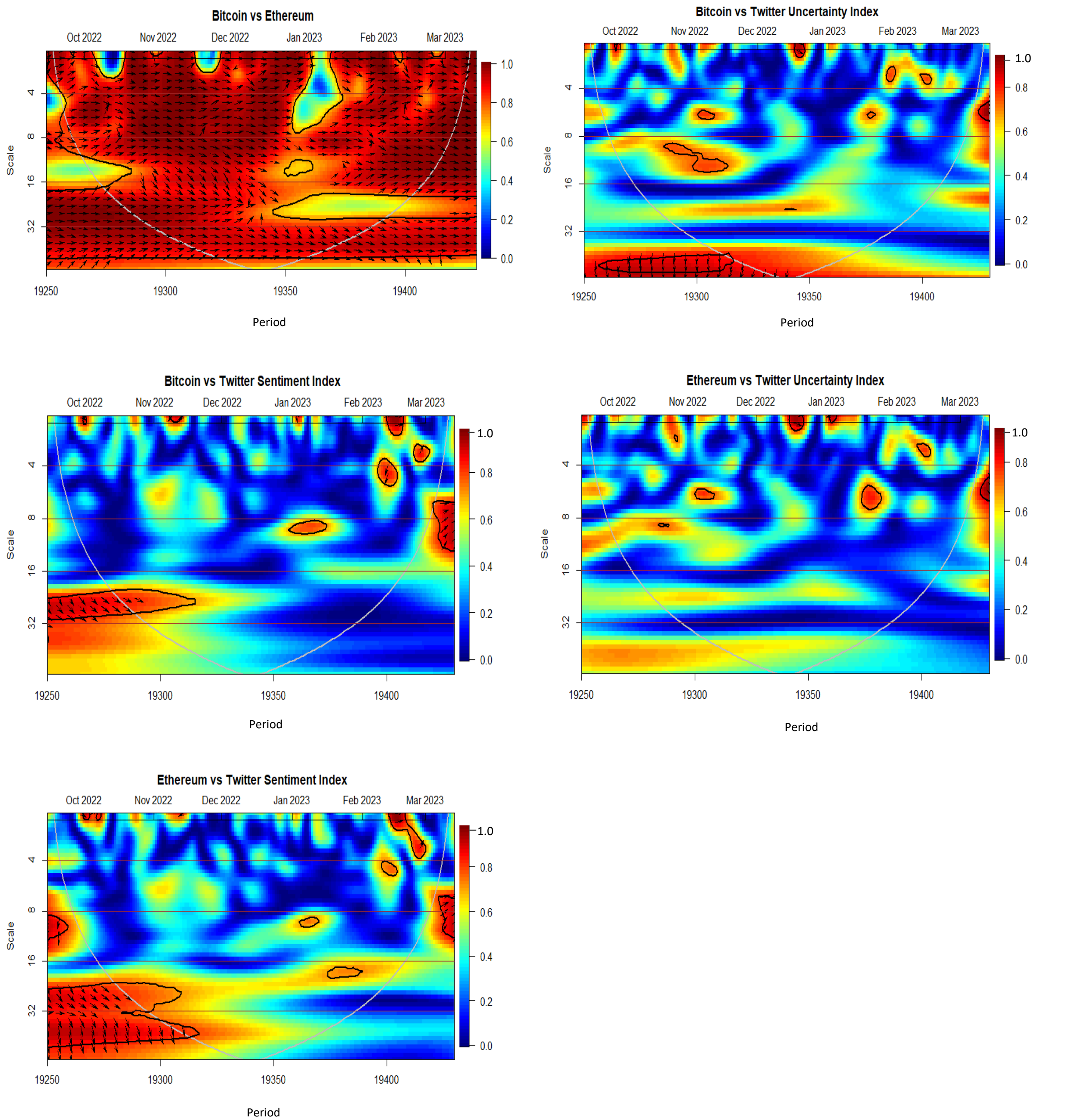
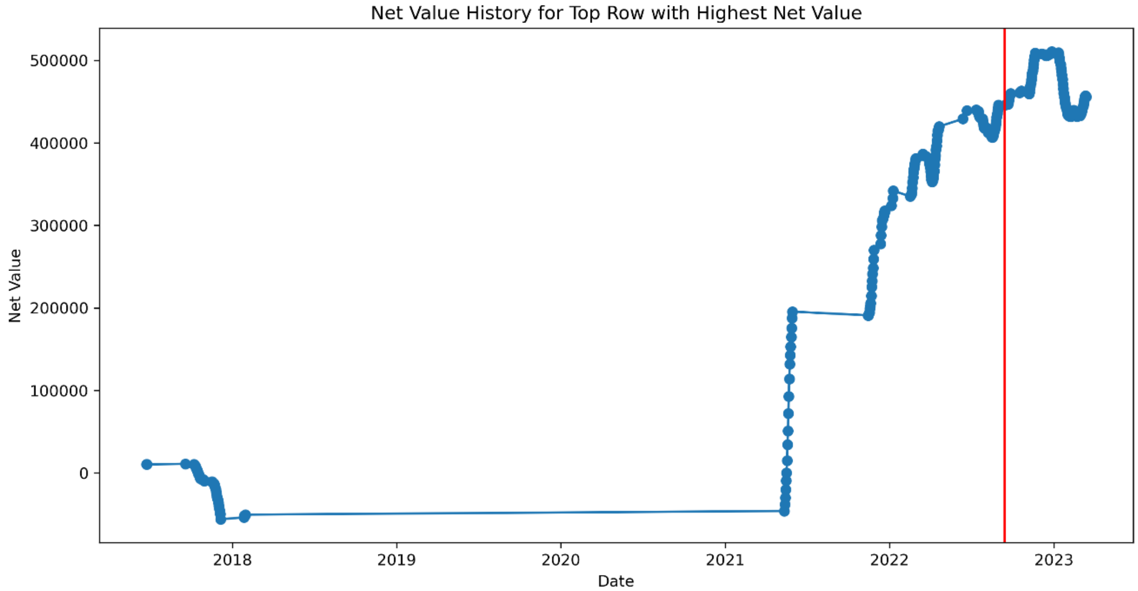


Figure 17 Ethereum lags Bitcoin for the total sample. The first graph shows the Net value of the strategy with a starting value of 10000. It rises when a sell order is higher than the associated buy order and lowers in value for the inverse when the sell order is lower than the buy value. The second graph represents the occurrences of buy orders indicated by green arrows and the sell order in red arrows. The red vertical line represents the merge date.



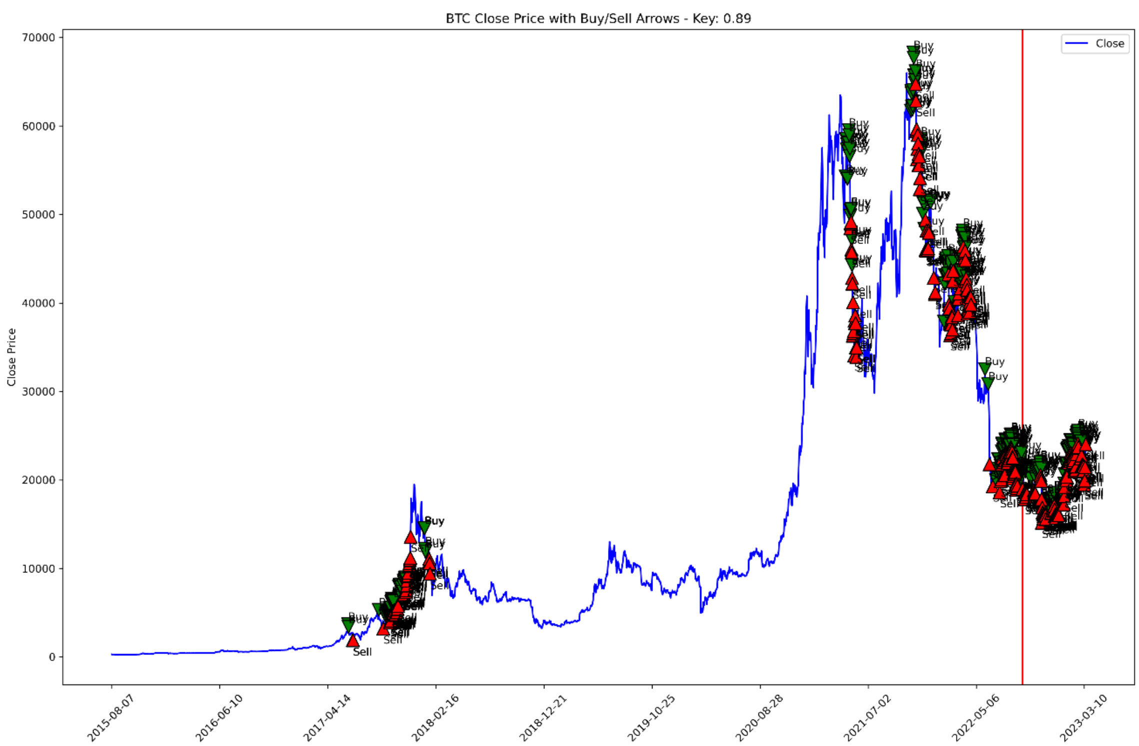
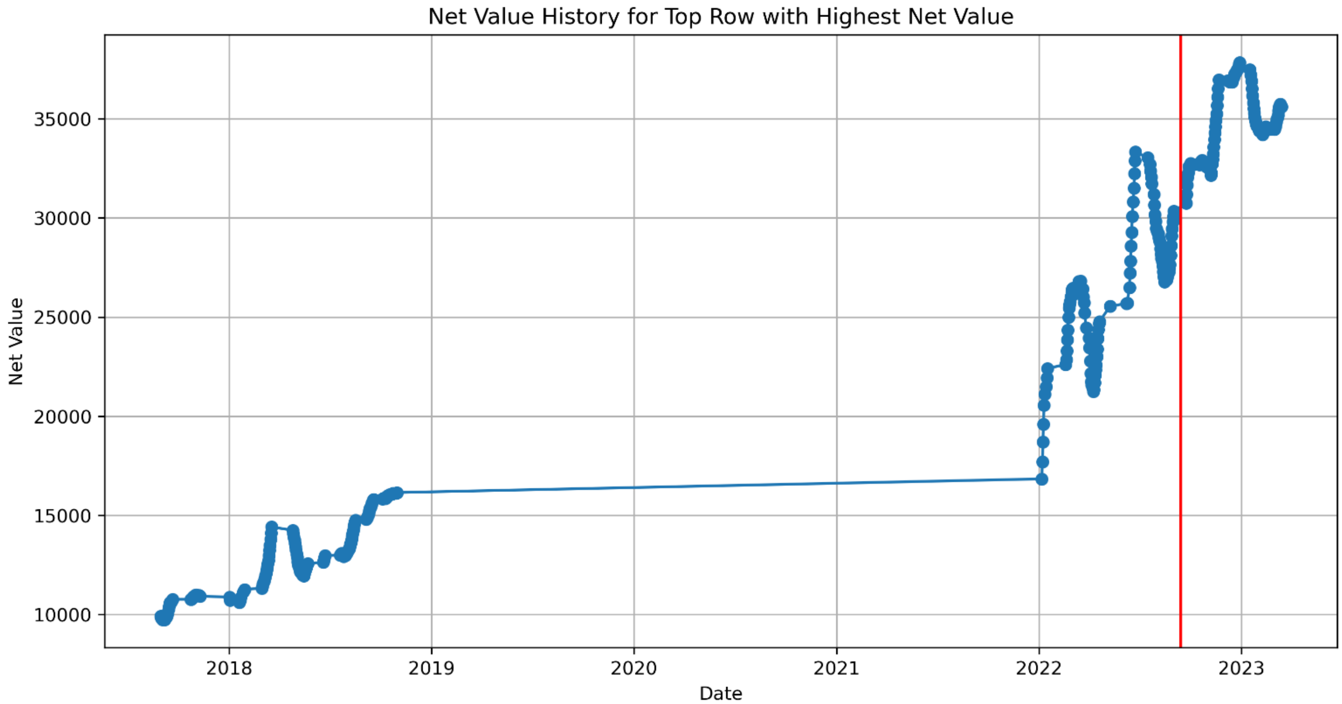


Figure 18 Bitcoin lags Ethereum Algorithm . The first graph shows the Net value of the strategy with a starting value of 10000. It rises when a sell order is higher than the associated buy order and lowers in value for the inverse when the sell order is lower than the buy value. The second graph represents the occurrences of buy orders indicated by green arrows and the sell order in red arrows. The red vertical line represents the merge date.



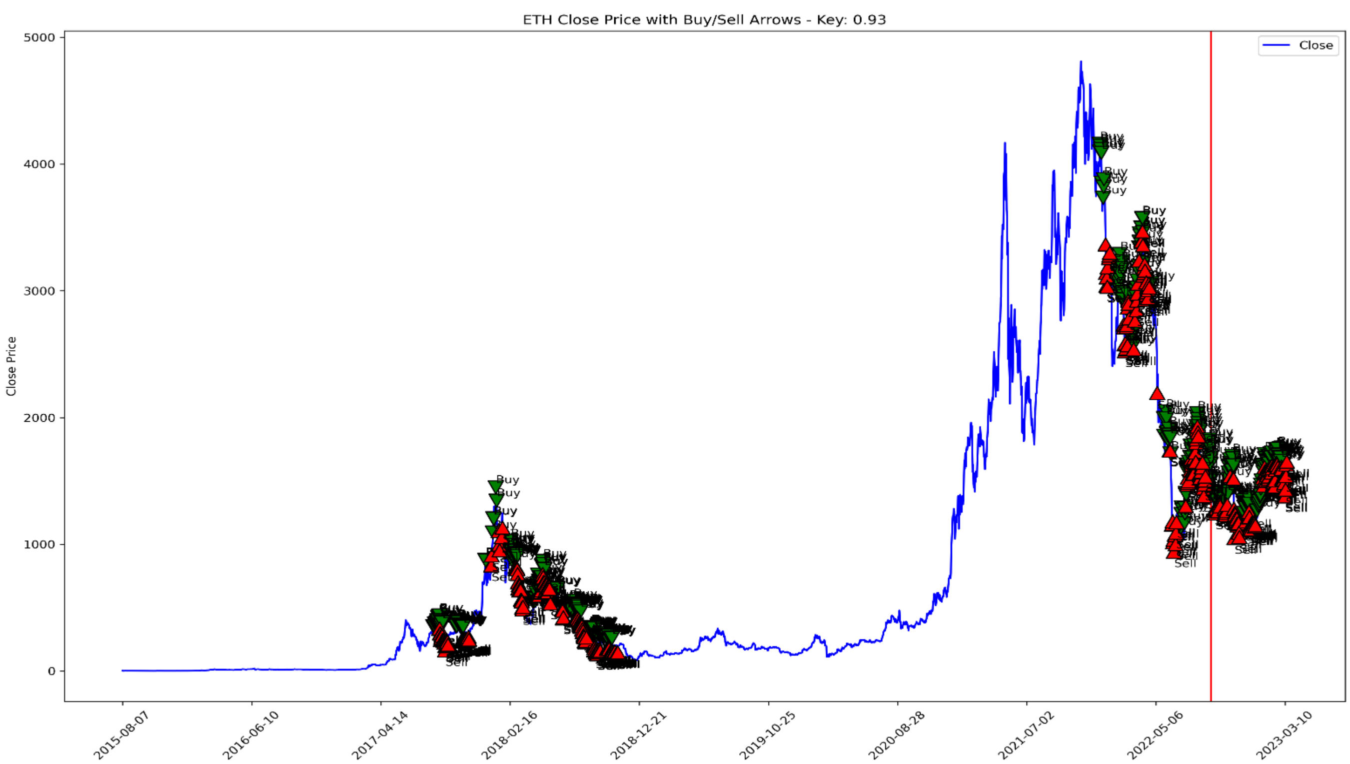
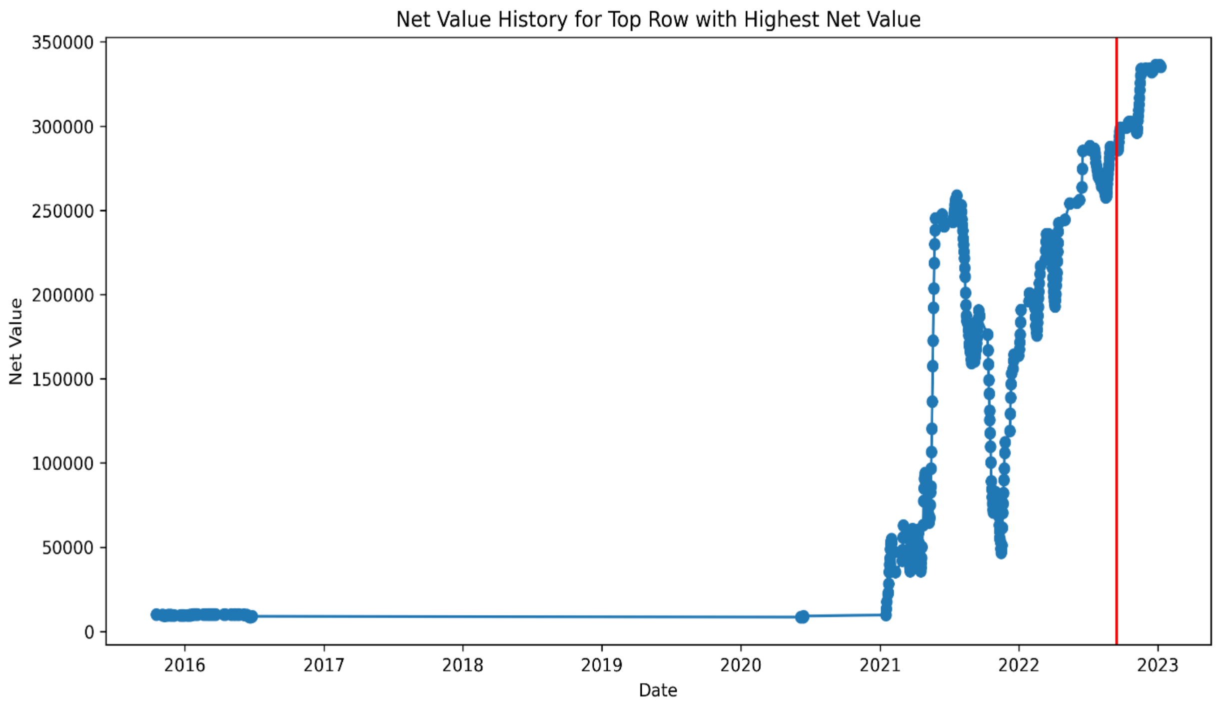


Figure 19 Ethereum granger causes Bitcoin trading strategy: The first graph shows the Net value of the strategy with a starting value of 10000. It rises when a sell order is higher than the associated buy order and lowers in value for the inverse when the sell order is lower than the buy value. The second graph represents the occurrences of buy orders indicated by green arrows and the sell order in red arrows. The red vertical line represents the merge date.



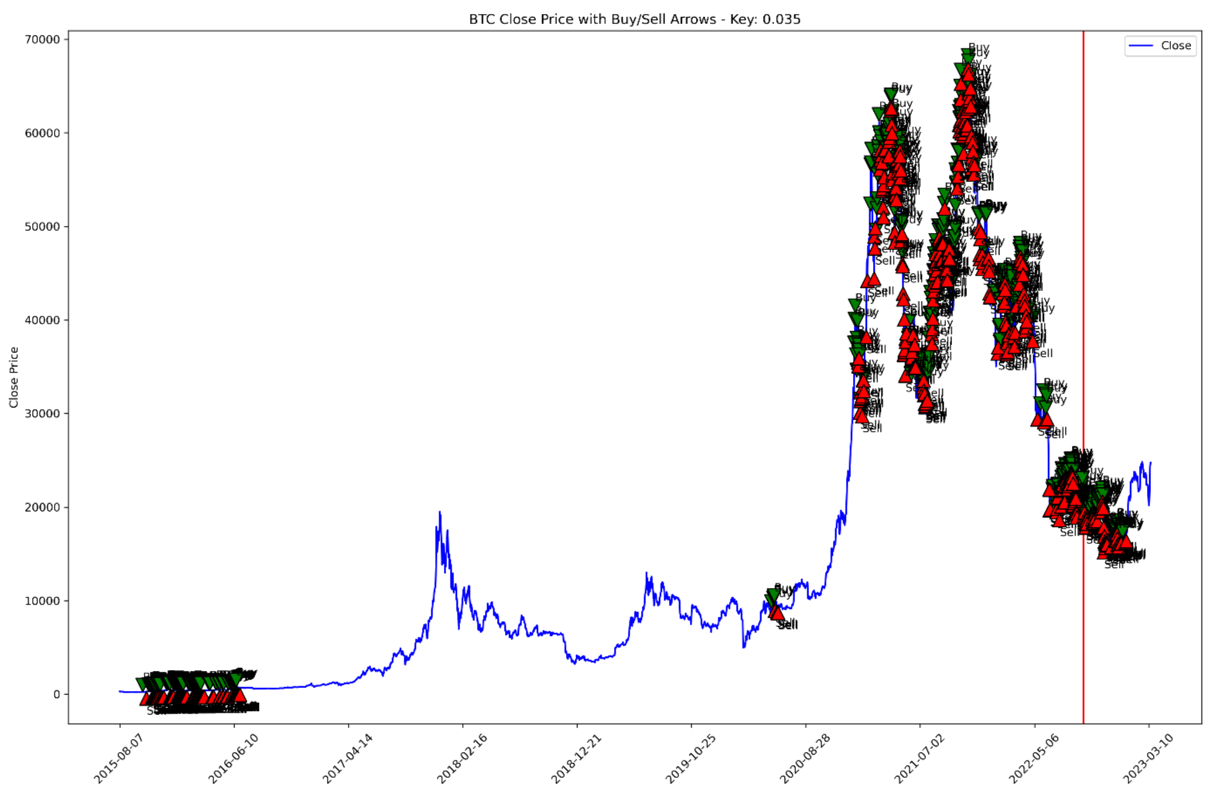
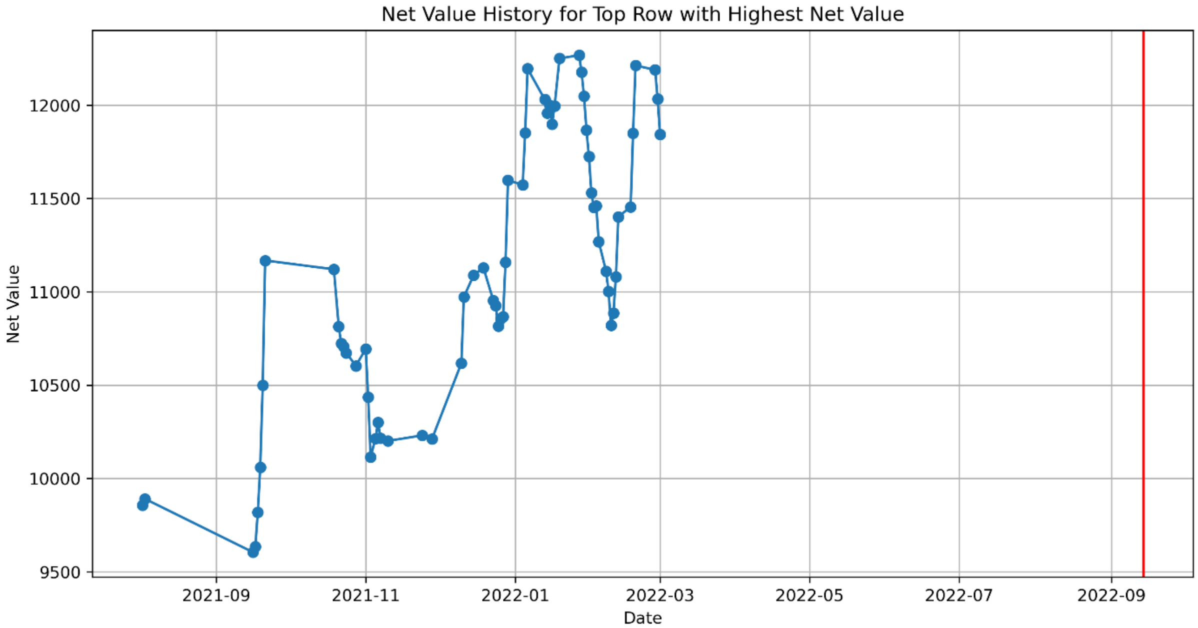


Figure 20 Bitcoin granger Causes Ethereum strategy : The first graph shows the Net value of the strategy with a starting value of 10000. It rises when a sell order is higher than the associated buy order and lowers in value for the inverse when the sell order is lower than the buy value. The second graph represents the occurrences of buy orders indicated by green arrows and the sell order in red arrows. The red vertical line represents the merge date.



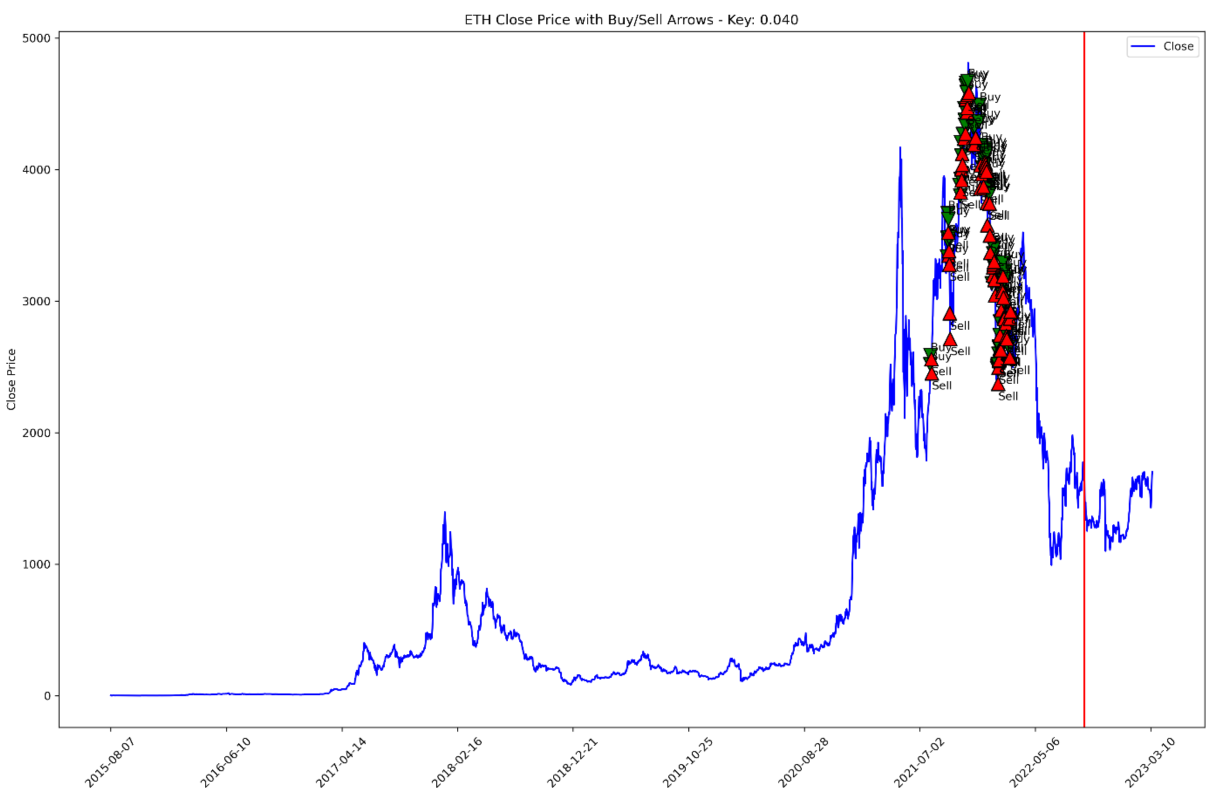
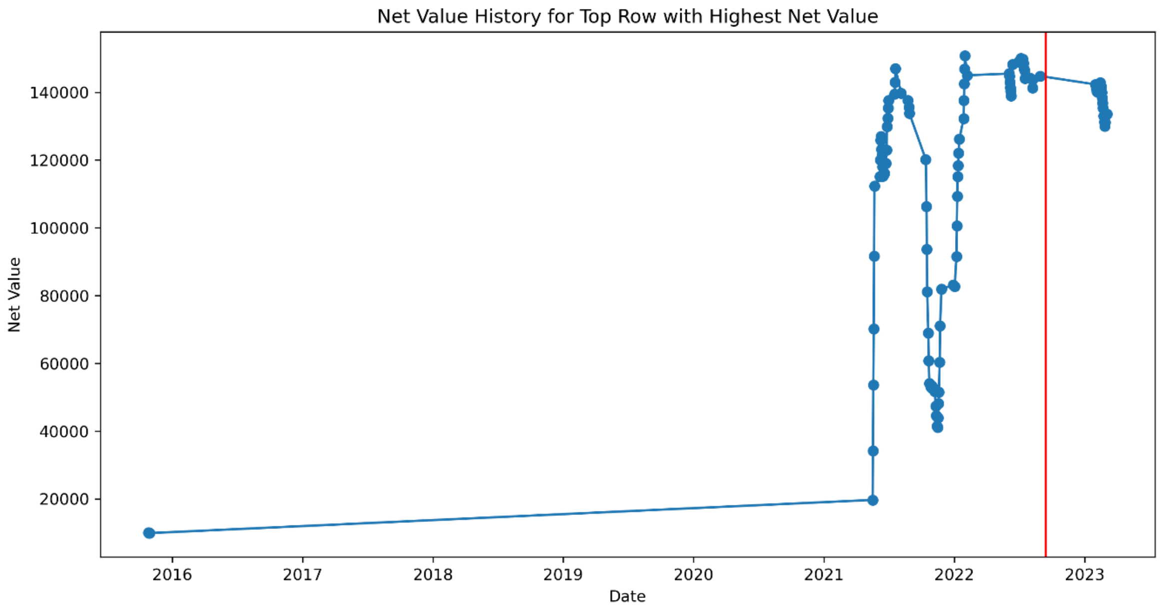


Figure 21 Twitter Sentiment Index granger causes Bitcoin strategy: The first graph shows the Net value of the strategy with a starting value of 10000. It rises when a sell order is higher than the associated buy order and lowers in value for the inverse when the sell order is lower than the buy value. The second graph represents the occurrences of buy orders indicated by green arrows and the sell order in red arrows. The red vertical line represents the merge date.



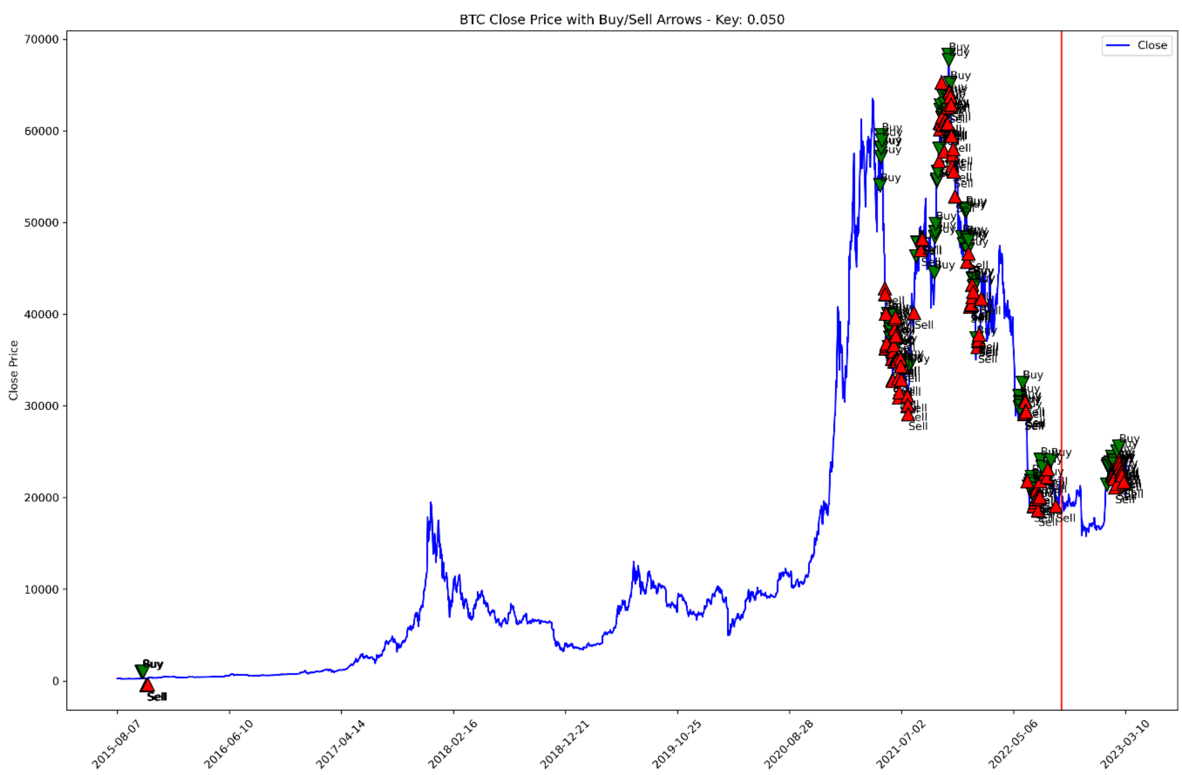
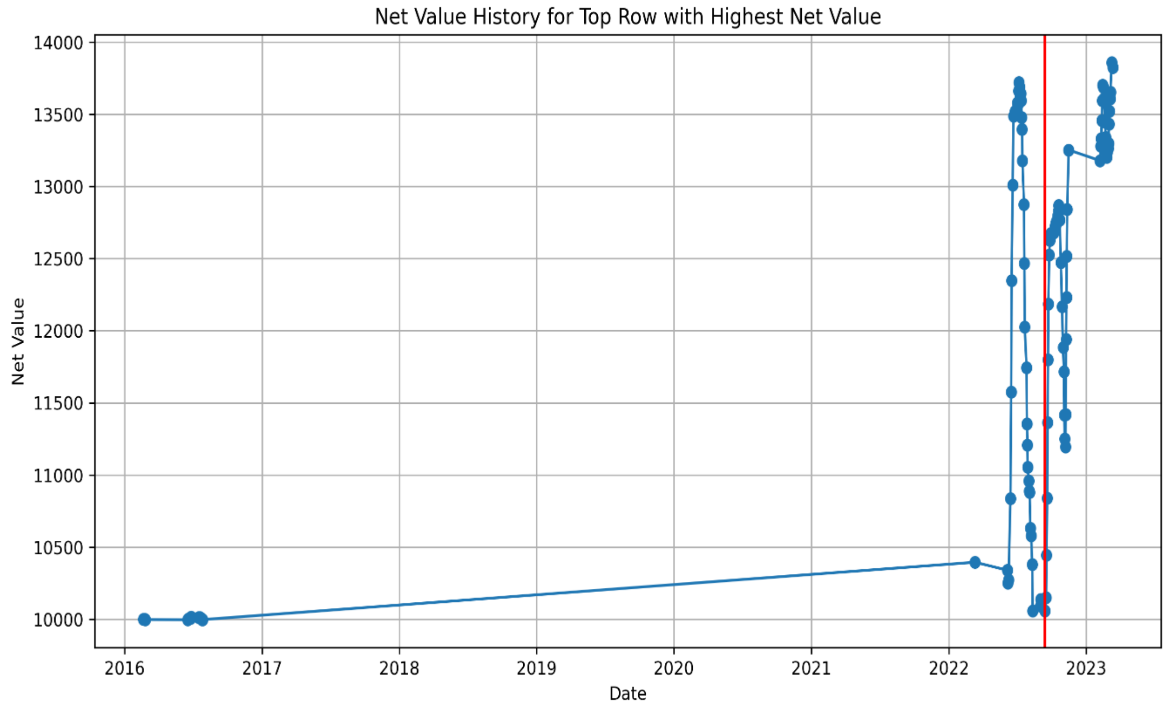


Figure 22 Twitter Sentiment Index– Ethereum . The first graph shows the Net value of the strategy with a starting value of 10000. It rises when a sell order is higher than the associated buy order and lowers in value for the inverse when the sell order is lower than the buy value. The second graph represents the occurrences of buy orders indicated by green arrows and the sell order in red arrows. The red vertical line represents the merge date.



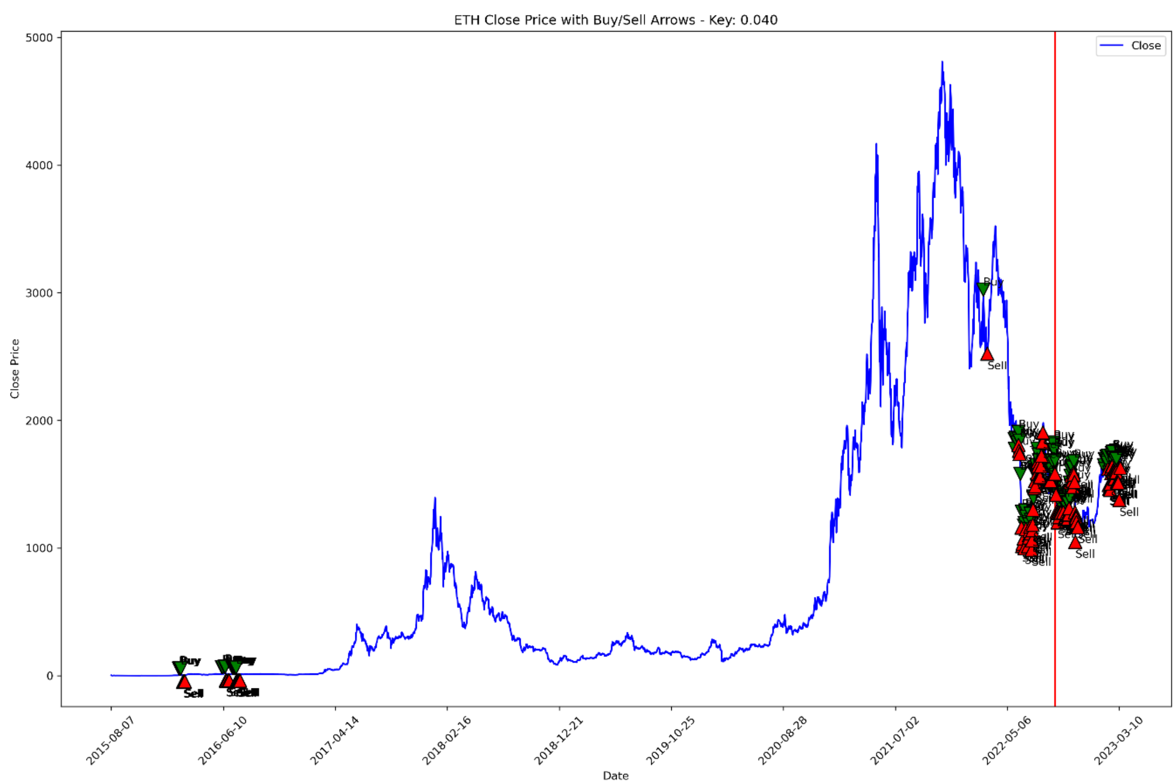
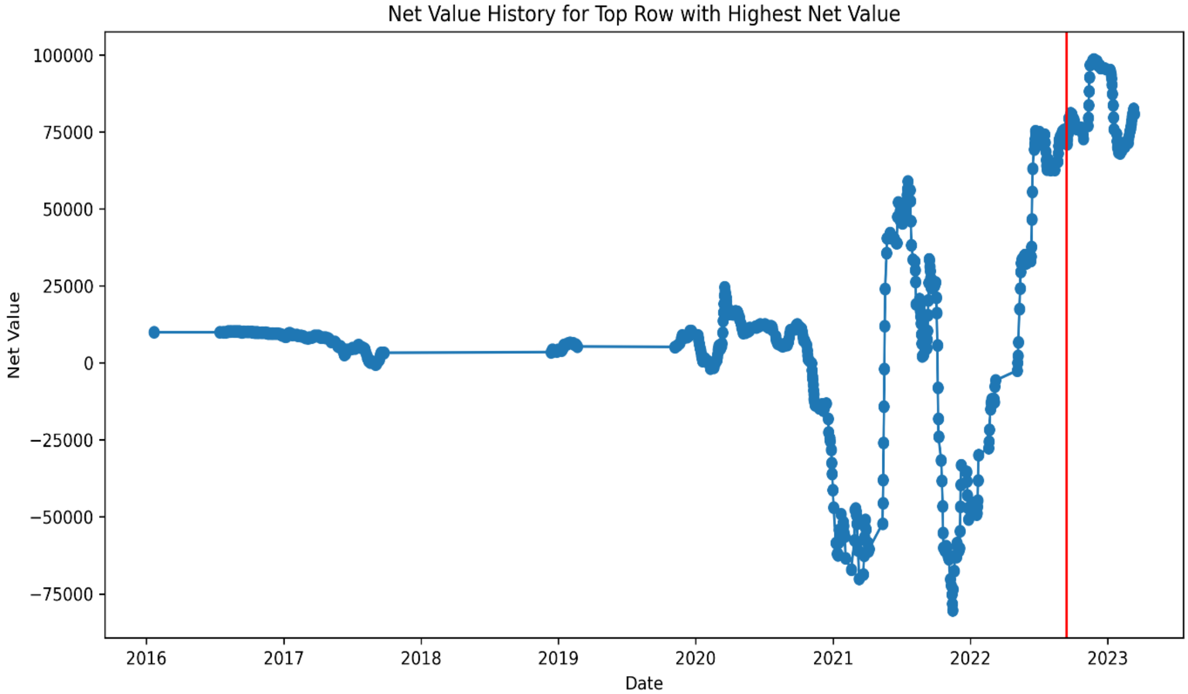


Figure 23 Twitter Uncertainty Index granger causes Bitcoin strategy : The first graph shows the Net value of the strategy with a starting value of 10000. It rises when a sell order is higher than the associated buy order and lowers in value for the inverse when the sell order is lower than the buy value. The second graph represents the occurrences of buy orders indicated by green arrows and the sell order in red arrows. The red vertical line represents the merge date.



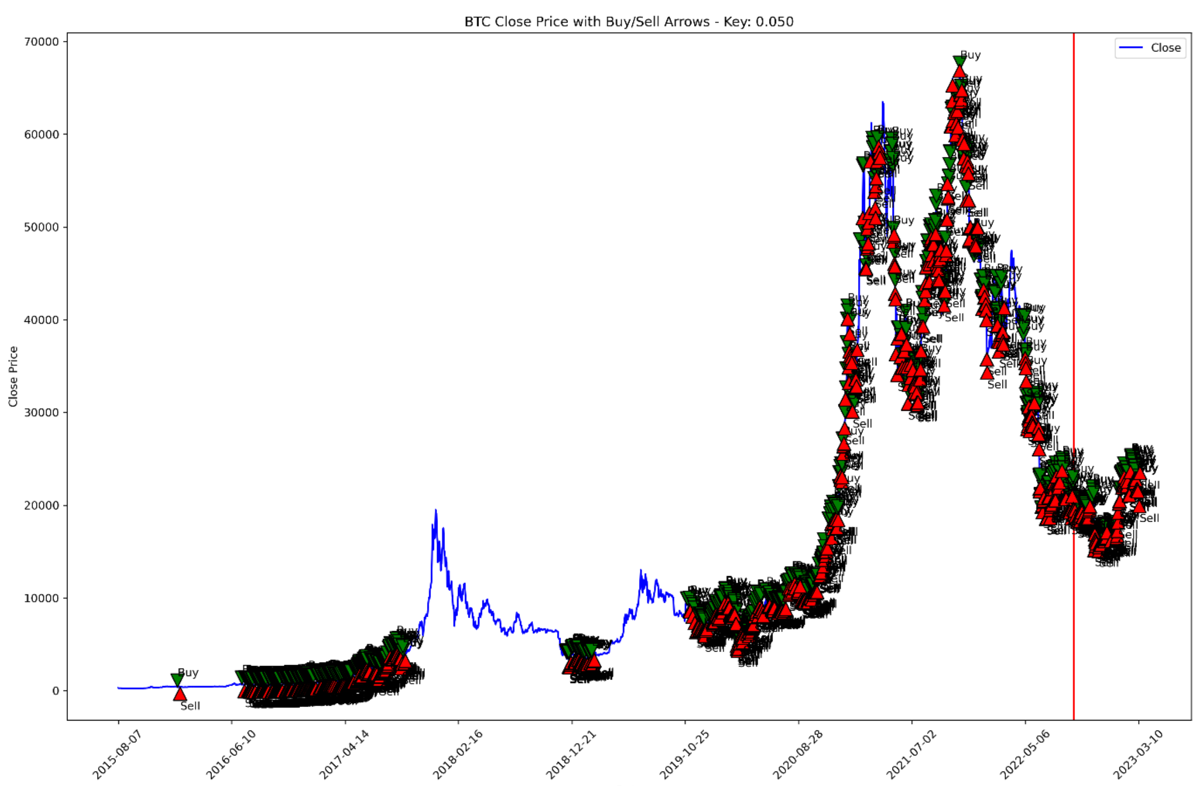
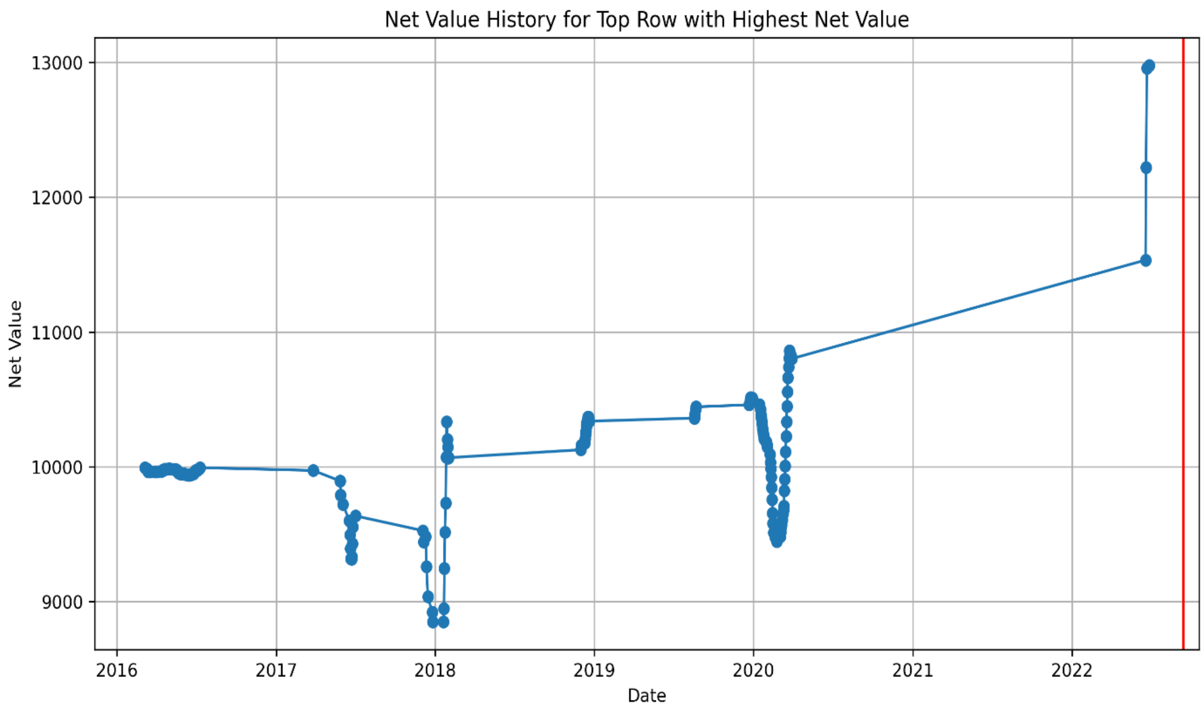


Figure 24 Twitter Uncertainty Index granger causes Ethereum strategy: The first graph shows the Net value of the strategy with a starting value of 10000. It rises when a sell order is higher than the associated buy order and lowers in value for the inverse when the sell order is lower than the buy value. The second graph represents the occurrences of buy orders indicated by green arrows and the sell order in red arrows. The red vertical line represents the merge date.



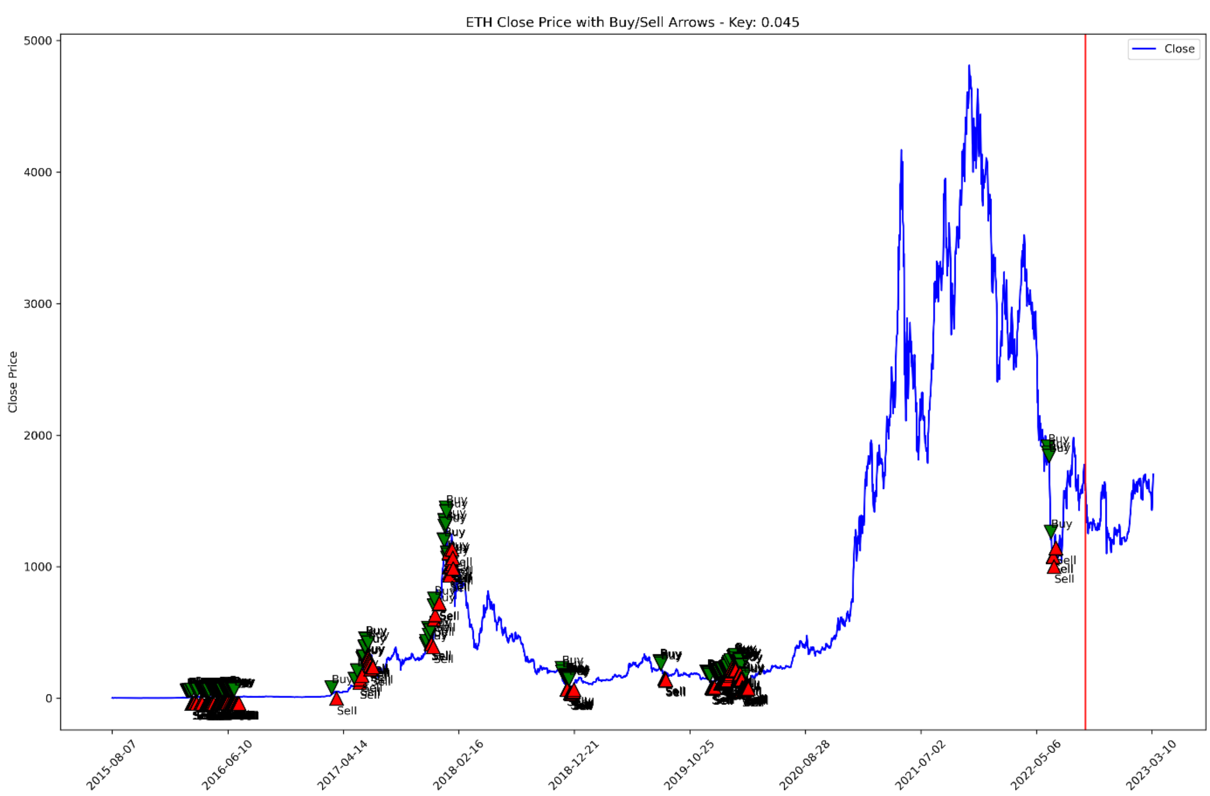
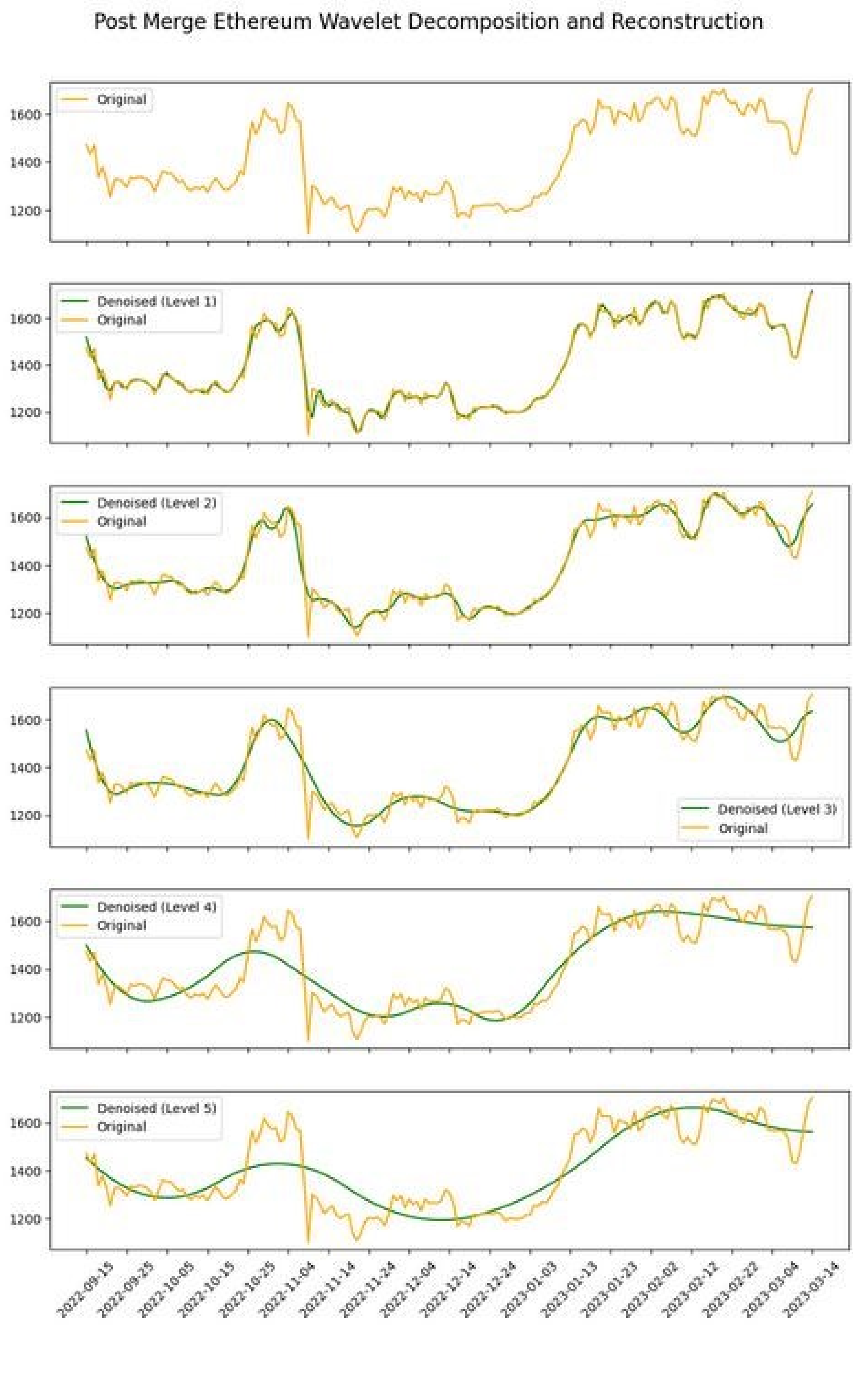


Figure 24 Wavelet Decomposition and reconstruction level illustration df_BITCOIN_TOTAL["Date"][2400:2500] original and for level 1 to 5.



Tables

Table 1

Total Descriptive Sample Statistics

In table 1, this data indicates for the Bitcoin Closing price time series and Ethereum closing price time series total descriptive sample statistics for the following three ranges of dates : Pre-Merge date range from 2015-08-07 to 2022-09-14, Post-Merge date range from 2022-09-15 to 2023-03-14 and Total date range from 2015-08-07 to 2023-03-14. These statistics are the mean, minimum, maximum, mode, median, variance, standard deviation, skewness, kurtosis, the percentile rank at the 25%,50% and 75 % thresholds. Additionally, the table shows the p-value of the augmented Dickey-Fuller test and the interpretation of the test result. Moreover, the series were tested for normality using the Jarque-Berra test and the corresponding results according to the P-value are shown.

	Pre-Bitcoin CLOSING PRICE	Post-Bitcoin CLOSING PRICE	Total-Bitcoin CLOSING PRICE	Pre-Ethereum CLOSING PRICE	Post-Ethereum CLOSING PRICE	Total-Ethereum CLOSING PRICE
Mean	14207.23	19696.61	14565.02	785.47	1404.68	825.83
Minimum	210.49	15787.28	210.49	0.43	1100.17	0.43
Maximum	67566.83	24829.15	67566.83	4812.09	1703.51	4812.09
Mode	1179.97	15787.28	1179.97	11.65	1100.17	11.65
Median	7785.29	19419.51	8321.01	243.64	1335.32	279.65
Variance	282715142.29	6730354.39	266554718.27	1262291.89	29705.40	1205284.30
Standard Deviation	16814.14	2594.29	16326.50	1123.52	172.35	1097.85
Skewness	1.41	0.28	1.38	1.70	0.23	1.60
Kurtosis	0.78	-1.19	0.85	1.79	-1.44	1.68
25%	1846.20	16974.83	2576.48	91.08	1264.27	116.58
50%	7785.29	19419.51	8321.01	243.64	1335.32	279.65
75%	19040.10	21870.87	20104.02	974.46	1569.17	1281.12
ADF P-Value	0.45	0.74	0.44	0.47	0.50	0.44
Stationary	No	No	No	No	No	No
JB P-value	0.00	0	0	0.00	0	0
Normal	No	No	No	No	No	No
N	2596	181	2777	2596	181	2777

Table 2

Total Descriptive Sample Statistics

In table 2, this data indicates for the Bitcoin Return time series and Ethereum Return time series total descriptive sample statistics for the following three ranges of dates: Pre-Merge date range from 2015-08-07 to 2022-09-14, Post-Merge date range from 2022-09-15 to 2023-03-14 and Total date range from 2015-08-07 to 2023-03-14. These statistics are the mean, minimum, maximum, mode, median, variance, standard deviation, skewness, kurtosis, the percentile rank at the 25%,50% and 75 % thresholds. Additionally, the table shows the p-value of the augmented Dickey-Fuller test and the interpretation of the test result. Moreover, the series were tested for normality using the Jarque-Berra test and the corresponding results according to the P-value are shown.

	Pre-Bitcoin Return	Post-Bitcoin return	Total Bitcoin return	Pre-Ethereum Return	Post-Ethereum Return	Total Ethereum Return
Mean	0.002	0.0015	0.0024	0.004	0.0009	0.0042
Minimum	-0.372	-0.14	-0.37	-0.728	-0.17	-0.73
Maximum	0.252	0.11	0.25	0.507	0.18	0.51
Mode	0.182	0.07	0.18	0.322	0.07	0.32
Median	0.002	0.00	0.00	0.001	0.00	0.00
Variance	0.002	0.00	0.00	0.004	0.00	0.00
Standard Deviation	0.039	0.03	0.04	0.062	0.04	0.06
Skewness	-0.129	-0.17	-0.13	0.143	-0.24	0.15
Kurtosis	6.985	6.55	7.14	14.324	6.81	14.73
25%	-0.013	-0.01	-0.01	-0.023	-0.01	-0.02
50%	0.002	0.00	0.00	0.001	0.00	0.00
75%	0.018	0.01	0.02	0.029	0.02	0.03
ADF P-Value	0	0	0	0	0	0
Stationary	Yes	Yes	Yes	Yes	Yes	Yes
JB P-value	0	0.00	0.00	0	0.00	0.00
Normal	No	No	No	No	No	No
N	2595	181	2776	2595	181	2776

Table 3

Total Descriptive Sample Statistics

In table 3, this table indicates for the Twitter Sentiment Index time series and Baker et al. TWITTER Uncertainty index time series total descriptive sample statistics for the following three ranges of dates: Pre-Merge date range from 2015-08-07 to 2022-09-14, post-Merge date range from 2022-09-15 to 2023-03-14 and Total date range from 2015-08-07 to 2023-03-14. The statistics are the mean, minimum, maximum, mode, median, variance, standard deviation, skewness, kurtosis, the percentile rank at the 25%,50% and 75 % thresholds. Additionally, the table shows the p-value of the augmented Dickey-Fuller test and the interpretation of the test result. Moreover, the series were tested for normality using the Jarque-Berra test and the corresponding results according to the P-value are shown.

	Pre-TWITTER SENTIMENT INDEX	Post-TWITTER SENTIMENT INDEX	Total-TWITTER SENTIMENT INDEX	Pre-Baker et al. TWITTER Uncertainty SENTIMENT	Post-Baker et al. TWITTER Uncertainty SENTIMENT	Total-Baker et al. TWITTER Uncertainty SENTIMENT
Mean	0.77	0.76	0.76	132.69	255.35	140.69
Minimum	0.50	0.62	0.50	6.13	96.07	6.13
Maximum	0.91	0.85	0.91	1476.20	452.63	1476.20
Mode	0.78	0.62	0.78	110.48	269.80	110.48
Median	0.77	0.76	0.77	106.65	251.85	112.41
Variance	0.00	0.00	0.00	9267.20	3168.43	9785.43
Standard Deviation	0.05	0.04	0.05	96.27	56.29	98.92
Skewness	-0.69	-0.75	-0.69	2.77	0.45	2.35
Kurtosis	1.24	0.55	1.23	18.74	0.90	14.83
25%	0.74	0.73	0.74	69.22	219.86	71.62
50%	0.77	0.76	0.77	106.65	251.85	112.41
75%	0.80	0.79	0.80	167.55	285.94	186.56
ADF P-Value	0.00	0.00	0.00	0.01	0.00	0.01
Stationary	Yes	Yes	Yes	Yes	Yes	Yes
JB P-value	0.00	0	0	0.00	0	0
Normal	No	No	No	No	No	No
N	2596	181	2777	2596	181	2777

Table 4

Best Trading Strategy Results

In table 4, this data indicates all the best results for both the strategies based on the Pearson Coefficient and the Granger Causality P-Value for our back testing strategies for our total date range from 2015-08-07 to 2023-03-14. The number of lags is the daily distance between the lagged and leading variables. The Pearson Coefficient is based on the calculation of the Pearson Correlation Coefficient and is the threshold to execute a trade based on our momentum trading strategy which is that if asset 1 rose from time T-n (n being the number of days) and that the Pearson Coefficient exceeded a certain threshold, we would buy asset 2 at time T and sell it at time T+n. The Granger Causality P-value is the threshold to execute a trade based on the Granger Causality test. Total gain is the sum of the positive trades that closed with a profit. Total loss is the sum of the negative trades that closed with a loss Total Trading Fees are calculated the following way: 3% of each buy and each sell to reflect the cost on a retail platform. The Net Value is Total Gain minus Total Loss minus the total trading fees. The Total Number of Transactions is the sum of the total number of buy and sell orders.

	Ethereum Close price lags Bitcoin Close price	Bitcoin Close price lags Ethereum Close price	Ethereum Close price lags Bitcoin Close price	Ethereum return lags Bitcoin Close price	Twitter Uncertainty lags Bitcoin Close price	Twitter Uncertainty lags Ethereum Close price	Twitter Sentiment Index lags Bitcoin Close price	Twitter Sentiment Index lags Ethereum Close price
Number of lags	13	14	3	10	7	13	13	11
Pearson Coefficient	0.89	0.93						
Granger Causality P-Value			0.04	0.035	0.05	0.045	0.05	0.04
Total Gain	688,385.03	45,917.56	6,036.24	810,715.24	553755.84	5994.36	282,301.84	20097.49
Total Loss	-242,558.27	-20,316.43	-4,193.36	-485,508.34	-482922.77	-3017.99	-158,758.01	-6224.03
Total Trading Fees	-27928.299	-987.0197	-306.888	-38886.707	-31100.358	-270.3705	-13231.796	-789.6456
Net Value	417,898.46	23,614.11	1,535.99	286,320.19	39,732.71	2,706.00	110,312.03	13,083.81
Total Number of Transactions	560	722	128	928	1530	346	226	232

Table 5

Trading Strategy Results

In table 5, this data indicates our top 5 trading results based the highest net value on the Ethereum Close Price lagging the Bitcoin Closing Price for our total date range from 2015-08-07 to 2023-03-14. The number of lags is the daily distance between the lagged and leading variables. The Pearson Coefficient is based on the calculation of the Pearson Correlation Coefficient and is the threshold to execute a trade based on our momentum trading strategy which is that if asset 1 rose from time T-n (n being the number of days) and that the Pearson Coefficient exceeded a certain threshold, we would buy asset 2 at time T and sell it at time T+n. Total gain is the sum of the positive trades that closed with a profit. Total loss is the sum of the negative trades that closed with a loss. Total Trading Fees are calculated the following way: 3% of each buy and each sell to reflect the cost on a retail platform. The Net Value is Total Gain minus Total Loss minus the total trading fees. The Total Number of Transactions is the sum of the total number of buy and sell orders. The initial_trading_amount_end is the starting among of 10,000 plus the Net Value. The number non trading days is our total number of days minus the total number of transactions. The number of Trades with positive payoff is the number of buy then sell trades that were positive. Instead of counting the buy plus the sell trade, we decided to count it as one. The same goes for the number of Trades with negative payoff.

Ethereum Close price lags Bitcoin Close price

Number of lags	Pearson Coefficient	Total gain	Total Loss	Total Trading Fees	Net Value	number non trading days	Total number of transactions	Trades with positive payoff	Trades with negative payoff	initial_trading_amount_end
13	0.89	688385.03	-242558.27	-27928.299	417898.5	2217	560	156	124	427898.5
14	0.89	655705.91	-235587.50	-26738.8	393379.6	2263	514	141	116	403379.6
10	0.9	602749.74	-210850.95	-24408.02	367490.8	2213	564	144	138	377490.8
12	0.89	669624.17	-284354.11	-28619.35	356650.7	2189	588	148	146	395270.06
14	0.86	902806.96	-521932.07	-42742.17	338132.7	1923	854	229	198	390874.89

Bitcoin Close price lags Ethereum Close price

Number of lags	Pearson Coefficient	Total gain	Total Loss	Total Trading Fees	Net Value	number non trading days	Total number of transactions	trades with positive payoff	trades with negative payoff	initial_trading_amount_end
14	0.93	45917.56	-20316.44	-1987.02	23614.10	2055	722	240	121	33614.10
13	0.93	44888.71	-20747.12	-1969.07	22172.52	2027	750	252	123	32172.52
11	0.93	43366.17	-21977.44	-1960.30	19428.42	1977	800	238	162	29428.42
14	0.92	61057.29	-39800.51	-3025.7	18231.05	1841	936	276	192	28231.05
12	0.93	42703.11	-21778.52	-1934.44	18990.14	2003	774	241	146	28990.14

Table 6

Trading Strategy Results

In table 6, this data indicates our top 5 (top 3 for the first strategy shown) trading results based the highest net value on the Bitcoin Close Price lagging the Ethereum Closing Price, the Ethereum Close price lags Bitcoin Close price and the Twitter Uncertainty Index lags the Ethereum Close price for our total date range from 2015-08-07 to 2023-03-14. The number of lags is the daily distance between the lagged and leading variables. Granger Causality P-value and is the threshold to execute a trade based on our momentum trading strategy which is that if asset 1 rose from time T-n (n being the number of days) and that the Pearson Coefficient exceeded a certain threshold, we would buy asset 2 at time T and sell it at time T+n. Total gain is the sum of the positive trades that closed with a profit. Total loss is the sum of the negative trades that closed with a loss. Total Trading Fees are calculated the following way: 3% of each buy and each sell to reflect the cost on a retail platform. The Net Value is Total Gain minus Total Loss minus the total trading fees. The Total Number of Transactions is the sum of the total number of buy and sell orders. The initial_trading_amount_end is the starting among of 10,000 plus the Net Value. The number non trading days is our total number of days minus the total number of transactions. The number of Trades with positive payoff is the number of buy then sell trades that were positive. Instead of counting the buy plus the sell trade, we decided to count it as one. The same goes for the number of Trades with negative payoff.

Bitcoin Close Price Lags Ethereum Close Price

Number of lags	Granger Causality P-Value	Total gain	Total Loss	Total Trading Fees	Net Value	number non trading days	Total number of transactions	trades with positive payoff	trades with negative payoff	initial_trading_amount_end
3	0.04	12072.43	-4193.36	-487.97	7391.10	2649	128	31	33	17391.10
3	0.035	2265.47	-649.86	-87.46	1528.15	2755	22	6	5	11528.15
3	0.03	685.94	-165.19	-25.53	495.22	2773	4	1	1	10495.22

Ethereum Close Price Lags Bitcoin Close Price

Number of lags	Granger Causality P-Value	Total gain	Total Loss	Total Trading Fees	Net Value	number non trading days	Total number of transactions	trades with positive payoff	trades with negative payoff	initial_trading_amount_end
10	0.035	1621430.00	-485508.35	-63208.1	1072713.50	1849	928	248	216	1082713.50
10	0.03	1611201.00	-484906.89	-62883.2	1063410.87	1897	880	231	209	1073410.87
10	0.04	1625436.00	-516800.28	-64267.0	1044368.63	1747	1030	263	252	1054368.63
10	0.025	1558008.00	-484822.33	-61284.9	1011900.76	1957	820	210	200	1021900.76
10	0.01	1525565.00	-475455.81	-60030.6	990078.57	2055	722	183	178	1000078.57

Twitter Uncertainty Index Lags ETH Close Price

Number of lags	Granger Causality P-Value	Total gain	Total Loss	Total Trading Fees	Net Value	number non trading days	Total number of transactions	Trades with positive payoff	Trades with negative payoff	initial_trading_amount_end
13	0.045	11988.74	-3018.00	-450.20	8520.54	2431	346	92	81	18520.54
13	0.05	28524.69	-12260.59	-1223.56	15040.54	2153	624	163	149	25040.54
9	0.04	57799.46	-28013.10	-2574.38	27211.98	2113	664	164	168	37211.98
13	0.035	1436.72	-132.04	-47.06	1257.62	2629	148	44	30	11257.62
8	0.035	1397.43	-132.35	-45.89	1219.19	2673	104	34	18	11219.19

Table 7

Trading Strategy Results

In table 7, this data indicates our top 5 trading results based the highest net value on the Twitter Uncertainty Index lags Bitcoin Close price, the Ethereum Close price lags Bitcoin Close price and the Twitter Uncertainty Index lags the Ethereum Close price for our total date range from 2015-08-07 to 2023-03-14. The number of lags is the daily distance between the lagged and leading variables. The Granger Causality P-value is the threshold to execute a trade based on our momentum trading strategy which is that if asset 1 rose from time T-n (n being the number of days) and that the Pearson Coefficient exceeded a certain threshold, we would buy asset 2 at time T and sell it at time T+n. Total gain is the sum of the positive trades that closed with a profit. Total loss is the sum of the negative trades that closed with a loss. Total Trading Fees are calculated the following way: 3% of each buy and each sell to reflect the cost on a retail platform. The Net Value is Total Gain minus Total Loss minus the total trading fees. The Total Number of Transactions is the sum of the total number of buy and sell orders. The initial_trading_amount_end is the starting among of 10,000 plus the Net Value. The number non trading days is our total number of days minus the total number of transactions. The number of Trades with positive payoff is the number of buy then sell trades that were positive. Instead of counting the buy plus the sell trade, we decided to count it as one. The same goes for the number of trades with negative payoff.

Twitter Uncertainty Index lags Bitcoin Close price

Number of lags	Granger Causality P-Value	Total gain	Total Loss	Total Trading Fees	Net Value	number non trading days	Total number of transactions	trades with positive payoff	trades with negative payoff	initial_trading_amount_end
7	0.05	1107512	-482922.77	-47713.04	576876.19	1247	1530	340	425	586876.19
9	0.04	1791649	-850414.21	-79261.90	861972.89	623	2154	465	612	871972.89
9	0.045	1797496	-860951.03	-79753.41	856791.56	599	2178	469	620	866791.56
9	0.05	1797588	-861021.04	-79758.27	856808.69	591	2186	471	622	866808.69
7	0.045	800390	-365570.53	-34978.82	399840.65	1425	1352	292	384	409840.65

Twitter Sentiment Index Lags Bitcoin Close price

Number of lags	Granger Causality P-Value	Total gain	Total Loss	Total Trading Fees	Net Value	number non trading days	Total number of transactions	trades with positive payoff	trades with negative payoff	initial_trading_amount_end
13	0.05	564603.67	-158758.01	-21700.85	384144.81	2551	226	166	125	394144.81
11	0.04	278019.63	-80032.23	-10741.56	187245.84	2639	138	167	141	197245.84
11	0.045	366143.55	-128238.14	-14831.45	223073.96	2539	238	251	216	233073.96
3	0.025	635136.64	-266783.12	-27057.59	341295.93	2041	736	188	148	351295.93
3	0.045	691388.37	-295818.45	-29616.20	365953.72	2005	772	192	165	375953.72

Twitter Sentiment Index Lags Ethereum Close price

Number of lags	Granger Causality P-Value	Total gain	Total Loss	Total Trading Fees	Net Value	number non trading days	Total number of transactions	trades with positive payoff	trades with negative payoff	initial_trading_amount_end
11	0.04	20097.49	-6224.03	-789.65	13083.81	2545	232	166	125	23083.81
11	0.045	29869.53	-14349.81	-1326.58	14193.14	2435	342	167	141	24193.14
11	0.05	32778.05	-16184.81	-1468.89	15124.35	2361	416	251	216	25124.35
12	0.01	50.56	-3.20	-1.61	45.75	2753	24	8	4	10045.75
11	0.02	35.50	-1.74	-1.12	32.64	2763	14	5	2	10032.64

Table 8

Wavelet Trading Strategy Results

In table 8, this data indicates all the best results based on the highest Net Value for our Pearson Coefficient back testing strategy based on wavelet decomposition level for our total date range from 2015-08-07 to 2023-03-14 for the Ethereum lags Bitcoin and the Bitcoin lags Ethereum lead-lag relationships. The decomposition level is based on the formula used in the pywt.wavedec python library. The number of lags is the daily distance between the lagged and leading variables. The Pearson Coefficient is based on the calculation of the Pearson Correlation Coefficient and is the threshold to execute a trade based on our momentum trading strategy which is that if asset 1 rose from time T-n (n being the number of days) and that the Pearson Coefficient exceeded a certain threshold, we would buy asset 2 at time T and sell it at time T+n. Total gain is the sum of the positive trades that closed with a profit. Total loss is the sum of the negative trades that closed with a loss. Total Trading Fees are calculated the following way : 3% of each buy and each sell to reflect the cost on a retail platform. The Net Value is Total Gain minus Total Loss minus the total trading fees. The Total Number of Transactions is the sum of the total number of buy and sell orders.

	Ethereum lags Bitcoin				Bitcoin lags Ethereum			
Wavelet for lagging variable	bior3.5	bior3.5	bior3.5	bior3.5	bior3.5	bior3.5	bior3.5	bior3.5
Wavelet for lead variable	bior3.5	bior3.5	bior3.5	bior3.5	bior3.5	bior3.5	bior3.5	bior3.5
Decomposition level	1	2	3	4	1	2	3	4
Number of lags	14	14	14	14	14	14	14	14
Pearson Coefficient	0.89	0.89	0.89	0.9	0.93	0.93	0.93	0.95
Total gain	680155.34	703791.12	702046.43	506770.02	44336.47	44641.32	42648.27	14219.46
Total Loss	-47631.45	-70257.17	-1851.4135	-4279.3313	-0089.07	-9831.07	-20812.40	-2662.59
Total Trading Fees	-21833.60	-23221.44	-21116.93	-15331.48	-1332.76	-1634.17	-1903.82	-506.46
Net Value	610,690.29	610,312.50	679,078.08	487,159.21	42,914.63	33,176.08	19,932.05	11,050.41
Total number of transactions	548	562	582	480	728	758	760	202

Table 9
Trading Strategy Results

In table 9, this data indicates our top 5 trading results based the highest net value on the Ethereum Close price lags Bitcoin Close price using level 3 Wavelet Decomposition and Bitcoin Close Price Lags Ethereum Close Price Using level 3 Wavelet Decomposition for our total date range from 2015-08-07 to 2023-03-14. The number of lags is the daily distance between the lagged and leading variables. The Pearson Coefficient is based on the calculation of the Pearson Correlation P-value and is the threshold to execute a trade based on our momentum trading strategy which is that if asset 1 rose from time T-n (n being the number of days) and that the Pearson Coefficient exceeded a certain threshold, we would buy asset 2 at time T and sell it at time T+n. Total gain is the sum of the positive trades that closed with a profit. Total loss is the sum of the negative trades that closed with a loss. Total Trading Fees are calculated the following way: 3% of each buy and each sell to reflect the cost on a retail platform. The Net Value is Total Gain minus Total Loss minus the total trading fees. The Total Number of Transactions is the sum of the total number of buy and sell orders. The initial_trading_amount_end is the starting among of 10,000 plus the Net Value. The number non trading days is our total number of days minus the total number of transactions. The number of Trades with positive payoff is the number of buy then sell trades that were positive. Instead of counting the buy plus the sell trade, we decided to count it as one. The same goes for the number of Trades with negative payoff.

Ethereum Close Price Lags Bitcoin Close Price Using Level 3 Wavelet Decomposition

Number of lags	Pearson Coefficient	Total gain	Total Loss	Total Trading Fees	Net Value	Number non trading days	Total number of transactions	Trades with positive payoff	Trades with negative payoff	initial_trading_amount_end
14	0.89	702046.43	-261851.41	-28916	411278.08	2195	582	166	125	421278.08
13	0.89	689894.16	-290598.46	-29414	369880.92	2159	618	167	141	379880.92
14	0.86	914291.42	-538725.72	-43590	331975.19	1843	934	251	216	341975.19
14	0.88	731442.67	-360190.03	-32748	338503.66	2105	672	188	148	348503.66
13	0.88	724629.89	-368444.84	-32792	323392.81	2063	714	192	165	333392.81

Bitcoin Close Price Lags Ethereum Close Price Using Level 3 Wavelet Decomposition

Number of lags	Pearson Coefficient	Total gain	Total Loss	Total Trading Fees	Net Value	number non trading days	Total number of transactions	Trades with positive payoff	Trades with negative payoff	initial_trading_amount_end
14	0.93	42648.27	-20812.4	-1903	19932.05	2017	760	230	150	29932.05
13	0.93	40876.41	-21029.466	-1857	17989.77	1977	800	244	156	27989.77
12	0.93	38318.19	-20804.3	-1773	15740.22	1977	800	232	168	25740.22
14	0.94	36072.88	-10382.64	-1393	24296.57	2157	620	198	112	34296.57
13	0.94	33875.02	-19434.44	-1599	12841.30	2143	634	202	115	22841.30