Essays in cryptocurrencies' forecasting and trading with technical analysis and advanced machine learning methods

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Abstract

This thesis mainly emphasizes two prediction fields in the cryptocurrency market: factor analysis and model examination. The first section summarises the general introduction, theoretical background, and description of performance metrics used in the empirical study (Chapter 3-5) are summarized in the first section (Chapter 1-2). Then, in Chapters 3 and 4, technical analysis and fundamental factors combined with statistical models are employed to explore the forecasting ability and profitability in the cryptocurrency market. Finally, in Chapter 5, advanced machine learning algorithms combined with leverage trading strategies and narrative sentiments are used to predict the Bitcoin (BTC) market.

Chapter 3 examines technical analysis's profitability and predictive power on cryptocurrency markets. This Chapter adopts the universe of technical rules proposed by Sullivan et al. (1999), while for data snooping purposes, I apply the Lucky Factors (LF) method proposed by Harvey and Liu (2021). Six mainstream cryptocurrencies and one cryptocurrency index from 2013 to 2018 are examined. The results demonstrate that short-term signals generated by technical rules outperform the traditional buy-and-hold strategy. However, the LF methodology shows that none of the top-performing rules in terms of profitability is consistent with actual forecasting performance.

The purpose of Chapter 4 is to investigate the prediction of cryptocurrency returns by applying a large pool of factors from both technical and fundamental aspects. The results find that most trading rules perform better than the buy-and-hold strategy, especially the moving average rules. However, this profitability may not be genuine but comes from data-snooping bias. In this way, a larger pool of factors from several aspects, including blockchain information, technical indicators, online sentiment indices, and conventional financial and economic indicators, is implemented from 08/08/2015 to 08/12/2018. The overall results suggest the new proposed technical indicator, Log-price Moving Average (PMA) ratio, a moving-average likely ratio has significant forecasting ability in cryptocurrencies after taking data-snooping bias into account.

Chapter 5 explores the forecasting ability of machine learning (ML) algorithms in the BTC market by combining the narrative sentiments and leverage trading strategy. First, the forecasting framework starts by selecting a pool of individual models. Secondly, ML algorithms are used further to improve the predictive performance of the individual model pool. Thirdly, both the best single predictor and ML models are fed into the process of forecasting ability examination, constructed by three different metrics. This step also takes data-snooping bias into account. At last, leverage trading strategies combined with narrative sentiments are applied to all forecasting models to examine their profitability. The results suggest that ML models consistently outperform the best individual model in forecasting ability and profitability. Gradient Boost Decision Tree (GBDT)-the family has the best performance.

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Declaration

I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the results of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

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Abbreviations

ADF	**Augmented-Dickey Fuller**
AI	**Artificial Intelligence**
AMH	**Adaptive Market Hypothesis**
AR	**Auto Regressive**
ARIMA	**Auto Regressive Integrated Moving Averages**
ARMA	**Auto Regressive Moving Averages**
BCH	**Blockchain**
BH	**Buy and Hold**
BP	**Back-propagation**
BTC	**Bitcoin**
BTS	**Bitstamp**
CB	**Coinbase**
CBOE	**Chicago Board Options Exchange**
CFTC	**Commodity Futures Trading Commission**
CRSP	**Centre for Research in Security Prices**
DeFi	**Decentralised Finance**
DJIA	**Dow Jones Industrial Average**
DLT	**Distributed Ledger Technology**
DT	**Decision Tree**
EFB	**Exclusive Feature Bundling**
EM	**Equilibrium Model**
EMA	**Exponential Moving Averages**
EMH	**Efficient Market Hypothesis**
EPU	**Economic Policy Uncertainty**
ETF	**Exchange Traded Funds**
FA	**Fundamental Analysis**
FDR	**False Discovery Rate**
FR	**Filter Rule**
FWER	**Family-Wise Error Rate**
GARCH	**Generalised Autoregressive**
GBDT	**Gradient Boosting Decision Tree**
GJR	**Glosten-Jagannathan-Runkle**

GOSS	**Gradient-based One Side Sampling**
GPU	**Gated Recurrent Unit**
GRS	**Gibbons, Ross, and Shanken**
HA	**Historical Average**
JB	**Jarque-Bera**
LB	**Ljung-Box**
LBM	**Light Gradient boosting Framework**
LF	**Lucky Factor**
LDA	**Latent Dirichlet Allocation**
LSTM	**Long-Short Term Memory**
MA	**Moving Averages**
MAE	**Mean Absolute Error**
MCS	**Model Confidence Set**
MDD	**Maximum Drawdown**
MDM	**Modified Diebold and Mariano**
MHT	**Multiple Hypothesis Tests**
ML	**Machine Learning**
MLP	**Multilayer Perceptron**
MSE	**Mean Squared Error**
MSFE	**Mean Squared Forecast Error**
NFT	**Non-Fungible Token**
NLP	**Natural Language Process**
NN	**Neural Networks**
OBV	**On-Balance Volume**
OLS	**Ordinary Least Square**
PCA	**Principle Component Analysis**
PMA	**Log-price Moving Averages**
RBF	**Radial Basis Function**
RC	**Reality Check**
RF	**Random Forest**
RFE	**Recursive Feature Elimination**
RMSE	**Root of Mean Squared Error**
RNN	**Recurrent Neural Networks**
SMA	**Simple Moving Averages**

SPA	**Superior Predictive Ability**
SR	**Support and Resistance**
STW	**Sullivan, Timmermann, and White**
SVM	**Support Vector Machine**
SVR	**Support Vector Regression**
TA	**Technical Analysis**
XGB	**Extreme Gradient Boosting**

Chapter 1 Introduction

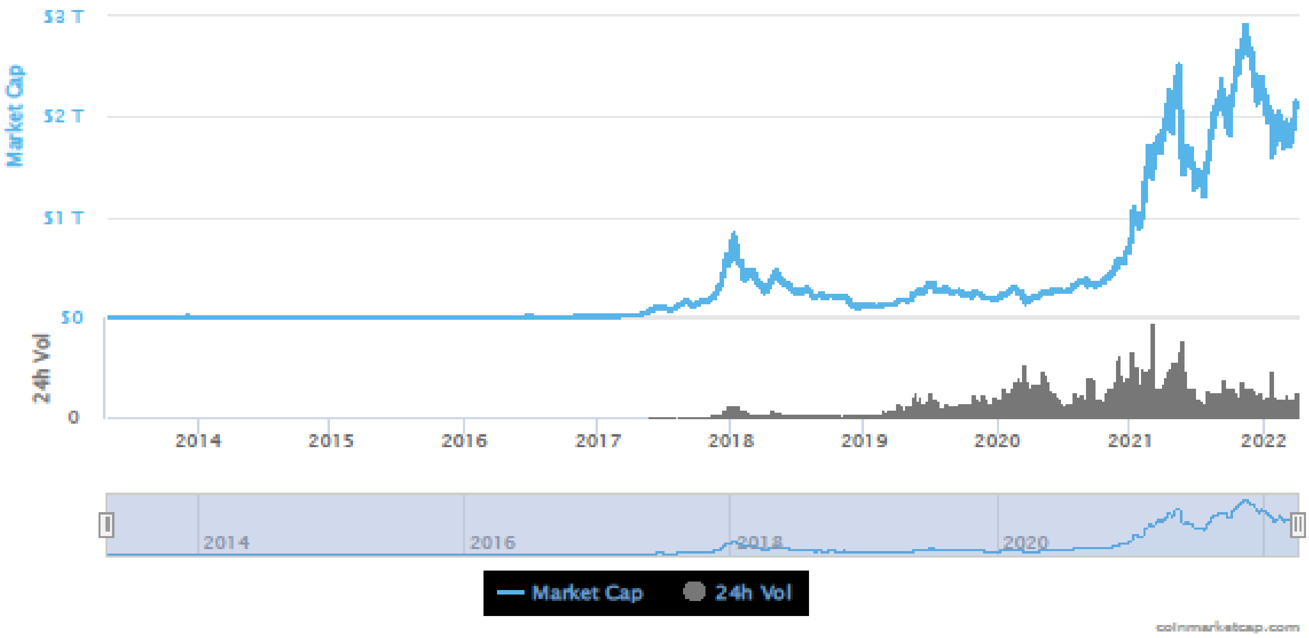
1.1 General Background and Motivations

Forecasting is a subject used for future prediction. Starting from the ancient history of humankind to modern scientific techniques, forecasting theories, methodologies, and utilities have evolved significantly. With the development in contemporary science, forecasting is no longer covered by mysterious rituals but has become a trackable, logical, stable, and reliable technique. In practice, various fields are needed for forecasting techniques, for example, weather, earthquake and other environmental changing alerts and transportation, tourism, and other humankind activities analysis. Take rainfall prediction as an example. The result depends on many factors, such as time, land pixels, magnitudes, and location. However, given detailed data and an appropriate information system, it is possible to infer the likely rainfall in the next period. Although errors and bias may occur, the accuracy and efficiency of prediction have grown far higher than in the old days.

The myriad of information sources provides researchers with enormous data. However, this also leads to inevitable miscalculation and misjudgement in making a decision. Compared to the traditional statistical tools, big data, machine learning, and other advanced techniques promise to make more comprehensive and accurate forecasting results. One possible solution to the difference should be attributed to the sample capacity. Conventional statistical tools are constrained mainly by sample capacity. Their results are deducted by specific or random components of the whole database. On the other hand, advanced forecasting techniques are able to deal with enormous amounts of data by employing complex algorithms. The ML algorithms are not a new invention. However, its application was not widely developed until significant improvements from hardware in recent decades. For example, proposed by Hinton (1986), multi-layer perceptron (MLP) can be optimized by the backpropagation (BP) algorithm, thus leading to its application in non-linear classification and other learning objectives. This achievement indicates that ML algorithms are capable of processing multiple tasks with computation efficiency. Apart from neuro network (NN) algorithms, different ML algorithms, such as AdaBoost, Support Vector Machine (SVM), and Random Forest (RF), are developed to tackle various problems. Another essential factor to the prosperity of ML algorithms is the development of computer hardware, making them achievable in practice. Nowadays, the challenging issue is dealing with different sources of information, such as pictures, text, and speech. With the proficiency and divergence of theoretical methods, ML techniques can solve the above tasks across different fields, including natural language, image recognition, and automated speech recognition.

Unsurprising, a market with more than a ten-billion-fold increase over merely ten years cannot be neglected. What drives the insane push-up of cryptocurrency thus becomes one of the most exciting puzzles in both academy and industry. Nonetheless, no clear clue can be drawn. Owing to the original design of Bitcoin (BTC) founder and developer Nakamoto Satoshi, BTC is meant to be the next-stage currency in the future. The inception of BTC is firstly regarded as an advanced form of money, possessing similar properties to regular currency, such as medium of value exchange, storage of value, and unit of account. Nowadays, however, as said by Ray Dalio, the founder of Bridgewater Associates, "Bitcoin "could serve as a diversifier to gold and other such store-hold of wealth assets." Researchers also treat BTC as a kind of digital gold, suggesting that cryptocurrencies should be classified as financial assets (Dyhrberg, 2016). With the development of Blockchain technology (BCH), cryptocurrencies are widely traded over the internet. Intuitively, like BTC, cryptocurrencies are mainly used as financial instruments rather than currencies. However, we also cannot neglect the monetary attribute of cryptocurrencies. With the rapid growth in public consensus and fast expansion of practical usage, more and more corporations have started to accept BTC as their payable currency (e.g., Microsoft, Tesla, CheapAir). Detailed use of BTC in ordinary life can be referred to Coinbase.com. Unlike fiat money, cryptocurrencies have no governmental authorities or assets serving as value support. Following the declaration of Alan Greenspan in 2017, no intrinsic value can be found in such digital currencies[1]. Under such circumstances, lower fees for transferring, lower costs and other relative convenience may lead to the genuine value of cryptocurrencies. However, it is rather difficult to quantify such convenience associated with the dynamic change in the cryptocurrency prices and the unstopping transaction system of the cryptocurrency market.

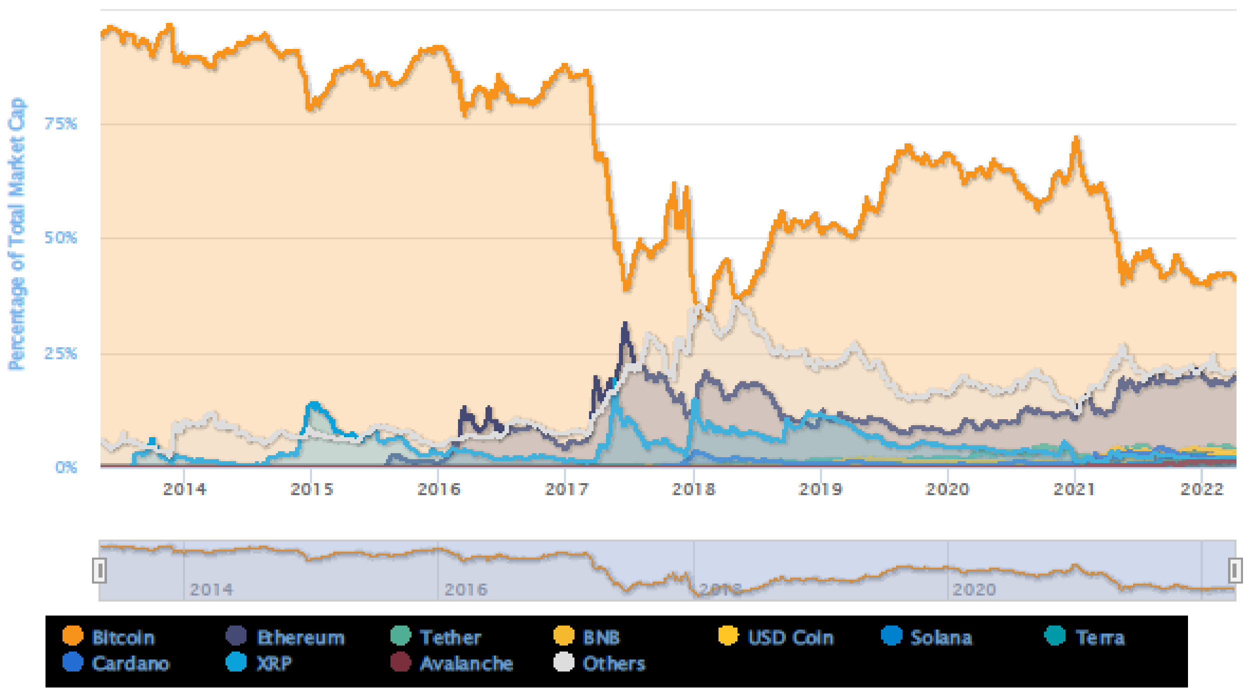
Figure 1. 1 Total Cryptocurrency Capitalization (Excluding Bitcoin)



Note: Data can be retrieved back to Coinmarketcap.com. Statistics are extracted in March 2022.

[1] The statement says, 'Human nature is such that if you get something like Bitcoin, you think there is some value there whether there is or there isn't'.

Figure 1. 2 Major Cryptoassets by Percentage of Total Market Capitalization (Bitcoin Dominance Chart)



Note: Data can be retrieved back to Coinmarketcap.com. Statistics are extracted in March 2022.

Apart from the focus on the BTC market, it is crucial to investigate the abundance and diversity of the cryptocurrency ecosystem. Figure 1.1 illustrates the development of the cryptocurrency market by excluding BTC. Figure 1.2 demonstrates variations of BTC dominance in the cryptocurrency market. The fast growth of blockchain applications, such as smart contract platforms, decentralized finance, and non-fungible tokens (NFT), is gradually decreasing the influence of BTC in the cryptocurrency market. In Jan 2018, the BTC dominance even reached nearly 30%. Excluding the impact of the Ponzi scheme and air-cryptocurrencies[2], Ethereum (ETH), Binance Coin (also known as BNB) and other coins also make significant contributions to the flourishing of the cryptocurrency market. The analysis of the correlation between other alternative cryptocurrencies (altercoins) and BTC is worth more discussion.

Technical analysis (TA), as a popular trading tool, fits perfectly with the cryptocurrency market. Based on the past prices, volumes or other data sources, the application of TA usually provides solid forecasting results for traders.

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[2] Cryptocurrency is usually an extensive application or product of a blockchain program. We call those cryptocurrencies whose program members do nothing but writing a white paper as air-cryptocurrency or air-coins.

Both forecasting ability and profitability are needed to get a satisfying trading performance. Forecasting tools, data collection, and measurement standards could influence the former factor. The later factor primarily relies on the settlement of trading strategy and traders' experience. Discussion of TA's profitability or forecasting ability in the cryptocurrency market is far less than in conventional financial markets (Deztol et al., 2018, Huang et al., 2019, Urquart and Hendenson, 2019, Ionious et al., 2020). That is, rare TA factors have ever been studied or published, suggesting considerable potential in this area. As indicated by Urquart (2018), the efficiency of the cryptocurrency market stays low, meaning TA seems to be one possible solution to cryptocurrency prediction. Unlike other financial markets, it is rather complex to use traditional fundamental indicators (e.g., factors extracted from accounting system) in the cryptocurrency market, thus making it more valuable to find useful TA indicators. Although TA usually has outstanding performance in conventional financial markets (e.g., stock market and currency exchange market), its abnormal returns may not be genuinely (See Lo, 1992; Scalliet and Baris, 2011). The forecasting outcomes are affected by data-snooping bias and generate seemingly good results based on the inappropriate measurements.

Under such circumstances, machine learning techniques have unique advantages in forecasting relevant issues., First, prediction tasks are always fuzzy and complex in the cryptocurrency market with full of non-linearity and noises inherited in data. As mentioned earlier, it is vital to build applicable forecasting models, obtain adequate data, and take rigorous measuring metrics to produce reliable and valuable forecasting results. In terms of forecasting ability, ML algorithms have shown their flexibility of application, inputs' compatibility, and prediction accuracy in extensive studies. After all, the inception of ML algorithms is meant to be reasonable, understandable, and learnable for users so that their utility adapts to the changing requirements of tasks. Secondly, cryptocurrency trading never stops, meaning enormous amounts of data could be available. On the other hand, statistical models are incapable of dealing with large amounts of data while not losing much information. Compared to conventional forecasting models, common data type and length requirements are needed to feed ML algorithms. Lastly, it is essential to apply appropriate metrics when measuring forecasting results produced by multiple-task algorithms. Otherwise, seemingly good results can be easily generated while not genuinely meaningful.

Like a coin has two sides, the merits of advanced algorithms come with drawbacks. Due to the complexity inherited in algorithms, it is necessary to take proper standards when measuring forecasting behaviour to avoid bias or errors, such as data-mining bias and over-fitting issues. These problems happen when dealing with large datasets and high-dimensional input factors. The typical approach to avoid over-fitting is to split the whole dataset into in-sample and out-of-sample periods. Thus, hyper-parameters are only adjusted within the in-sample period, while genuine forecasting results are produced in the out-of-sample period. The critical process to solving the high-dimensionality issue is extracting valuable factors while not losing much information, also known as feature selection. Traditional selection methods (e.g., principal component analysis and correlation filter method) are always useful. Still, advanced selection algorithms, such as the random forest method, may better solve the sparse matrix or other modern issues. In addition, sceptics always question the interpretability of ML algorithms. Due to the complexity of computational needs, the calculation process for some ML algorithms, such as NNs, usually cannot be well explained or illustrated by statistical methods. This problem is inevitable when higher accuracy is expected because simplified algorithms always fail to outperform complex algorithms. In addition, the debate over revealing the transparency of the so-called 'black-box' system remains unchanged (see Lipton, 2018, Gilpin et al., 2019, Krishnan, 2019).

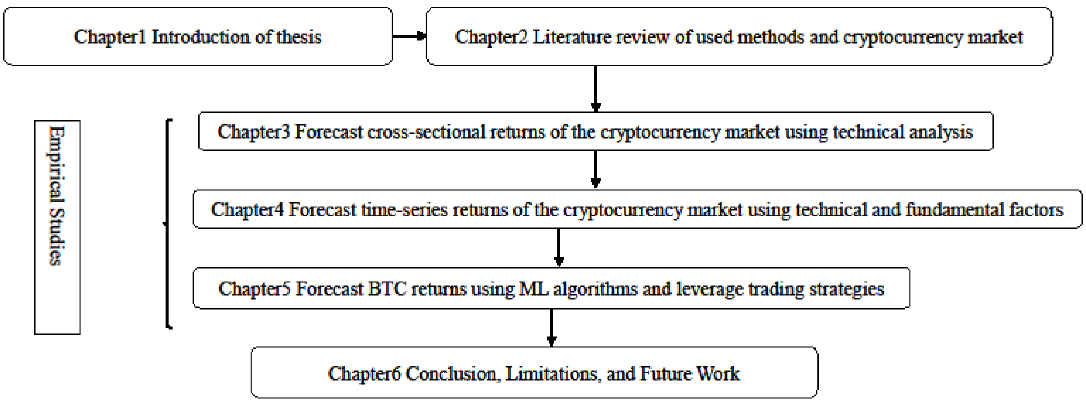
The consensus strength, either good or bad, only pushes forward the development of the cryptocurrency market, making it known to more people. Undoubtedly, the sudden and significant movements in cryptocurrency prices draw the media's attention. Namely, the relationship between cryptocurrency price changes and media influence is mutual causality. With the establishment of a narrative sentiment index, traders obtain a comprehensive understanding of the aggregated consensus of the public to make favourable decisions. Take Dogecoin as an example. Its price surged roughly 5% in less than an hour after Elon Musk's tweet on Oct 22, 2021. The natural language process (NLP) algorithm is always an excellent choice to extract information from tons of words to analyse and quantify context. With proper application of the NLP algorithm and automated trading system, it is possible to respond immediately to any online information or other sources. Several studies also give empirical evidence that sentiment from different sources, such as tweets, Google Trends and online news and articles, have a causal relationship with cryptocurrency prices (Lamon, Nielsen and Redondo, 2017; Abraham et al., 2018; Vo et al., 2019; Rognone, Hyde and Zhang, 2020).

1.2 Structure and Contributions

1.2.1 Thesis Structure

Chapter 2 provides a review of technical analysis, a description of cryptocurrency trading and a summary of data snooping bias is provided. Three Chapters (Chapters 3-5) present empirical applications. Finally, an overall conclusion is drawn in Chapter 6. Meanwhile, limitations and future work are also explained in this section. An overview graph of thesis structure is illustrated in Figure 1.3. A brief introduction of empirical studies (Chapters 3-5) is shown as follows:

Figure 1. 3 Overview of the thesis structure



Note: The figure presents the overview structure of this thesis.

In Chapter 3, a universe of trading rules is applied to explore cross-section returns in the cryptocurrency market. The total number of trading rules is nearly 8000, which may cause data-snooping bias. Under such circumstances, a framework of multiple hypothesis test ‘Lucky Factor (LF)’ proposed by Harvey and Liu (2021) can be helpful to reduce the influence of data-snooping bias. In terms of profitability measurement, two famous metrics, Sharp and Sortino ratios, are used across each period. The overall result suggests that technical trading rules overperform the ‘buy-and-hold’ trading strategy. Moving Average (MA) strategies beat other technical indicators in forecasting ability and profitability. In addition, TA factors organized by daily or higher time-based constraints do not possess genuine predictive power over cross-section cryptocurrency returns.

In Chapter 4, a comprehensive investigation that combines technical factors with fundamental factors is implemented for time-series prediction in the cryptocurrency market. The whole sample is split into in-sample and out-of-sample periods to avoid over-fitting. At first, A bi-variant statistical model is applied to examine the forecasting ability of each factor. Then, once any factor is identified as significant, each of the rest factors will be tested, looking for additional contributions they can make to improve the forecasting ability of the primary model. Two techniques, the superior predictive ability test and the LF method, are used to control the impact of data-snooping bias. Finally, the general trading performance of each factor is also examined.

In Chapter 5, a two-step framework combined with individual statistical models and ML models is proposed. With extensive efforts in factor analysis, more consideration is put into the examination of forecasting models by applying kinds of combined forecasting techniques. An NLP model, called Latent Dirichlet Allocation (LDA), builds sentiment index. Starting with selection in a traditional statistical model pool, this presents the best individual forecasting model to compare with advanced ML models in terms of forecasting ability. Then, all individual forecasting models will be fed into different combined forecasting techniques to improve their forecasting ability further. In addition, two different factor reduction models are applied to avoid the high-dimension issue. Different leverage trading strategies based on volatility and narrative sentiment are applied to improve the trading performance of forecasting models. Our result indicates that even the best single predictor is inferior to the advanced ML algorithm. Particularly, Extreme Gradient Boosting (XGB) model has the best performance among all forecasting models. As for trading performance, the time-variant hybrid leverages based on the combination of volatility and sentiment outperform other strategies.

1.2.2 Contribution

This thesis contributes to cryptocurrency returns' forecasting and trading mainly from factor analysis, model selection, and trading strategy. In addition, each chapter has its unique value in terms of motivations, technical application, and empirical outcomes.

Due to the lack of supervision and regulation, the exploration of a cross-sectional study in cryptocurrency can be constrained. While much research has been done on the power of technical analysis in many markets, little research has been done specifically to examine its forecasting ability in cryptocurrencies' returns. However, this market experiences enormous upswings and unexpected downturns regularly. Chapter 3 makes an attempt to investigate the explanatory power of technical analysis in the cryptocurrency market. Compared to prior studies, this chapter contributes to examining superior predictive ability by controlling the data-snooping bias (Kristjanpoller and Minutolo, 2018; Corbet et al., 2019; Grobys et al., 2020; Zhang et al., 2021; Jia et al., 2021). Unlike Anghel (2021), this chapter adopts the Lucky Factor framework proposed by Harvey and Liu (2021), which focuses on the multiple hypothesis tests by controlling the data-snooping bias. The result indicates that moving average rules outperform other technical rules within the universe of trading rules. However, the superior performance of technical rules may suffer from data-snooping bias. This chapter expands the literature on the use of technical analysis and data-snooping bias in the cryptocurrency market.

Unlike the previous chapter, Chapter 4 emphasises examining the forecasting ability of TA and FA factors in the time-series returns of cryptocurrencies. Furthermore, two techniques are applied to reduce the influence of data-mining bias: the LF and SPA methods. This chapter contributes to the current literature mainly from three aspects. At first, the link between the cryptocurrency market and the traditional financial market is examined by applying fundamental factors. Secondly, specific fundamental factors extracted from cryptocurrency are proposed and examined. Thirdly, both single factor's and augmented factor pool's forecasting ability are examined. Finally, the results suggest that Blockchain (BCH) information and PMA ratios possess genuine forecasting ability in cryptocurrencies' returns by controlling the data-snooping bias.

Chapter 5 focuses on model selection and sentiment analysis in the BTC market compared to previous chapters. In particular, this chapter implements a two-step forecasting framework by combining statistical and ML models. Then, the author proposes a hybrid trading strategy compromised of sentiments and volatility leverages. This chapter contributes to the current literature in the cryptocurrency market from two fields: examining models' predictive power and the trading performance of strategies. In terms of model selection, this chapter examines the forecasting ability of ML algorithms based on a pool of individual models. The forecasting combination techniques further improve the predictive performance of simple models. This chapter is the first study constructing a hybrid trading strategy in the cryptocurrency market using both sentiment and volatility leverages to the best of my knowledge. The results show that ML algorithms outperform individual models, and XGB has the best performance in terms of forecasting accuracy. In addition, the trading performance of the hybrid strategy beats the traditional buy-and-hold strategy, which is the benchmark for all tested strategies.

Chapter 2 Cryptocurrency trading, technical analysis and data snooping bias

2.1 Review of Technical Analysis

Technical analysis plays a vital role in financial markets. Charles Dow, who established the Wall Street Journal and Dow Jones Industrial Average (DJIA), laid down the foundation of technical analysis at the end of 1800 (Brock et al., 1992; Vanstone and Finnie, 2009). In essence, technical analysis is a financial tool package constructed by different trading rules or predefined patterns that are used to simulate or forecast the possible movements of asset prices. Unlike other indicators, technical indicators are extracted from historical market information, such as prices, trading volumes, transaction costs, etc. Although countless kinds of technical rules there are, they are mainly built upon three basic assumptions for professional analysts: (1) market action discounts everything; (2) prices move in trends; (3) history repeats itself (Murphy, 1999). Technicians reckon that any factor that may influence the price is reflected in that specific market price, indicating the only focus is price. A common belief is that actions of price fluctuation fully reflect the relationship between demand and supply, which leads to another statement that the goal of charting price actions is to catch transaction trends for identifying the directions of these trends. Lastly, future movements in price can be traced back to its past trajectories, which means history is a repetition of itself.

Researchers provide theoretical support and contribute to the development of technical analysis. Brown and Jennings (1989) and McNichols (1989) show that continuous-period stock price movements reveal basic information, and Cutler et al. (1991) provide empirical evidence of stock returns and autocorrelation. Furthermore, the fact that stock returns and autocorrelation can be traced back to two main reasons: (1) ignoring the microstructural bias caused by the so-called "non-synchronous" trading (Scholes and Williams,1977; Lo and Mackinlay, 1990); (2) anticipated time-varying risk premium in the short term (Fama and French, 1988; and Conrad and Kaul, 1988). In the case of asynchronous transactions, portfolios of different assets are influenced by news from different periods and are autocorrelated in their returns, and even it is set to be a time-independent process (Lo and MacKinlay, 1989). On the other hand, Roll (1984) demonstrates that dealers or market makers are compensated by the so-called "buy-offer spread", leading to the first lag in the price change. Jegadeesh (1992) finds that the continuous stock return rate is negative autocorrelation, lags two months, and positive autocorrelation has a more extended lag period. Blume et al. (1994) propose that trading volume plays a vital role in technical analysis. Investors who use past market information can research and obtain more information about current market conditions. Chen et al. (2008) state that negative autocorrelation is in long-term stock returns and is negatively correlated with conditional volatility. Teixeira and de Oliveira (2010) provide strong evidence and demonstrate that technical analysis is profitable by combining intelligence prediction systems with traditional technical rules. Menkhoff (2011) collected and analysed a comprehensive survey of 692 fund managers from five markets and showed that most managers' preferences are technical analysis. Han et al. (2013) found an abnormal abundance of portfolios sorted by volatility by applying technology trading rules and suggested that it is effective to investigate the cross-sectional performance of technical trading rules. Neely et al. (1997) explored a genetic programming approach for predicting foreign exchange rates and found strong evidence of the profitability of technical rules in foreign exchange markets.

Recent studies combine artificial intelligence (AI) techniques with technical analysis and conventional statistical models. Chavarnakul and Enke (2009) propose that AI systems can control the uncertainty in the stock market. Similar findings are found in foreign the exchange market (Sermpinis et al., 2012). Other technical indicators (e.g., charting patterns, momentum-based indicators, or price-based indicators) combined with advanced computational algorithms (e.g., genetic algorithm, evolutionary reinforcement learning algorithm) are also found to have good trading performance in the stock market (see Neely 2003; Austin et al., 2004; Lin et al., 2011; Creamer, 2012; Fortuny et al., 2014; Taylor, 2014). Based on flag pattern recognition, Cervelló-Royo et al. (2015) provide further evidence that the performance of technical trading rules is superior to DJIA.

2.2 Efficient Market Hypothesis and Adaptive Market Hypothesis

In terms of forecastable prices, opponents of technical analysis believe stock prices move randomly and cannot be predicted (Brock, Lakonishok, and LeBaron, 1992; Menkhoff, 2010). Samuelson (1965) claims that prices randomly fluctuate if they anticipate properly, which is the origin of the Efficient Market Hypothesis (EMH). Once the market is functioning effectively and fully meets the participants' expectations, the participants can obtain all the information and cannot predict the changes in the stock price. Fama (1970) further summarizes EMH that there are three levels of market efficiency based on the participant's information set. Malkiel (2003) revisited EMH and proposed that investors cannot be entirely rational, and even professional or institutional investors cannot surpass the market's shortcomings. Timmermann and Granger (2004) point out that EMH is not inconsistent with prediction, which can be achieved through information collection and analysis. They also stated that investors could obtain abnormal gains in the short term before their methods are widely spread.

As a further study achievement of EMH, Lo (2004) proposes the Adaptive Market Hypothesis (AMH), which provides a theoretical basis for the profitability of technical trading rules. AMH offers a broader assumption than traditional EMH. These contain the evolutionary rationality of investors, the natural choice of path dependence in equity-risk premiums, cyclical profitability and losses, and variable market efficiency. Empirical evidence is also found across different financial markets. Kim et al. (2011) demonstrate that as market conditions change and predict changes in US stock returns, return forecasts change with market volatility and other economic factors. This finding implies that return prediction varies as market conditions change, including the natural selection of AMH. From a computational intelligence perspective, Butler and Kazakov (2012) demonstrate that cyclical profitability in the financial market is very rich, and nonlinear dependence can improve the accuracy prediction of financial time series. Charles et al. (2012) provide empirical evidence in the foreign exchange market that the prophecy of the foreign exchange rate varies with the change in market conditions, suggesting the existence of AMH in the currency market. Zhou and Lee (2013) find that the stage of market development mainly drives the market efficiency of real estate investment trusts. Therefore, the income forecast of real estate investment trusts alters with time and the change in market conditions. Other empirical results also suggest that AMH and stock and foreign exchange market returns are more consistent than EMH (Neely et al., 2009; Urquhart and Hudson, 2013).

2.3 Cryptocurrency and technical analysis

2.3.1 An overview of cryptocurrency market

Undoubtedly, cryptocurrency, the next generation of currency, is worthy of investigation (Smith and Weismann, 2014). Since 2009, Nakamoto Satoshi has spent a few months transforming the idea of the white paper of BTC into a real virtual currency. Although the total number of BTCs is limited and non-renewable, which is 21 million, the holder only needs a fraction of one BTC to trade, such as 0.0001 BTC (Fowler, 2014; Tucker, 2013). So far, over 19 million BTCs have been created, but due to the nature of BTC mining, it has become more difficult to tap more coins. In this case, no currency printer or central bank can quickly increase or decrease BTC amount in any market. Under this scenario, the traditional monetary policy may not control this non-renewable resource.

A feature of cryptocurrency is decentralisation, which invalidates the supervision of any intermediary authority in the cryptocurrency holder transaction. However, policymakers may face challenges of exchange rate volatility, audit management, money laundering and other severe problems (Nakamoto, 2008; Grant and Hogan, 2015). On the other hand, the decentralised cryptocurrencies provide small businesses with lower costs but faster transaction speed and help them avoid fraud, such as using a credit card “refund” (Simonite, 2017). From a macro perspective, BTC and other cryptocurrencies, as an anti-poverty tool, can help people in third world countries access technical services and build a better credit system. In a brief statement, cryptocurrencies should not be considered only a pest but valuable tools to make a better life.

Previous literature mainly focuses on the monetary essence of cryptocurrency, revolving around research in computer science and relative laws (Grinberg, 2012; Cobert et al., 2018). However, virtual currencies like BTC cannot replace fiat currencies. Luther and White (2014) declared that the acceptance of BTC is still limited, although BTC capitalisation has quadrupled from March 2013 to December 2014. Luther (2016) asserts that BTC cannot be recognised or accepted as a widespread currency without government support. Baur, Hong and Lee (2018) further demonstrate that investors hold BTC rather than serve as a medium of exchange.

On the other hand, cryptocurrencies like BTC can be utilised as currency storage or informal financial instruments. The market value of BTC in December 2014 was $4.7 billion, while the market share of Lithuanian litas was $5.8 billion, that of Guatemalan quetzal was $5.5 billion, and that of Costa Rican colon was $3.3 billion. For this burgeoning market, academic studies generally focus on cryptocurrency regulation and its effects on current economies (Böhme et al., 2015; Cheah and Fry, 2015). Yermack (2013) considers BTC a speculative investment, and Kristoufek (2015) further indicates that peculiar factors can influence BTC prices. (2014) also stated that the search frequency of social media or famous websites (e.g., *Google Trends* and *Wikipedia*) could affect the BTC price. In 2014, the Commodity Futures Trading Commission (CFTC) granted full registration to BTC, allowing investors to trade BTC as a commodity and conduct appropriate regulations. Chu et al. (2015) then focused on fitting the exchange rate of BTC against major currencies, like USD, GBP, Japanese Yen, and Euro. Popper (2015) and Baur et al. (2015) pointed out that BTC is a kind of virtual gold, which can be regarded as a mixture of the usual currency and precious metals. Bouoiyour et al. (2016) demonstrate that long-term fundamental factors can drive changes in BTC prices. Wang and Vergne (2017) showed that buzzing factors could not adequately affect cryptocurrency. Instead, the main drivers of cryptocurrency gains are due to technological development. Fry and Cheah (2016) made further contributions to the bubble and crash investigations in the cryptocurrency market. They also explained the vital relationship between economic physics and cryptocurrency. Dyhrberg (2016) demonstrates some of the general characteristics of gold, dollars and BTC, noting that BTC can be included as a commodity in portfolio management. In this way, cryptocurrency trading is more like a bridge for foreign exchange trading, showing similar functions to hedge funds (Luther, 2016). Henriques and Sadorsky (2018) also find that portfolios included with BTC have high returns, which can substitute gold. Demir *et al.* (2018) further state that BTC can be used to hedge against uncertainty during a bull market. Shahzad et al. (2019) find a similarly safe-haven property across BTC, Gold and Commodity.

2.3.2 DeFi and cryptocurrency trading

As the general promise of BTC whitepaper, the Decentralized Finance (DeFi) plays an essential role in BCH's applications. Defi can be summarized as a peer-to-peer financial system with four properties: non-custodial, permissionless, openly auditable, anonymous, and potentially new capital efficiencies (Werner et al., 2021). DeFi complex is designed to solve five main problems arising from Centralized Finance: centralized control, limited access, inefficiency, lack of interoperability, and opacity (Harvey, Ramachandran, and Santoro, 2021). Similar to the rocket rising of BTC, the asset under management (also known as total value locked (TVL)) of DeFi has grown from 142 million USD at the end of 2017 to over 100 billion USD at the end of 2021 (DEFI PULSE, 2022). Powered by BCH, DeFi users do not need to be censored by a third party because programming protocols automatically deliver their transactions based on smart contracts. The ETH price has increased more than 300 times from the end of 2019 to 2021 because the Ethereum network had more than 55% share of the TVL at the end of 2021. Due to the deflation model of ETH, more than 1.5 million ETH have been destroyed since early August 2021 (Glassnode). Although the flourishing of DeFi further accelerates the development of the cryptocurrency market, altercoins based on the ETH platform have gradually taken dominance of the whole market.

Nonetheless, sceptics state that the ecosystem of cryptocurrency is not healthy. That is to say, DeFi is nothing but a novel form of financial crimes, such as Ponzi, pyramid schemes and other financial scams. One reason could be attributed to the numerous cases of cyberattacks and loss of funds. Werner et al. (2021) suggested that technical and economic security are two main problems of DeFi. Since most protocols are built upon ETH and written by Solidity, various types of technical issues are associated with the vulnerability of smart contracts. For example, a loss of 10.8 million USD was caused by a logical bug in Compounder protocols. Attacks based on technical principles are risk-free, which cost hackers no more than a few gas fees (also known as transaction fees). On the other hand, inadequate supervision and regulation in the cryptocurrency market lead to economic insecurity. Unlike technique risks, threats in the cryptocurrency economy cannot be risk-free. Cong et al. (2021) demonstrate manipulation in the cryptocurrency market is not rare, accompanied by significant profits. Moreover, policy intervention has also caused dramatic variation in the cryptocurrency market. On September 24, 2021, ten government authorities jointly issued a notice declaring cryptocurrency as an illegal tender. Then, the BTC price drops 2000 USD after announcing the banning of cryptocurrencies.

Due to technological innovation, there are several differences between trading in traditional financial markets and crypto markets. Unlike stock and other conventional markets, the cryptocurrency market is available anytime and anywhere between individuals with access to the net. In addition, cryptocurrencies do not require any physical delivery due to their virtual essence. Although the blockchain technique grants most cryptocurrencies the anonymity property, exchanges, especially centralized exchanges, like Coinbase and Binance, usually ask users to provide identification information by setting up Know-Your-Customer (KYC) measures. However, supervision in the cryptocurrency market is far less rigorous than that of other financial markets. Without the involvement of a financial institution intermediary, cryptocurrency transaction has no censoring or supervision from third parties, so trading costs are significantly reduced. Furthermore, given the application programming interface (API), the cryptocurrency market can achieve automatic trading via computers. Nonetheless, the defects and potential risks of cryptocurrencies trading cannot be neglected. Cyberattacks in cryptocurrency trading are not rare compared to stock and commodity markets, mainly because of two reasons. The first reason is the lack of regulation and supervision, and the second reason is technological vulnerability. A classic example is the collapse of Mt Gox, suggesting that any shocks in the market leader may easily trigger an earthquake in the cryptocurrency market. (Cheung, Roca, and Su, 2015 and Kumar and Ajaz, 2019). In addition, money laundry, financial terrorists, and other financial crimes can be accelerated by cryptocurrency trading (Fang et al., 2022).

2.3.3 Technical analysis and investment strategies

One of the critical factors to achieve profitable technical rules is market inefficiency. Researchers reckon that the market is under informational inefficiency in early periods of BTC (roughly from 2010 to 2016) (Urquhart, 2016; Nadarajah and Chu, 2017; Bariviera, 2017). Afterwards, conflicted statements about the inefficiency of the cryptocurrency market increased along with its' rapid development. As Urquhart (2016) suggested, the BTC market gradually transfers to an efficient market. Further studies also provide empirical evidence that informational efficiency exists in the BTC market by employing long-range dependence estimators (Khuntia and Pattanayak, 2018; Sensoy, 2019; Tiwari et al., 2019). Others, however, advocate that the BTC market remains in a weak-form pricing efficiency. This statement is mainly supported by empirical results of technical rules in the cryptocurrency market (Charfeddine and Maouchi, 2019; Corbet et al., 2019; Grobys and Sapkota, 2019; Grobys, Ahmed and Sapkota, 2020). The debatable discussion over inefficiency in the cryptocurrency market leads to the hypothesis that the examination of technical analysis could be a possible answer.

With the rapid growth of the cryptocurrency market, the literature on the investment strategy and prediction of cryptocurrencies is moving fast. Panagiotidis, Stengos and Vravosinos (2018) state BTC is not isolated from traditional stock markets, especially for Dow Jones and Nasdaq indices. Catania, Grassi and Ravazzolo (2019) also show that stock indices as predictors can improve the point forecasting for BTC and ETH. Guesmi et al. (2018) state that a short position in the BTC market can significantly hedge the portfolio risk against kinds of financial assets, currencies, commodities, and stocks, to name but a few. Fang et al. (2019) imply a strong bond between BTC and global economic indicators, suggesting another way to risk management referring to BTC contracts in the CBOE. Luis, Gabriel and Javier (2019) indicate that the demand for Bitcoin in the short run is driven by the speculators, while this influence has no power in the long run. Makarov and Schoar (2020) find that almost 1 billion USD profit of arbitrage exists across online exchanges, suggesting that BTC trading matches arbitrageurs who are constantly chasing equal prices across exchanges and noise traders with unstable sentiment leading the variation across exchanges. Compared to traditional financial markets, like stock, gold and currency markets, the BTC market is the most inefficient, suggesting a high possibility of arbitrage (Yahyaee, Mensi and Yoon, 2018). Almudhaf and Almudhaf (2018) also provide evidence of price inefficiency in BTC investment trusts, indicating a high possibility of arbitrage.

Compared to the traditional research methods, many researchers also display good performance of machine learning approaches and computational intelligence techniques in predicting BTC prices. By applying the machine learning approach and SVR-GARCH model, Peng et al. (2018) present evidence that the traditional GARCH model does not have forecasting ability in BTC and other cryptocurrencies. Phaladisailoed and Numnonda (2018) also provide the good performance of the Gated Recurrent Unit (GPU), which is a stepwise method of Long-Short Term Memory (LSTM) in predicting BTC returns. McNally, Roche and Caton (2018) and Jiang and Lee (2018) show that the Bayesian Neural Network outperforms linear or non-linear models in predicting BTC returns. Atsalakis G.S. et al. (2019) demonstrate that the profitability of computational intelligence models in forecasting BTC and other cryptocurrencies are much higher than the traditional buy-and-hold strategy. Instead of using BTC returns, Akcora *et al.* (2018) apply Addresses and Transactions of BTC and subgraph them into chainlets, showing high predictive ability in BTC prices.

2.4 Data Snooping bias and Multiple Hypothesis Test

Numerous empirical results, such as Sweeney (1989), Blume et al. (1994), Lo et al. (2000), and Savin (2007), show that technical indicators are profitable. However, there may be negligence in data snooping or data mining biases. Data-snooping bias happens when a given data set is used more than once for inference or model selection. Any satisfactory results obtained from data reuse are always subject to the possibility that they are simply the result of chance rather than any inherent merit in the method that produced the results. Valid results can be seen as a carefully drawn picture of overfitting: beautiful but meaningless. That is to say, applying different technical rules to the same data set will produce substantial results, resulting in "lucky factors" due to data snooping bias. The problem of data snooping bias is closely related to the more general problem of multiple hypothesis testing in statistical and econometric applications, which is known as the multiple comparisons problem. This issue has been extensively discussed in the scientific and medical fields and the empirical finance literature.

White (1999) proposed a Reality Check (RC) methodology that handles multiple hypothesis tests, taking into account data monitoring bias. By applying the RC test, Sullivan et al. (1999) found the empirical results that traditional technical rules did not predict the majority of U.S. stock indexes after the mid-1980s. Further literature also explains the negative impact of data snooping bias and the relative empirical performance of hedge funds (Lo and Mackinlay, 1990; Kosowki et al., 2007). Hanse (2005) proposes a more efficient method to test superior predictive ability (SPA) to compare multiple hypotheses with benchmarks. The following empirical study by Hanse et al. (2004) illustrates significant calendar effects. Hsu et al. (2010) demonstrate a stepwise approach to SPA that provides empirical evidence in emerging markets' exchange-traded funds (ETFs). For more complex nonlinear regression models, Sermpinis et al. (2015) propose a combination of neural networks and adaptive differential evolution to test the traditional technical strategies without using data mining biases and determine technical analysis through complex nonlinear regression. Through collecting and analysing 316 related financial factors, Harvey et al. (2016) offer multiple testing frameworks for data mining in cross-section financial data through various measuring tools.

Early studies focused on multiple hypothesis testing, beginning with the solving of extreme value problems by Mosteller (1948) and Nair (1948), which was not published until Mill (1966). Shaffer (1995) demonstrated a multiple test process through controlling the family-wise error rate (FWER) proposed by Holm (1979). One of the well-known metrics taken for multiple hypothesis tests is the probability of more than one Type I error in multiple tests using FWER. On the other hand, Benjamini and Hochberg (1995), Benjamini and Yekutieli (2001), and Farcomeni (2007) chose to conduct multiple processes by controlling the false discovery rate (FDR). Compared to FWER, FDR is less stringent because it has numerous errors in measuring statistical expectations. This article will measure the test statistics by controlling both FWER and FDR.

Foster et al. (1997) show that a problem when selecting multiple variables is attributed to dependence on numerous test statistics. Bootstrap is one of the best approaches to solve this problem. Since the study of Politis and Romano (1994), the fixed bootstrap method has been widely used to resampling techniques. Please refer to Neely et al. (1997), Sullivan et al. (1999), Bajgrowicz and Scaillet (2012), and Neely et al. (2014) for detailed discussion. Another function of the guidance method mentioned by Kosowski et al. (2007) and Fama and French (2010) is evaluating the performance of mutual fund managers. Due to the essence of financial data, there are different levels of dependence among data sets, thus making it vital to reduce data monitoring bias when selecting variables. The Bootstrapping method can preserve the uncertainty of the original dataset sampling and the dependencies among datasets (Harvey and Liu, 2018). Unlike traditional bootstrap usage, we prefer to use pivotal statistics for key estimation parameters and extend the impact of bootstrap on statistical power so that bootstrap can reflect the null hypotheses (Hall and Wilson, 1991).

2.5 Lucky Factor

This section summarises the lucky factor method, which is applied to both Chapter 4 and Chapter 5. The new framework proposed by Harvey and Liu (2021) uses the bootstrap methodology to disentangle data mining problems. Assuming we have $T*1$ vector R of returns to predict and $T*G$ matrix of technical indicators, in this case, denotes the time-series of technical indicator k *(0≤k≤G)*. The aim is to construct the regression model by selecting a set of *G* variables with genuine predictive power. Denote Φ as the summary of statistics to measure the good-of-fitness. By the application of the bootstrap methodology, our method allows no requirement for the distributional assumption of our summary statistic. That is, an arbitrary performance measure of the model can be applied. This approach consists of three main steps as follows:

2.5.1 Step1: Orthogonalization Under the Null

Given a conventional regression model, as follows:

$$r_t^i = \alpha_t^i + \sum_{k=1}^{k} \beta_k^i X_{k,t} + \varepsilon_t^i \quad \textbf{(1)}$$

Where r_t^i is return on cryptocurrency or index *i* at day t, α_t^i is the regression intercept of indicator *i*, β_k^i is factor loading of cryptocurrency or index *i* on technical indicator *k*, $X_{k,t}$ is return of indicator *i* at day t and ε is the residual.

With k *(0≤k≤G)* selected variables, we want to test if there is any other significant variable among the set of *(M-k)* $\{X_{k+j}$, *j=1, 2, …, M-k*$\}$ and pick them up once the candidate variable set X_{k+j} has any significant indicators. Following White (2000) and Foster et al. (1997), we set the null hypothesis that there can be no more explanatory power for any other factor in the candidate variable set. To modify *X* and make the null hypothesis true in-sample, we need to demean factor returns at first. That is, we project R_t onto $X_{k,t}$,

$$R_t = \alpha + \beta X_{k,t} + \varepsilon \quad \textbf{(1)}$$

And we can get residual vector $R^{e,k}$, reflecting the unexplanatory information within pre-selected factors. Then, we demean the candidate *(G-k)* factors and project $X_{k+1}, X_{k+2} \ldots X_G$ one by one on $R^{e,k}$. In this way, we can get

$$X_{k+j} = a_j + b_j R^{e,k} + X_{k+j}^e,\ j = 1 \ldots G-k, \quad \textbf{(2)}$$

where a_j is the intercept and β_j is the slope.

Then, we obtain the residual vector or demeaned candidate factors X_{k+j}^e. In this case, there should be no correlation between $R^{e,k}$ and X_{k+j}^e. It not only maintains as much information as possible but also grants no requirement to distribution of data. Similar approach has been applied by Kosowski et al. (2006), Fama and French (2010) and Harvey and Liu (2021). Unlike to FSW (1997), the new frame applies real data rather than simulation to intentionally generate independent variables for measuring the impact of multiple tests. Meanwhile, they also apply bootstrap and block bootstrap to estimate the distribution of test statistic. Detailed discussion can be seen in Harvey and Liu (2021).

2.5.2 Step 2: Bootstrap

Following Harvey and Liu (2021) bootstrap process, we put the pre-selected variables into $X^s = [X_1, X_2, \dots, X_k]$ and the orthogonalized candidate variables into $X^e = [X^e_{k+1}, X^e_{k+2}, \dots, X^e_G]$. As the authors suggest, the empirical distributions of summary statistic for each regression model are obtained by a bootstrap for the example of three time periods, as following. Assuming the original time index for three periods is $[t_1 = 1, t_2 = 2, t_3 = 3]'$ and one pre-selected variable X^s, one candidate variable X^e and $R^{e,k}$, then one possible bootstrapped time index is $[t_1 = 3, t_2 = 1, t_3 = 2]'$. The following diagram shows the transition from the original matrix to the bootstrapped one.

$$[R^{e,k}, X^s, X^e] = \underbrace{\begin{bmatrix} y_1^e, x_1^s, x_1^e \\ y_2^e, x_2^s, x_2^e \\ y_3^e, x_3^s, x_3^e \end{bmatrix} \begin{pmatrix} t_1 = 1 \\ t_2 = 2 \\ t_3 = 3 \end{pmatrix}}_{originaldatamatrix} \Rightarrow \underbrace{\begin{pmatrix} t_1^b = 3 \\ t_2^b = 1 \\ t_3^b = 2 \end{pmatrix} \begin{bmatrix} y_3^e, x_3^s, x_3^e \\ y_1^e, x_1^s, x_1^e \\ y_2^e, x_2^s, x_2^e \end{bmatrix}}_{bootstrappeddatamatrix} = [R^{ek}, X^{bk}, X^{eb}] \quad \textbf{(3)}$$

Generalizing this process, we can have *k* and *(G-k)* pre-selected and candidate variables respectively. With the same time periods for pre-selected variables, candidate variables and residuals vector, we then bootstrap and run *(G −k)* regressions. And we can get the bootstrapped set, formed by bootstrapped pre-selected variables set X^{bk}, bootstrapped candidate variables set X^{eb} and bootstrapped residual vector R^{eb}. In each regression, we project R^{eb} onto a bootstrapped candidate variable X^{eb}. In this way, we obtain the responding summary test statistic $\Phi^{k+1,b}, \Phi^{k+2,b}, \dots, \Phi^{G,b}$. Following White (2000), we select the largest statistic among the summary to control data snooping bias and denote the maximum as Φ_I^b.

$$\Phi_I^b = \underbrace{\max\{\Phi^{k+j,b}\}}_{j \in \{1,2,\dots,G-k\}} \quad \textbf{(4)}$$

With *(G-k)* candidate factors, it is possible to have significant indicators due to the random opportunity. By using the maximum of summary statistic, we can control the multiple tests. That is, Φ_I^b examines the best-fitting model augmenting the pre-selected regression models with one orthogonalized candidate variables. To measure the incremental contribution given by the additional candidate variable, we denote Φ_I^b for the statistic of *b*-th bootstrapped sample. Setting *B* = 10, 000 times in the bootstrapped procedure, we obtain the bootstrapped samples $(\Phi_I)^B$ as

$$(\Phi_I)^B = \{\Phi_I^B, b = 1, 2, \dots, B\}. \quad \textbf{(5)}$$

After bootstrapping the same number of time periods as the original data set, we disentangle the sampling uncertainty. By applying block bootstrap, we can also overcome the little time dependence in the data. Once none of the orthogonalized predictor is true, $(\Phi_I)^B$ represents the distribution of maximal additional contribution of bootstrapped samples when the null hypothesis is true, that is, none of these orthogonalized factors has genuine explanatory power.

2.5.3 Step 3: Hypothesis Testing and Variable Selection

We denote Φ_o as the statistical result of original data by applying the same approach and Φ_I^b as the maximal statistical result among bootstrapped sets. Following Harvey et al. (2016), we setup a significance level α as 5%. Then, we can reject the null hypothesis that none of candidate variable can have explanatory power if $\Phi_o$is larger than the (1－α)-th percentile of Φ_I^b, which is

$$\Phi_o \geq (\Phi_I)_{1-\alpha}^b \tag{6}$$

where $(\Phi)_{1-\alpha}^b$ denotes the (1－α)-th percentile of Φ_I^b.

Under this measuring standard, we can examine the significance of selected regressor among *(G-k)* candidate variable list. Once the Equation (6) is satisfied, we can declare the selected candidate variable is significant and classified as the pre-selected variables. Then, we repeat the above procedure until we try all the predictors in candidate variable list. On the other hand, the null would be true if the maximal bootstrapped statistics is larger than the maximal original statistics. In this way, we terminate the algorithm and conclude that there is no more significant predictor in the candidate list. As suggested by Harvey and Liu (2021), we use R^2 as measuring standard in Chapter 5.

2.5.4 Panel Regression Models

Based on the framework, I further extend to the panel regression model, which is applied in Chapter 4. Following the same procedure, that is, demeaning the factor returns to produce zero impacts on explaining the cross-section of expected returns, the ability to explain variation in time-series factors in asset returns is restored. That is to say, no factor that has predictive power is set as the null hypothesis. Next, the bootstrap method is needed to acquire the empirical distribution of the cross-section of pricing errors. Comparing the cross-section of pricing error generated by the original data set with the cross-section of pricing error generated by bootstrapped data set, the significance of candidate variables is declared. The panel regression model can be described as follows:

Without loss of generality, suppose we have a one-factor model.

$$R_{it} - R_{ft} = a_i + b_{i1} f_{1t} + e_{it} \tag{7}$$

where $R_{it} - R_{ft}$ is the mean excess return of asset *i*. By extracting the in-sample mean of f_{1t} from its time-series, Equation (9) can be rewritten as follows:

$$R_{it} - R_{ft} = \left[\underbrace{a_i + b_{i1}E(f_{1t})}_{Meanexcessreturn = E(R_{it} - R_{ft})} \right] + \underbrace{b_{i1}\left[f_{1t} - E(f_{1t}) \right]}_{Demeanedfactorreturn} + e_{it} \quad \textbf{(8)}$$

To make the one-factor model work, we need $a_i = 0$ for all assets. Taking unconditional expectations for both sides of Equation (10), we have,

$$b_{i1}E(f_{1t}) = E(R_{it} - R_{ft}) \quad \textbf{(9)}$$

That is, the cross-section of $b_{i1}E(f_{1t})$ must have a linear relationship with expected returns to fully remove the impacts of intercepts in time-series regressions. In addition, factor f_{1t} totally has no impact on the cross-section of expected asset returns when setting $E(f_{1t}) = 0$. That is, the cross-section of intercepts from time-series regressions is exactly equal to the cross-section of average asset returns as what the factor model should do in the first place. Based on the above discussion, we define a pseudo factor $\tilde{f}_{1t}$ by extracting the in-sample mean of f_{1t} from its time-series. Thus, the demeaned factor preserves all the time-series predictability of f_{1t} with no explanatory power on the cross-section of expected returns. Then, bootstrap the pseudo factor to acquire the distribution of statistics and compare the maximal result with statistics of the original data set.

The above procedure can be extended to test multiple factors. At first, project the (K+1)-th factor onto the pre-selected factors through a time-series regression to obtain the residual as our new pseudo factor. What comes next is bootstrap to acquire the distribution of the cross-section pricing errors. Different from the one-factor model, the original K factors in the model for both the original regression and the bootstrapped regressions based on the pseudo factor are maintained. In addition, it is necessary to obtain the minimal statistic (in general case, we obtain the maximal statistic) since the average pricing error mentioned in the earlier section is used. In this way, the incremental contribution of the candidate factors is obtained.

2.5.5 Equal Weighted Statistics

As for the test statistics, we do not apply the traditional method of GRS (Gibbons, Ross, and Shanken, 1989). On the other hand, the scaled intercept will be used to measure the additional contribution of one candidate variable to the baseline model with pre-selected k factors. Denote $\{a_i^b\}_{i=1}^N$ and $\{a_i^g\}_{i=1}^N$ as the cross-sectional regression intercepts for the original convention model and augmented model (with candidate variables), respectively. Let $\{a_i^b\}_{i=1}^N$ be the cross-sectional standard errors for regression intercept under the origin model. To be robust to some extreme situations, we set a pivotal test statistic below. Equation (10) measures the mean of the variable group.

$$SI_{ew}{}^{m} = \left(\frac{1}{N}\sum_{i=1}^{N} \left|a_i^g\right| \Big/ s_i^b - \frac{1}{N}\sum_{i=1}^{N} \left|a_i^b\right| \Big/ s_i^b\right) \Bigg/ \frac{1}{N}\sum_{i=1}^{N} \left|a_i^b\right| \Big/ s_i^b \qquad \textbf{(10)}$$

where SI is the scaled intercept, ew represents equal weighting and m is mean.

This equation represents the percentile difference in the absolute scaled intercept of cross-sectional standard errors for regression intercept under the origin model. If the candidate variable has a more substantial explanatory power of explaining the cross-sectional returns than the baseline model without the candidate variable, $\left|a_i^g\right|$ should be smaller than $\left|a_i^b\right|$. In this way, we expect *SI* to be a negative number as small as possible.

Chapter 3 Technical Analysis and Lucky Factors in Cryptocurrency Markets

3.1 Introduction

Investment in cryptocurrencies has grown in recent years, as they are one of the main highlights of the FinTech revolution. On the other hand, investment in BTC or altercoins is risky, as its extreme volatility and significant downfalls within each year. Previous literature shows that investors cannot accept this monetary concept or use cryptocurrencies for general consumption (Luther and White, 2014; Luther, 2016). One reason could be attributed to the lack of development and actual applications in the real world. Although cryptocurrency trading is illegal in some countries (e.g., China), most online cryptocurrencies exchanges can still be used without intervention (Elendner et al., 2018). Unlike stock exchanges or other exchanges, cryptocurrencies exchanges operate all the time. Although the direct transaction of cryptocurrencies is made on Decentralized Ledger Technology on the blockchain, nearly 92% of BTC trading volume took place on online platforms in China, like Huobi and OK coin (Bitcoin.io, 2016). In addition, nearly 82% of UK BTC users acquire bitcoin through online platforms, while only 18% of anticipants directly get BTC through mining.

The motivation behind this chapter is 'crypto-revolution' and the fact that online trading platforms link cryptocurrency performance with technical indicators[3]. After 2008, thousands of blockchain programs were created, but many quickly deceased. By 9 Nov 2021, the market value of Bitcoin (BTC) has exceeded 1.1 trillion US dollars, while the entire market value of cryptocurrencies has exceeded 2.9 trillion US dollars.[4] Undoubtedly, the general desire for blockchain technology innovation and the convenience of BTC's open resources have led to prosperity in cryptocurrency investment. Nevertheless, BTC dominance decreases with the growth of other blockchain programs. This study examines six crypto coins (Bitcoin (BTC), DASH, Ethereum (ETH), Litecoin (LTC), Ripple (XRP), Stellar (XLM)) and cryptocurrency index (CRIX) from 2013 to 2018. BTC is the first cryptocurrency ever launched and the benchmark of coin-to-coin transactions against other cryptocurrencies in almost all online platforms. Built upon the data source of BTC, DASH focuses on anonymous payment and lower premiums for transactions with a much longer life for coin generation. ETH is the so-called 2.0 version of cryptocurrency. Based on the ETH platform, smart contracts and decentralized applications (DAPPs) can be built and used all the time. Meanwhile, ETH can be traded as a digital currency and used as a primary fuel supporting the running of DAPPs and smart contracts on its

[3]For example, see, amongst many others, https://www.bittsanalytics.com/, https://www.coinigy.com/, https://www.markets.com.

[4] Data can be found on Coinmarketcap.com.

platform. LTC is the second cryptocurrency after the birth of BTC. Unlike BTC, LTC applies a different hash algorithm, allowing GPU to mine coins and improve its processing speed and cybersecurity. Developed by an official company, XRP is managed by several independent servers controlled by the Ripple network. In addition, XRP is the most efficient settlement for financial institutions with the fastest transaction confirmation. Based on the same protocol as XRP, XLM is aimed at low-cost financial services and cross-asset transfer. However, XLM is run by a non-profit organization, and the platform is decentralized with open source. All coins have maximum supply, except ETH. Finally, The CRIX is a crypto-market index and follows the Laspeyres derivation, where each cryptocurrency is weighted with its market capitalization.

In order to investigate the genuine performance of technical trading rules, we apply the universe of trading rules proposed by Sullivan, Timmermann, and White (STW, 1999) and select the fifteen top-performing rules in terms of different performance metrics across cryptocurrencies and periods under study. Previous studies show that technical rules provide practical value and incremental information on stock markets (Lo 1992; Bajgrowicz and Scaillet 2012). One reason could be attributed to the inevitably data-snooping issues when analysing thousands of factors' genuine performance. To overcome this data-snooping bias, we adopt the framework proposed by Harvey and Liu (2021). The authors suggest that the LF method can measures each additional variable's explanatory power added on a baseline model. Additionally, the method is also robust to the general distributional characteristics of both factors and asset returns.

In terms of our results, we find that technical indicators generate relatively higher profits than the buy-hold strategy. Across all cryptocurrency series, we manage to always identify the top-fifteen rules under each metric. However, the LF method fails to recognise genuine predictive power of the selected rules on cryptocurrencies (in terms of Sharpe ratios and Sortino ratios). Meanwhile, these results also go towards this strand of the literature that suggests that the actual performance of technical trading rules in trading is limited.

The remaining of the paper is organised as follows. Section 4.2 describes the data used in this chapter, and section 4.3 describes the empirical findings. Finally, section 4.4 gives some concluding remarks.

3.2 Data and Descriptive Statistics

To ensure the accuracy and convenience of measuring the cryptocurrency market, we use CRIX, a reputable index in the cryptocurrency market. Like S&P 500, CRIX provides summary information on cryptocurrencies. CRIX chooses the most representative cryptocurrency and tracks the average price volatility at the beginning of each month. Just like a rebalanced portfolio, CRIX has its unique information metrics to select the coins it represents and measure each coin by its corresponding market value (Härdle and Trimborn, 2018). Furthermore, the number of cryptocurrencies included in CRIX uses as many cryptocurrencies as possible in the market, ensuring the reliability and comprehensiveness of the index.

Since the introduction of BTC, thousands of cryptocurrencies have been created. However, most of them are built upon the cryptocurrency generator by applying BTC's coding resource. To construct a trading universe, we use six mainstream cryptocurrencies, namely BTC, Ethereum (ETH), Ripple (XRP), Stellar (XLM), Litecoin (LTC), Dash (DASH) and one cryptocurrency index, CRIX. Due to the different launching times to market, we plan to adapt the daily return for each start time to January 4, 2018. Data for the six cryptocurrencies is available at https://coinmarketcap.com, and the data of cryptocurrency indexes are available from http://crix.hu-berlin.de. Description of our data can be found in the Table 3.1.

Table 3. 1 Cryptocurrency series and periods under study

Series	Sample Period	Maximum Supply	Launched
BTC (BTC)	28/04/2013-04/01/2018	21million	01-03-2009
Dash (DASH)	14/02/2014-04/01/2018	18.9 million	01-08-2014
Ethereum (ETH)	07/08/2015-04/01/2018	No Limit	07-30-2015
Litecoin (LTC)	28/04/2013-04/01/2018	84 million	10-07-2011
Ripple (XRP)	04/08/2013-04/01/2018	100 million	07-01-2013
Stellar (XLM)	05/08/2014-04/01/2018	100 million	08-04-2014
Cryptocurrency Index (CRIX)	31/07/2014-28/02/2018	-	07-31-2014

Note: All data is available from coinmarketcap.com.

Following STW and Bajgrowicz and Scaillet (2012), we use Sharpe ratio to measure the performance criteria. In order to properly construct Sharpe ratio, we need to calculate the excess return, which is the difference between the trading rule's return and risk-free interest rate. Following STW, we also employ the one-month fund management constant expiration rate in the CRSP file based on monthly frequency. We convert the monthly interest rate into a daily series by the following methods.

$$r_d = \frac{\ln(1+r_{mon})}{30} \quad \textbf{(11)}$$

Where r_d is the daily risk-free rate, r_{mon} is the monthly interest rate and 30 is the average number of trading days in a month.

Furthermore, we also apply Sortino ratio as an execution indicator. As a correction of Sharpe ratio (which is also applied), the Sortino ratio uses the downside risk. That is, an asset is considered to be risky only if its return is lower than the expected target returns to capture the asymmetry of the distribution of income. The metric is defined as follows:

$$S = \frac{R-T}{TDD}, \text{ TDD=} \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Min(0, Xi-T))^2} \quad \textbf{(12)}$$

where R is the periodical mean return, T is the target return, and TDD is the target downside deviation. In this paper, we set the default target return value to 0.

Table 3. 2 Descriptive Data for Six Cryptocurrencies and Cryptocurrency Index

Series	Cryptocurrencies						
Name	**BTC**	**DASH**	**ETH**	**LTC**	**XRP**	**XLM**	**CRIX**
N	1713	1424	882	1713	1615	1249	1309
μ	1217.43	73.13	100.96	15.67	0.06	0.01	5249.12
σ	2474.44	191.73	169.47	36.96	0.21	0.05	10711.15
SE	59.79	5.08	5.71	0.89	0.01	0	296.05
Max	19497.4	1550.85	980.92	358.34	3.2	0.9	62895.26
Min	68.43	0.31	0.43	1.16	0	0	342.07
S	4.49	4.22	2.15	5.81	9.28	9.75	3.04
K	22.6	20.18	5.03	39.49	108.45	125.43	9.14
AD	342.09***	307.82***	129.86***	341.08***	385.16***	329.79***	257.73***
LB (5)	7968***	6441***	3999.8***	7640***	5062.***	3170***	6355.2***
JB	42300***	28470***	1624.4***	121250***	816620***	841310***	6598.7***

Notes: This table reports the sample statistics of prices for the cryptocurrencies and cryptocurrency index. N is the number of observations; μ is the mean; σ is the standard deviation; SE is the standard error; S is the skewness; K is the excess kurtosis; and D is the Anderson-Darling statistic (5% critical value is 1.36/N, where N is size of sample). LB (5) are the Ljung–Box statistics, respectively, distributed as χ^2 *with n degrees of freedom, where n is the number of lags. Significance level: * 10%, ** 5%, *** 1%. JB is the Jarque-Bera test. The Anderson-Darling test is a powerful test of the hypothesis of normality.*

Based on Table 3.2, the average price of BTC is more than ten times larger than other cryptocurrencies. Apparently, both cryptocurrencies and cryptocurrency index demonstrate relatively high positive skewness. That is, investors may get huge profits, while they may also meet huge losses as their usual experience in cryptocurrency market. As can be seen from the table above, the sample sequence is significantly skewed and highly leptokurtic. In terms of normality test, the author applies both the Anderson-Darling test and the Jarque-Bera test. The results are consistent with the description of skewness and kurtosis. The rejection of normal hypotheses can be attributed to the time dependencies in successive moments. In addition, LB (5) statistical results are all significant, indicating temporal dependencies exist at the first moment of the cryptocurrency price distribution.

3.3 Empirical Results

In order to test the relationship between profitability and genuine predictive ability, we select and examine the best fifteen technical rules under two different performance metrics, Sharpe ratio and Sortino ratio. We have run the LF method using the whole universe too. The significant rules obtained are shown in Appendix C. The results, though, show that in some periods, we either do not have any selections or rejections in others. Using a preselection rule like ours allows the practitioner to test the genuine performance of the rules that he/she would expect to be well-performing. Table 3.3 and Table 3.4 show the best 15 technical rules ranked by Sharp ratio with corresponding. periodical mean return

From Table 3.3 to 3.4, the best rule 15 consists of two different moving average (MA) rules, one with a multiplication ban and the other with a time delay filter. Taking BTC as an example, the best rule has the largest multiplicative scale, which is 0.05 with short ma periods. Moreover, most rules with good-performance work in very short days, that is, 5-day-slow MA line and 1-day-fast ma line with the fixed multiplicative band, turning out that the daily change of BTC is volatile. Only the last two rules are two MA lines with a delay filter. Not surprisingly, the high volatility of daily BTC prices may be the best reason why the fixed percentage band filter performs better than the time delay filter. Altercoins with good performance also show similar results, although some have long time delays. That is to say, altercoins need more time to deal with the changing price of BTC, thus interacting with the market. (da Gama Silva et al., 2019) also found that herding effects are prevalent in the cryptocurrency market. Compared to BTC, most altercoins perform better on 10-day or 15-day MA rules, and the multiplicative filter still plays a vital role in all the good-performance rules. An intuitive feature is that CRIX shows almost the same results as BTC. This could be attributed to the fact that BTC is a leader in its composition. Another interesting finding is the composition of DASH's good performance rules, which are Filter rules and MA rules.

Although BTC's daily yield may be very high, even reaching 22.31%, BTC's daily yield may be very low, falling to -22.26% (Elendner et al., 2018). Similar results are also shown in altercoins. That is, technical rules generate higher returns than buy-and-hold strategies. With the collapse of Mt. Gox, which was one of the largest cryptocurrency exchanges and banned cryptocurrency transactions in China, there is no wonder that BTC and altercoins did not perform well in the second period. Cryptocurrency transactions are primarily conducted on online platforms. Therefore, the failure of large exchanges will dramatically influence the cryptocurrencies prices. Furthermore, due to the lack of efficient supervision, cryptocurrency exchange can facilitate criminal activity or cryptocurrency fraud (Motsi-Omoijiade, 2018). Meanwhile, governmental interventions, such as preventing cryptocurrency transactions by the state and the spread of negatively encrypted currency information on different media, also contributed to price declines.

Table 3. 3 Profitability performance of best performing rules (Sharpe ratio).

Panel A: Four Cryptocurrencies (BTC-DASH-ETH-LTC)

BTC	**Rule**	**Period1** 2013/04/28 2014/06/28	**Period2** 2014/06/28 2015/07/31	**Period3** 2015/07/31 2016/10/31	**Period4** 2016/10/31 2018/01/04	**DASH**	**Rule**	**Period1** 2013/04/28 2014/06/28	**Period2** 2014/06/28 2015/07/31	**Period3** 2015/07/31 2016/10/31	**Period4** 2016/10/31 2018/01/04
1	MA(2,1,0.05)	0.195(0.03)	0.343(0.013)	0.215(0.014)	0.191(0.031)	**1**	MA(2,1,10)	-	0.178(0.025)	0.451(0.034)	0.369(0.052)
2	MA(5,1,0)	0.194(0.013)	0.343(0.013)	0.215(0.014)	0.189(0.031)	**2**	MA(2,1,0.005)	-	0.178(0.025)	0.451(0.034)	0.368(0.052)
3	MA(5,1,0.001)	0.187(0.013)	0.337(0.013)	0.213(0.014)	0.181(0.031)	**3**	F(0.005,5)	-	0.174(0.018)	0.451(0.016)	0.359(0.033)
4	MA(5,1,0.005)	0.179(0.012)	0.313(0.012)	0.193(0.013)	0.178(0.03)	**4**	F(0.045,5)	-	0.174(0.025)	0.429(0.033)	0.356(0.051)
5	MA(5,1,0.01)	0.173(0.012)	0.304(0.011)	0.193(0.013)	0.169(0.029)	**5**	F(0.14,5)	-	0.170(0.024)	0.407(0.032)	0.346 (0.05)
6	MA(5,1,0.05)	0.174(0.012)	0.297(0.01)	0.161(0.012)	0.165(0.03)	**6**	F(0.005.10)	-	0.169(0.024)	0.377 (0.03)	0.334(0.049)
7	MA(5,2,0)	0.169(0.011)	0.288(0.011)	0.160(0.012)	0.143(0.028)	**7**	MA(2,10.015)	-	0.168(0.024)	0.375 (0.03)	0.325(0.048)
8	MA(5,2,0.001)	0.162(0.011)	0.286(0.011)	0.159(0.012)	0.136(0.028)	**8**	F(0.045,10)	-	0.163(0.023)	0.369(0.028)	0.317(0.048)
9	MA(5,2,0.005)	0.156(0.011)	0.280(0.011)	0.156(0.012)	0.135(0.028)	**9**	F(0.05,5)	-	0.153(0.022)	0.366(0.029)	0.296(0.046)
10	MA(5,2,0.01)	0.155(0.011)	0.279(0.01)	0.155(0.012)	0.132(0.028)	**10**	F(0.16,5)	-	0.153(0.022)	0.357(0.029)	0.289(0.046)
11	MA(5,2,0.015)	0.153(0.011)	0.24(0.009)	0.121(0.01)	0.125(0.029)	**11**	F(0.14,5)	-	0.152(0.023)	0.318(0.026)	0.296(0.046)
12	MA(10,1,0.05)	0.151(0.01)	0.239(0.01)	0.121(0.012)	0.123(0.027)	**12**	F(0.01,5)	-	0.151(0.022)	0.311(0.028)	0.286(0.045)
13	MA(10,2,0)	0.144(0.01)	0.233(0.009)	0.114(0.011)	0.123(0.028)	**13**	F(0.01,10)	-	0.151(0.022)	0.307(0.028)	0.286(0.046)
14	MA(2,1,5)	0.144(0.01)	0.202(0.008)	0.119(0.011)	0.122(0.027)	**14**	MA(10,2,0)	-	0.150(0.023)	0.302(0.026)	0.279(0.045)
15	MA(5,1,5)	0.143(0.01)	0.201(0.009)	0.114(0.011)	0.121(0.027)	**15**	MA(2,1,0.02)	-	0.147(0.022)	0.293(0.025)	0.276(0.044)
ETH	**Rule**	**Period1** 2013/04/28 2014/06/28	**Period2** 2014/06/28 2015/07/31	**Period3** 2015/07/31 2016/10/31	**Period4** 2016/10/31 2018/01/04	**LTC**	**Rule**	**Period1** 2013/04/28 2014/06/28	**Period2** 2014/06/28 2015/07/31	**Period3** 2015/07/31 2016/10/31	**Period4** 2016/10/31 2018/01/04
1	MA(10,2,10)	-	-	0.138(0.016)	0.401(0.042)	**1**	MA (10,2,5)	0.279(0.022)	0.193(0.015)	0.185(0.042)	0.135(0.014)
2	MA(10,2,0.01)	-	-	0.138(0.016)	0.401(0.042)	**2**	MA(10,2,0.015)	0.278(0.022)	0.188(0.014)	0.184(0.041)	0.135(0.014)
3	MA(10,2,0.015)	-	-	0.137(0.016)	0.396(0.041)	**3**	MA (10,5,5)	0.278(0.022)	0.183(0.014)	0.185(0.041)	0.135(0.014)
4	MA(10,2,0.02)	-	-	0.136(0.015)	0.389 (0.04)	**4**	MA(10,5,0.005)	0.259(0.021)	0.154(0.012)	0.180(0.041)	0.128(0.013)
5	MA(10,2,0.03)	-	-	0.136(0.016)	0.383 (0.04)	**5**	MA (10,5,0.01)	0.242 (0.02)	0.156(0.011)	0.174 (0.04)	0.124(0.013)
6	MA(10,2,0.04)	-	-	0.135(0.015)	0.371(0.038)	**6**	MA(10,5,0.015)	0.238(0.019)	0.156(0.013)	0.162(0.039)	0.106(0.011)
7	MA(10,5,10)	-	-	0.129(0.015)	0.359(0.038)	**7**	MA (10,5,0.02)	0.214(0.018)	0.136(0.012)	0.152(0.037)	0.102(0.009)
8	MA(10,5,0.01)	-	-	0.129(0.014)	0.349(0.036)	**8**	MA (10,5,0.03)	0.216(0.018)	0.134(0.012)	0.149(0.036)	0.092(0.009)
9	MA(10,5,0.015)	-	-	0.127(0.015)	0.313(0.035)	**9**	MA (10,5,0.04)	0.209(0.017)	0.133(0.012)	0.148(0.036)	0.090(0.009)
10	MA(10,5,0.02)	-	-	0.126(0.015)	0.313(0.035)	**10**	MA(15,5,0.001)	0.204(0.017)	0.131(0.012)	0.142(0.035)	0.089(0.009)
11	MA(10,5,0.03)	-	-	0.126(0.015)	0.313(0.035)	**11**	MA(15,5,0.005)	0.203(0.016)	0.109 (0.01)	0.142(0.036)	0.089 (0.01)
12	MA(10,5,0.04)	-	-	0.124(0.013)	0.312(0.035)	**12**	MA (15,5,0.01)	0.201(0.017)	0.107 (0.01)	0.129(0.034)	0.079 (0.01)
13	MA(10,5,0.05)	-	-	0.123(0.014)	0.312(0.034)	**13**	MA (15,5,0.02)	0.201(0.017)	0.106 (0.01)	0.126(0.035)	0.079(0.009)
14	MA(10,2,3)	-	-	0.123(0.014)	0.311(0.034)	**14**	MA (10,2,2)	0.199(0.017)	0.105(0.011)	0.125(0.035)	0.078(0.009)
15	MA(10,5,3)	-	-	0.119(0.014)	0.308(0.033)	**15**	MA (10,5,2)	0.197(0.017)	0.105(0.011)	0.125(0.035)	0.076(0.009)

Note: This table presents the sharp rations and mean returns (in parenthesis) of the top 15 technical rules. MA are Moving Average rules, F are the Filter rules and OBV are On-Balance Volume rules. For example, MA (5,1,10) represents MA rule with 5-day slow MA, 1-day fast MA and 10-day position held. F (0.005,5) represents 0.005 position initiation, 5-day holding period. Finally, OBV (10,5,0.01) represents 10-day and 5-day on-balance volume, 0.01 band. Although we do not show the performance of benchmark here, the authors set the buy-and-hold strategy as comparison.

Table 3. 4 Profitability performance of best performing rules (Sharpe ratio).

Panel B: Two Cryptocurrencies and Cryptocurrency Index (XRP-XLM-CRIX)											
XRP	**Rule**	**Period1**	**Period2**	**Period3**	**Period4**	**XLM**	**Rule**	**Period1**	**Period2**	**Period3**	**Period4**
		2013/04/28	2014/06/28	2015/07/31	2016/10/31			2013/04/28	2014/06/28	2015/07/31	2016/10/31
		2014/06/28	2015/07/31	2016/10/31	2018/01/04			2014/06/28	2015/07/31	2016/10/31	2018/01/04
1	MA(10,2,10)	0.137(0.015)	0.379(0.027)	0.123(0.015)	0.202(0.062)	**1**	MA(10,2,10)	-	0.107(0.009)	0.179(0.022)	0.249(0.068)
2	MA(10,2,0.01)	0.135 (0.014)	0.376(0.027)	0.121(0.015)	0.195(0.062)	**2**	MA(10,2,0.01)	-	0.106(0.009)	0.179(0.023)	0.247 (0.068)
3	MA(10,2,0.015)	0.135 (0.014)	0.370(0.027)	0.121(0.015)	0.191(0.062)	**3**	MA(10,2,0.015)	-	0.103(0.009)	0.175(0.023)	0.246 (0.068)
4	MA(10,2,0.02)	0.131 (0.014)	0.363(0.026)	0.097(0.014)	0.191(0.061)	**4**	MA(10,5,10)	-	0.101(0.008)	0.165(0.021)	0.240 (0.068)
5	MA(10,2,0.03)	0.124 (0.013)	0.342(0.024)	0.097(0.012)	0.186(0.063)	**5**	MA(10,5,0.01)	-	0.090(0.007)	0.148(0.020)	0.239 (0.067)
6	MA(10,2,0.04)	0.118 (0.013)	0.333(0.023)	0.097 (0.011)	0.191(0.061)	**6**	MA(10,5,0.015)	-	0.084(0.007)	0.153(0.020)	0.236 (0.063)
7	MA(10,5,10)	0.117 (0.012)	0.326(0.024)	0.082(0.014)	0.174(0.059)	**7**	MA(10,5,10)	-	0.077(0.006)	0.129(0.018)	0.236 (0.066)
8	MA(10,5,0.015)	0.113 (0.012)	0.308(0.023)	0.08 (0.013)	0.165(0.057)	**8**	OBV(10,5,0.01)	-	0.055(0.005)	0.126(0.018)	0.235 (0.066)
9	MA(10,5,0.02)	0.112 (0.012)	0.302(0.022)	0.079(0.013)	0.161(0.056)	**9**	MA(10,5,0.015)	-	0.055(0.005)	0.111 (0.016)	0.227 (0.065)
10	MA(10.2.10)	0.111 (0.012)	0.302(0.022)	0.073(0.013)	0.160(0.056)	**10**	OBV(10,5,0.02)	-	0.051(0.004)	0.109(0.017)	0.223 (0.063)
11	MA(5,2,2)	0.0.11(0.010)	0.298(0.020)	0.064(0.010)	0.161(0.046)	**11**	MA(10,5,0.03)	-	0.043(0.005)	0.109(0.018)	0.193 (0.058)
12	MA(10,2,3)	0.111 (0.013)	0.297(0.022)	0.064(0.012)	0.157(0.055)	**12**	MA(10,5,0.04)	-	0.068(0.006)	0.106(0.017)	0.190 (0.058)
13	MA(10,5,0.05)	0.111 (0.012)	0.297(0.022)	0.053 (0.011)	0.154(0.054)	**13**	MA(10,5,0.05)	-	0.045(0.004)	0.106(0.018)	0.188 (0.057)
14	MA(10,5,0.04)	0.092 (0.010)	0.295(0.021)	0.052(0.013)	0.153(0.055)	**14**	MA(10,2,3)	-	0.045(0.004)	0.104(0.018)	0.187 (0.057)
15	MA(10,5,0.01)	0.089 (0.011)	0.277(0.020)	0.012(0.009)	0.153(0.058)	**15**	MA(10,5,3)	-	0.044(0.004)	0.104(0.016)	0.184 (0.058)

	Rule	**Period1**	**Period2**	**Period3**	**Period4**
CRIX		2013/04/28	2014/06/28	2015/07/31	2016/10/31
		2014/06/28	2015/07/31	2016/10/31	2018/01/04
1	MA(5,1,10)	-	0.042(0.003)	0.367(0.014)	0.543(0.033)
2	MA(5,1,0.005)	-	0.041(0.003)	0.364(0.014)	0.541(0.033)
3	MA(5,1,0.01)	-	0.035(0.002)	0.349(0.013)	0.539(0.033)
4	MA(5,1,0.015)	-	0.030(0.002)	0.338(0.013)	0.537(0.033)
5	MA(5,1,0.02)	-	0.027(0.002)	0.345(0.013)	0.520(0.031)
6	MA(5,2,10)	-	0.016(0.001)	0.317 (0.011)	0.504(0.031)
7	MA(5,2,0.005)	-	0.016(0.001)	0.313(0.013)	0.476(0.030)
8	MA(5,2,0.01)	-	0.016(0.001)	0.311 (0.012)	0.473(0.030)
9	MA(5,2,0.015)	-	0.009(0.002)	0.313(0.012)	0.470(0.029)
10	MA(5,2,0.02)	-	0.006(0.001)	0.304(0.012)	0.457(0.028)
11	MA(5,2,0.03)	-	0.035(0.001)	0.297 (0.011)	0.458(0.028)
12	MA(10,2,10)	-	0.030(0.001)	0.279(0.010)	0.452(0.030)
13	MA(10,2,0.015)	-	0.021(0.001)	0.273(0.010)	0.445(0.028)
14	MA(5,1,2)	-	0.011 (0.001)	0.271 (0.011)	0.428(0.027)
15	MA(10,5,3)	-	0.008(0.001)	0.271 (0.011)	0.425(0.027)

Note: This table presents the sharp rations and mean returns (in parenthesis) of the top 15 technical rules. MA are Moving Average rules, F are the Filter rules and OBV are On-Balance Volume rules. For example, MA (5,1,10) represents MA rule with 5-day slow MA, 1-day fast MA and 10-day position held. F (0.005,5) represents 0.005 position initiation, 5-day holding period. Finally, OBV (10,5,0.01) represents 10-day and 5-day on-balance volume, 0.01 band. Although we do not show the performance of benchmark here, the authors set the buy-and-hold strategy as comparison.

Furthermore, the last three periods clearly illustrate an upward trend, and the average return of the last period is nearly four times the average return for the first period of all cryptocurrencies, except for CRIX and DASH. Another interesting finding is that trading rules with higher average returns have lower Sharpe ratios, which is consistent with the argument for the high degree of instability of cryptocurrencies (Elendner et.al, 2018).

Table 3. 5 Lucky Factors for BTC (Sharpe Ratio)

BTC	Period 1 (Panel A: Baseline = No Factor)				Period 2 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA(p-value)	SI_{ew}^{m}	5th perc.	p-value	SPA(p-value)
1	0.174	-0.469	0.577	1	2.118	-0.782	0.947	1
2	0.161	-0.467	0.57	1	2.117	-0.788	0.948	1
3	0.100	-0.47	0.541	1	2.115	-0.797	0.943	1
4	0.029	-0.468	0.486	0.632	1.982	-0.814	0.942	0.632
5	-0.033	-0.469	0.438	1	1.943	-0.8	0.939	1
6	-0.010	-0.476	0.448	1	1.756	-0.818	0.933	1
7	-0.200	-0.475	0.282	0.632	1.807	-0.796	0.940	1
8	-0.154	-0.476	0.326	1	1.932	-0.785	0.937	1
9	-0.194	-0.473	0.289	0.632	1.735	-0.777	0.941	1
10	-0.219	-0.47	0.256	1	1.783	-0.814	0.935	1
11	-0.122	-0.475	0.356	1	1.613	-0.81	0.928	1
12	-0.291	-0.459	0.188	0.632	1.606	-0.778	0.934	1
13	-0.296	-0.466	0.188	1	1.583	-0.827	0.928	1
14	-0.361	-0.474	0.123	1	1.140	-0.734	0.918	1
15	-0.378	-0.481	0.108	1	1.180	-0.731	0.923	1
	Multiple test: Min: -0.068 P-Value: 0.181				Multiple test: Min: -0.439 P-Value:0.956			
BTC	Period 3 (Panel A: Baseline = No Factor)				Period 4 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA(p-value)	SI_{ew}^{m}	5th perc.	p-value	SPA(p-value)
1	0.520	-0.407	0.841	1	0.226	-0.278	0.785	1
2	0.514	-0.407	0.839	1	0.213	-0.282	0.766	1
3	0.616	-0.401	0.858	1	0.182	-0.277	0.736	1
4	0.463	-0.405	0.818	0.632	0.191	-0.277	0.746	1
5	0.435	-0.404	0.803	1	0.044	-0.262	0.553	1
6	0.263	-0.408	0.716	1	0.159	-0.273	0.711	1
7	0.184	-0.404	0.667	1	-0.036	-0.260	0.397	1
8	0.143	-0.41	0.637	1	-0.062	-0.257	0.349	1
9	0.137	-0.408	0.627	1	-0.064	-0.257	0.354	1
10	0.152	-0.409	0.64	1	-0.076	-0.252	0.318	1
11	0.006	-0.395	0.466	1	0.104	-0.263	0.646	1
12	0.200	-0.399	0.677	1	-0.045	-0.274	0.397	1
13	0.145	-0.404	0.632	1	-0.038	-0.256	0.402	1
14	0.020	-0.415	0.492	1	-0.145	-0.269	0.189	1
15	-0.018	-0.41	0.447	1	-0.163	-0.268	0.171	1
	Multiple test: Min: 0.099 P-Value:0.591				Multiple test: Min: -0.013 P-Value: 0.272			

Note: The table summarizes the LF results for BTC. The difference in the equally weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). The value of 0.174 (Panel 1, rule 1) means there is an increment of 17.4% in the mean absolute scaling intercept, which has no contribution to the explanation of our model. SI_{ew}^{m} computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5th percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).

Table 3. 6 Lucky Factors for CRIX (Sharpe Ratio)

CRIX	Period 2 (Panel A: Baseline = No Factor)				Period 3 (Panel A: Baseline = No Factor)			
Rank	SI^{m}_{ew}	5th perc.	p-value	SPA(p-value)	SI^{m}_{ew}	5th perc.	p-value	SPA(p-value)
1	0.948	-0.525	0.815	1	0.035	-0.37	0.974	1
2	0.965	-0.525	0.818	1	0.041	-0.364	0.975	1
3	0.791	-0.526	0.793	1	0.007	-0.365	0.971	1
4	0.604	-0.527	0.761	1	0.038	-0.364	0.97	0.632
5	0.656	-0.539	0.772	1	0.073	-0.372	0.97	1
6	0.238	-0.551	0.661	1	0.016	-0.374	0.967	1
7	0.532	-0.529	0.753	1	0.089	-0.346	0.964	1
8	0.546	-0.53	0.755	1	0.112	-0.353	0.965	1
9	0.629	-0.529	0.763	1	0.085	-0.365	0.967	1
10	0.497	-0.537	0.746	1	0.101	-0.364	0.971	1
11	0.485	-0.532	0.73	1	0.087	-0.384	0.966	1
12	0.007	-0.551	0.534	1	0.043	-0.393	0.96	1
13	0.181	-0.537	0.639	1	0.007	-0.391	0.964	1
14	0.279	-0.537	0.679	1	0.005	-0.363	0.968	1
15	0.328	-0.547	0.693	1	-0.030	-0.369	0.967	1
	Multiple test: Min: 0.068 P-Value: 0.181				Multiple test: Min: -0.439 P-Value:0.956			

CRIX	Period 4 (Panel A: Baseline = No Factor)			
Rank	SI^{m}_{ew}	5th perc.	p-value	SPA(p-value)
1	1.578	-0.189	0.999	1
2	1.553	-0.191	0.999	1
3	1.602	-0.192	0.999	1
4	1.604	-0.191	0.999	1
5	1.499	-0.196	0.999	1
6	1.555	-0.194	0.999	1
7	1.345	-0.189	0.999	1
8	1.361	-0.193	0.999	1
9	1.359	-0.193	0.999	1
10	1.373	-0.206	0.999	1
11	1.317	-0.195	0.999	1
12	1.501	-0.194	0.999	1
13	1.295	-0.196	0.999	1
14	1.186	-0.18	0.999	1
15	1.227	-0.184	0.999	1
	Multiple test: Min: 0.099 P-Value:0.591			

Note: The table summarizes the LF results for CRIX. The difference in the equally weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). SI^{m}_{ew} computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5th percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).

We chose to use the bootstrapped distribution of the smallest statistic for multi-factor testing. Since orthogonalization eliminates the cross-sectional effect of the indicator, the minimum statistic illustrates the lucky possibility of the most significant reduction of intercept. After the bootstrapped process, we obtain the minimum statistics from all the indicators, the largest intercept reduction. By comparing the true minimum statistic with the minimum statistic of the bootstrapped data, we obtained the p-value at a 5% significance level. In this case, the p-value of minimal statistic is 0.181, which indicates that the rules are insignificant from a multiple testing perspective. Therefore, we declare that the indicators are statistically irrelevant from the perspective of a single test and multiple tests. Detailed discussion about other cryptocurrencies is shown in our appendix. We find one case of significant rule for DASH and all other rules show no more significance. In the above tables, the minimum statistics of all cryptocurrencies suggest that the tested rules are insignificant and cannot explain the expected returns from a multiple-factor perspective. That is to say, the top fifteen technical rules measured by Sharpe Ratio cannot explain the variations in the expected return of the cryptocurrency. Meanwhile, results based on the SPA test also show that good-performance rules are not superior to the basic model, which means we cannot reject the null hypothesis that none of the technical rules has predictive power. Although a large number of technical rules have proven to be significant in the early stages, when we consider risk-free interest rates, rules with high profitability may not become predictable. Bajgrowicz and Scaillet (2012) showed similar results in the stock market that there is an inverse relationship between the profitability and predictive power of technical rules in DJIA. Since the cryptocurrencies' regular rate of return is lower than other financial instruments, the risk-free rate used may exceed the measurement standard. Another reason can be attributed to the inefficiency of the cryptocurrency market, that is, there are some abnormal changes in cryptocurrency prices (Kurihara and Fukushima, 2017).

Tables 3.7 and 3.8 illustrate the top fifteen technical rules under the Sortino ratio. Consistent with the results of the Sharpe ratio, the best fifteen rules under the Sortino rule consist of the time-delay band and the multiplication-band ma rules. As a general rule, the Sortino ratio can be better than the Sharp ratio in measuring high volatility assets because the Sortino ratio eliminates the effects of upside volatility. Meanwhile, we can see that the best performance rules in BTC are different from those under the Sharpe ratio, which changes into the ma rule with a fixed holding time band (5,1,10). Similar results are also shown in altercoins. For example, the best performance rule in Dash, LTC, and ETH are not the same as measured by the Sharpe ratio. Due to the high volatility of cryptocurrencies, high-sensitivity rules with short periods can capture slight fluctuations in prices and immediately reflect price changes.

Furthermore, there is also a cyclically inverse relationship between the average return and the Sortino ratio in some cryptocurrencies. Taking BTC as an example, several rules with a higher Sortino ratio have lower average returns in the second period. Other coins have similar behaviour. One reason could be attributed to the downside risk. The Sortino ratio achieves a target rate of return below the target rate of return and a low target rate of return, resulting in a higher ratio of rules and a lower average yield. Therefore, this happens when the cryptocurrency produces low returns, such as in the second phase of the BTC. Under a more conservative metric, technical rules still perform better than the buy-and-hold strategy. However, no clear clue has been drawn to the predictive power of selected rules. Tables 3.9 and 3.10 show the empirical results of examining selected rules.

Table 3. 7 Profitability performance of best performing rules (Sortino ratio).

Panel A: Four Cryptocurrencies (BTC-DASH-ETH-LTC)											
BTC	**Rule**	**Period 1** 2013/04/28-2014/06/28	**Period 2** 2014/06/28-2015/07/31	**Period 3** 2015/07/31-2016/10/31	**Period 4** 2016/10/31-2018/01/04	**DASH**	**Rule**	**Period 1** 2013/04/28-2014/06/28	**Period 2** 2014/06/28-2015/07/31	**Period 3** 2015/07/31-2016/10/31	**Period 4** 2016/10/31-2018/01/04
1	MA(5,1,10)	0.39 (0.013)	1.412 (0.013)	1.597 (0.014)	1.973 (0.031)	**1**	MA(5,2,0.01)	-	0.387 (0.025)	0.916 (0.034)	0.411 (0.052)
2	MA(5,1,0.005)	0.388 (0.013)	1.309 (0.013)	1.520 (0.014)	1.951 (0.031)	**2**	F(0.5)	-	0.386 (0.025)	0.856 (0.034)	0.403 (0.052)
3	MA(5,1,0.01)	0.368 (0.013)	1.291 (0.013)	1.529 (0.014)	1.915 (0.031)	**3**	MA(5,2,0.015)	-	0.381 (0.025)	0.779 (0.033)	0.362 (0.051)
4	MA(5,1,0.015)	0.354 (0.012)	1.183 (0.012)	1.408 (0.013)	1.912 (0.030)	**4**	F(0.005,20)	-	0.379 (0.025)	0.764 (0.033)	0.357 (0.051)
5	MA (5,1,0.02)	0.343 (0.012)	1.090 (0.010)	1.279 (0.012)	1.842 (0.030)	**5**	F(0.01,20)	-	0.371 (0.024)	0.626 (0.032)	0.323 (0.050)
6	MA (5,1,0.03)	0.340 (0.012)	1.047 (0.011)	1.183 (0.013)	1.683 (0.029)	**6**	F(0.0.15,20)	-	0.366 (0.024)	0.477 (0.030)	0.281 (0.049)
7	MA (5,2,10)	0.316 (0.011)	1.025 (0.011)	1.045 (0.012)	1.558 (0.028)	**7**	MA (5,2,0.02)	-	0.365 (0.024)	0.484 (0.030)	0.255 (0.048)
8	MA(5,2,0.005)	0.315 (0.011)	0.956 (0.011)	1.015 (0.012)	1.528 (0.028)	**8**	F(0.025,20)	-	0.355 (0.023)	0.399 (0.026)	0.165 (0.046)
9	MA (5,2,0.01)	0.314 (0.011)	0.949 (0.010)	1.010 (0.012)	1.498 (0.027)	**9**	MA (5,2,0.03)	-	0.345 (0.023)	0.397 (0.026)	0.151 (0.045)
10	MA(5,2,0.015)	0.302 (0.011)	0.915 (0.011)	0.989 (0.012)	1.484 (0.028)	**10**	F(0.03,20)	-	0.343 (0.022)	0.360 (0.025)	0.148 (0.044)
11	MA (5,2,0.02)	0.288 (0.010)	0.790 (0.009)	0.899 (0.011)	1. 464(0.027)	**11**	F(0.01,1)	-	0.330 (0.022)	0.324 (0.029)	0.136 (0.046)
12	MA (5,2,0.03)	0.280 (0.010)	0.699 (0.010)	0.888 (0.012)	1.446 (0.027)	**12**	F(0.015,1)	-	0.328 (0.022)	0.295 (0.029)	0.130 (0.046)
13	MA (5,2,0.04)	0.278 (0.010)	0.577 (0.008)	0.887 (0.010)	1.431 (0.027)	**13**	F(0.02,1)	-	0.328 (0.022)	0.290 (0.028)	0.130 (0.046)
14	MA(10,2,0.005)	0.278 (0.010)	0.478 (0.008)	0.791 (0.011)	1.310 (0.027)	**14**	F(0.005,1)	-	0.325 (0.022)	0.289 (0.029)	0.127 (0.045)
15	MA (5,1,3)	0.271 (0.010)	0.469 (0.007)	0.72 (0.008)	1.184 (0.025)	**15**	MA (5,2,0.04)	-	0.322 (0.022)	0.283 (0.022)	0.109 (0.041)
ETH	**Rule**	**Period 1** 2013/04/28-2014/06/28	**Period 2** 2014/06/28-2015/07/31	**Period 3** 2015/07/31-2016/10/31	**Period 4** 2016/10/31-2018/01/04	**LTC**	**Rule**	**Period 1** 2013/04/28-2014/06/28	**Period 2** 2014/06/28-2015/07/31	**Period 3** 2015/07/31-2016/10/31	**Period 4** 2016/10/31-2018/01/04
1	MA (10,2,0.01)	-	-	0.468 (0.016)	1.704 (0.042)	**1**	MA (10,2,5)	0.309 (0.014)	1.466 (0.020)	1.116 (0.014)	1.685 (0.041)
2	MA(10,2,0.015)	-	-	0.464 (0.016)	1.685 (0.042)	**2**	MA(10,2,0.015)	0.309 (0.014)	1.386 (0.020)	1.066 (0.015)	1.662 (0.042)
3	MA (10,2,0.02)	-	-	0.459 (0.016)	1.684 (0.041)	**3**	MA (10,5,5)	0.309 (0.014)	1.358 (0.020)	1.040 (0.014)	1.648 (0.041)
4	MA (10,2,0.03)	-	-	0.459 (0.015)	1.679 (0.040)	**4**	MA(10,5,0.005)	0.295 (0.013)	1.219 (0.019)	1.006 (0.012)	1.617 (0.041)
5	MA (10,2,0.04)	-	-	0.456 (0.016)	1.661 (0.040)	**5**	MA (10,5,0.01)	0.286 (0.013)	1.185 (0.018)	0.976 (0.011)	1.579 (0.040)
6	MA(10,5,0.001)	-	-	0.457 (0.015)	1.597 (0.038)	**6**	MA(10,5,0.015)	0.266 (0.012)	1.127 (0.017)	0.949 (0.010)	1.375 (0.039)
7	MA(10,5,0.005)	-	-	0.425 (0.015)	1.477 (0.038)	**7**	MA (10,5,0.02)	0.235 (0.011)	0.970 (0.017)	0.777 (0.013)	1.479 (0.039)
8	MA (10,5,0.01)	-	-	0.422 (0.014)	1.330 (0.036)	**8**	MA (10,5,0.03)	0.226 (0.009)	0.859 (0.014)	0.778 (0.007)	1.449 (0.036)
9	MA(10,5,0.015)	-	-	0.415 (0.013)	1.300 (0.035)	**9**	MA (10,5,0.04)	0.207 (0.010)	0.686 (0.015)	0.731 (0.011)	1.283 (0.034)
10	MA (10,5,0.02)	-	-	0.415 (0.013)	1.215 (0.033)	**10**	MA(15,5,0.001)	0.206 (0.009)	0.685 (0.015)	0.699 (0.011)	1.171 (0.035)
11	MA (10,5,0.03)	-	-	0.415 (0.015)	0.823 (0.035)	**11**	MA(15,5,0.005)	0.204 (0.010)	0.684 (0.014)	0.689 (0.010)	1.089 (0.036)
12	MA (10,5,0.04)	-	-	0.414 (0.015)	0.817 (0.035)	**12**	MA (15,5,0.01)	0.204 (0.009)	0.681 (0.014)	0.589 (0.012)	1.971 (0.035)
13	MA (10,5,0.05)	-	-	0.406 (0.014)	0.817 (0.034)	**13**	MA (15,5,0.02)	0.194 (0.009)	0.677 (0.014)	0.576 (0.012)	0.962 (0.037)
14	MA (10,2,2)	-	-	0.405 (0.014)	0.805 (0.034)	**14**	MA (10,2,2)	0.186 (0.009)	0.654 (0.015)	0.553 (0.011)	0.954 (0.035)
15	MA (10,5,2)	-	-	0.388 (0.014)	0.792 (0.033)	**15**	MA (10,5,2)	0.164 (0.009)	0.645 (0.014)	0.551 (0.011)	0.953 (0.035)

Note: This table presents best 15 Sortino ratios and corresponding mean returns (in parenthesis) of each kind of technical rules for seven cryptocurrencies and cryptocurrency index. MA are Moving Average rules, F are the Filter rules and OBV are On-Balance Volume rules. For example, MA (5,1,10) represents MA rule with 5-day slow MA, 1-day fast MA and 10-day position held. F (0.005,5) represents 0.005 position initiation, 5-day holding period. Finally, OBV (10,5,0.01) represents 10-day and 5-day on-balance volume, 0.01 band.

Table 3. 8 Profitability performance of best performing rules (Sortino ratio).

Panel B: Two Cryptocurrencies and Cryptocurrency Index (XRP-XLM-CRIX)

XRP	Rule	Period 1 2013/04/28-2014/06/28	Period 2 2014/06/28-2015/07/31	Period 3 2015/07/31-2016/10/31	Period 4 2016/10/31-2018/01/04	XLM	Rule	Period 1 2013/04/28-2014/06/28	Period 2 2014/06/28-2015/07/31	Period 3 2015/07/31-2016/10/31	Period 4 2016/10/31-2018/01/04
1	MA (10,2,10)	0.274 (0.013)	2.355 (0.024)	0.95 (0.011)	1.248 (0.063)	**1**	MA (10,2,10)	-	0.209 (0.008)	0.819 (0.021)	1.412 (0.068)
2	MA(10,2,0.005)	0.271 (0.013)	2.268 (0.023)	0.887 (0.010)	1.211 (0.061)	**2**	MA((10,2,0.005)	-	0.206 (0.007)	0.817 (0.02)	1.342 (0.067)
3	MA (10,2,0.01)	0.263 (0.014)	2.203 (0.027)	0.840 (0.014)	1.148 (0.062)	**3**	MA (10,2,0.01)	-	0.204 (0.009)	0.807 (0.022)	1.314 (0.068)
4	MA (10,2,0.02)	0.248 (0.015)	1.953 (0.027)	0.811 (0.014)	1.088 (.0620)	**4**	MA (10,2,0.015)	-	0.197 (0.009)	0.791 (0.023)	1.301 (0.068)
5	MA (10,5,10)	0.235 (0.011)	1.781 (0.020)	0.792 (0.008)	0.909 (0.058)	**5**	MA (10,5,10)	-	0.176 (0.009)	0.785 (0.022)	1.256 (0.068)
6	MA(10,5,0.005)	0.236 (0.014)	1.718 (0.026)	0.720 (0.013)	0.804 (0.061)	**6**	MA (10,5,0.005)	-	0.163 (0.007)	0.740 (0.020)	1.250 (0.063)
7	MA (10,5,0.01)	0.226 (0.012)	1.353 (0.024)	0.720 (0.013)	0.790 (0.059)	**7**	MA (10,5,0.01)	-	0.151 (0.006)	0.672 (0.018)	1.248 (0.066)
8	MA(10,5,0.015)	0.225 (0.010)	1.203 (0.016)	0.713 (0.006)	0.784 (0.056)	**8**	MA (10,5,0.015)	-	0.110 (0.005)	0.637 (0.016)	1.207 (0.065)
9	MA (10,5,0.02)	0.224 (0.010)	1.166 (0.020)	0.703 (0.01)	0.743 (0.046)	**9**	MA (10,5,0.02)	-	0.105 (0.002)	0.623 (0.014)	1.207 (0.062)
10	MA (10,5,0.03)	0.222 (0.012)	1.145 (0.023)	0.687 (0.012)	0.702 (0.057)	**10**	OBV(5,2,0.001)	-	0.105 (0.005)	0.586 (0.017)	1.194 (0.066)
11	MA (10,5,0.04)	0.222 (0.012)	1.132 (0.022)	0.647 (0 .012)	0.684 (0.056)	**11**	OBV(10,5,0.03)	-	0.100 (0.004)	0.581 (0.018)	1.194 (0.066)
12	MA (15,2,5)	0.208 (0.012)	1.113 (0.022)	0.646 (0.012)	0.682 (0.056)	**12**	MA (10,5,0.04)	-	0.100 (0.004)	0.549 (0.018)	0.994 (0.057)
13	MA (5,2,2)	0.187 (0.013)	1.094 (0.022)	0.622 (0.011)	0.680 (0.055)	**13**	MA (10,5,0.05)	-	0.190 (0.004)	0.513 (0.018)	0.975 (0.050)
14	MA (10,2,2)	0.183 (0.012)	0.855 (0.022)	0.438 (0.010)	0.674 (0.054)	**14**	MA (15,2,5)	-	0.089 (0.004)	0.446 (0.016)	0.946 (0.058)
15	MA (10,5,2)	0.178 (0.010)	0.795 (0.021)	0.322 (0.012)	0.669 (0.055)	**15**	MA (10,2,2)	-	0.052 (0.004)	0.446 (0.015)	0.941 (0.058)

CRIX	Rule	Period 1 2013/04/28-2014/06/28	Period 2 2014/06/28-2015/07/31	Period 3 2015/07/31-2016/10/31	Period 4 2016/10/31-2018/01/04
1	MA(5,1,10)	-	0.108 (0.002)	1.643 (0.013)	2.269 (0.033)
2	MA(5,1,0.005)	-	0.105 (0.003)	1.489 (0.014)	2.073 (0.033)
3	MA(5,1,0.015)	-	0.087 (0.002)	1.485 (0.013)	2.082 (0.033)
4	MA (5,1,0.02)	-	0.070 (0.003)	1.404 (0.014)	1.993 (0.033)
5	MA (5,1,0.03)	-	0.054 (0.001)	1.319 (0.011)	1.969 (0.031)
6	MA (5,2,10)	-	0.059 (0.002)	1.315 (0.013)	1.866 (0.031)
7	MA(5,2,0.005)	-	0.058 (0.002)	1.036 (0.010)	1.689 (0.030)
8	MA(5,2,0.001)	-	0.051 (0.001)	1.034 (0.012)	1.761 (0.030)
9	MA(5,2,0.015)	-	0.053 (0.001)	1.032 (0.013)	1.357 (0.030)
10	MA (5,2,0.02)	-	0.051 (0.001)	1.018 (0.011)	1.297 (0.028)
11	MA (5,2,0.03)	-	0.033 (0.001)	0.976 (0.012)	1.275 (0.028)
12	MA (5,2,0.04)	-	0.030 (0.001)	0.954 (0.008)	1.274 (0.028)
13	MA(10,2,0.03)	-	0.020 (0.001)	0.839 (0.010)	1.251 (0.028)
14	MA (5,1,3)	-	0.018 (0.001)	0.733 (0.010)	1.237 (0.027)
15	MA (5,2,3)	-	0.010 (0.001)	0.730 (0.010)	1.203 (0.027)

Note: This table presents best 15 Sortino ratios and corresponding mean returns (in parenthesis) of each kind of technical rules for seven cryptocurrencies and cryptocurrency index. MA are Moving Average rules, F are the Filter rules and OBV are On-Balance Volume rules. For example, MA (5,1,10) represents MA rule with 5-day slow MA, 1-day fast MA and 10-day position held. F (0.005,5) represents 0.005 position initiation, 5-day holding period. Finally, OBV (10,5,0.01) represents 10-day and 5-day on-balance volume, 0.01 band.

Table 3. 9 Lucky Factors for BTC (Sortino Ratio)

Panel A: Crypto-Coin								
BTC	Period 1 (Panel A: Baseline = No Factor)				Period 2 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)
1	0.170	-0.469	0.577	1	2.118	-0.810	0.945	1
2	0.160	-0.467	0.57	1	2.117	-0.810	0.946	1
3	0.100	-0.47	0.541	1	2.115	-0.800	0.950	1
4	0.030	-0.468	0.486	1	1.982	-0.810	0.947	0.948
5	-0.010	-0.476	0.448	1	1.756	-0.820	0.943	1
6	-0.030	-0.469	0.438	1	1.943	-0.820	0.949	1
7	-0.150	-0.476	0.326	0.632	1.932	-0.810	0.945	1
8	-0.200	-0.475	0.282	1	1.807	-0.830	0.944	1
9	-0.220	-0.470	0.256	1	1.783	-0.800	0.942	1
10	-0.190	-0.473	0.289	1	1.735	-0.810	0.945	1
11	-0.300	-0.466	0.188	1	1.583	-0.840	0.935	1
12	-0.290	-0.459	0.188	1	1.606	-0.830	0.938	1
13	-0.330	-0.466	0.150	1	1.431	-0.810	0.927	1
14	-0.360	-0.474	0.123	1	1.140	-0.730	0.939	1
15	-0.280	-0.467	0.189	1	1.160	-0.830	0.923	1
	Multiple test: Min: -0.361**P-Value:** 0.206				**Multiple test: Min:** 2.704 **P-Value:**0.957			
BTC	Period 3 (Panel A: Baseline = No Factor)				Period 4 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)
1	1.197	0.121	1	1	1.094	-0.045	0.890	1
2	1.191	0.134	1	1	1.085	-0.046	0.887	1
3	1.259	0.155	1	1	1.068	-0.035	0.888	1
4	1.199	0.221	1	0.854	1.072	-0.018	0.887	1
5	1.114	0.199	0.999	1	1.062	0.010	0.886	1
6	1.167	0.178	1	1	0.984	-0.012	0.892	1
7	1.025	0.219	0.999	1	0.920	0.002	0.890	1
8	1.035	0.187	0.999	1	0.935	0.008	0.889	1
9	1.030	0.226	0.999	1	0.909	-0.004	0.882	1
10	1.018	0.191	0.999	1	0.910	0.012	0.889	1
11	1.045	0.244	0.999	1	0.935	-0.017	0.876	1
12	1.035	0.170	0.999	1	0.970	-0.022	0.878	1
13	0.996	0.254	0.999	1	0.956	0.023	0.883	1
14	0.995	0.138	0.999	1	0.933	-0.024	0.904	1
15	0.880	0.228	0.998	1	0.959	0.006	0.884	1
	Multiple test: Min: -0.257 **P-Value:**0.290				**Multiple test: Min:** -0.015**P-Value:** 0.925			

Note: The table summarizes the LF results for BTC. The difference in the equally-weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). The value of -0.28 (Panel A, rule 15) means there is a reduction of 28% in the mean absolute scaling intercept, which has no contribution to the explanation of our model. SI_{ew}^{m} *computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5th percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. Panel A of each panel following the notation of Harvey and Liu (2021) shows a separate test for each good-performance rule for Sharpe ratio measurements. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).*

Table 3. 10 Lucky Factors for CRIX (Sortino Ratio)

Panel B: Crypto-Index								
CRIX	Period 2 (Panel A: Baseline = No Factor)				Period 3 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)
1	0.928	-0.652	0.76	1	0.426	-0.394	0.818	1
2	1.447	-0.662	0.804	1	0.415	-0.391	0.831	1
3	1.214	-0.649	0.787	1	0.399	-0.389	0.813	1
4	1.473	-0.666	0.809	1	0.432	-0.389	0.836	0.632
5	0.369	-0.655	0.652	1	0.187	-0.387	0.694	1
6	1.001	-0.655	0.756	1	0.430	-0.378	0.815	1
7	-0.005	-0.637	0.532	1	-0.048	-0.381	0.437	1
8	0.834	-0.680	0.742	1	0.170	-0.394	0.671	1
9	0.812	-0.680	0.742	1	0.201	-0.386	0.694	1
10	0.747	-0.656	0.731	1	0.190	-0.402	0.691	1
11	0.758	-0.643	0.73	1	0.088	-0.395	0.617	1
12	-0.471	-0.634	0.192	1	-0.346	-0.376	0.066	1
13	0.283	-0.649	0.623	1	0.036	-0.394	0.547	1
14	-0.017	-0.648	0.519	1	-0.110	-0.379	0.336	1
15	0.172	-0.665	0.603	1	-0.203	-0.387	0.223	1
	Multiple test: Min: -0.471**P-Value:** 0.350				**Multiple test: Min:** -0.346 **P-Value:**0.154			

CRIX	Period 4 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)
1	0.394	-0.258	0.921	1
2	0.356	-0.261	0.908	1
3	0.390	-0.264	0.924	1
4	0.319	-0.263	0.888	1
5	0.318	-0.264	0.885	1
6	0.233	-0.272	0.828	1
7	0.238	-0.262	0.835	1
8	0.023	-0.260	0.523	1
9	-0.002	-0.263	0.486	1
10	-0.044	-0.258	0.398	1
11	0.041	-0.260	0.581	1
12	0.145	-0.270	0.722	1
13	-0.078	-0.263	0.347	1
14	-0.123	-0.259	0.262	1
15	-0.095	-0.257	0.307	1
	Multiple test: Min: -0.123 **P-Value:**0.399			

Note: The table summarizes the LF results for CRIX. The difference in the equally-weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). The value of -0.471 (Panel B, rule 12) means there is a reduction of 28% in the mean absolute scaling intercept, which has no contribution to the explanation of our model. SI_{ew}^{m} computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5^{th} percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. Panel A of each panel following the notation of Harvey and Liu (2021) shows a separate test for each good-performance rule for Sharpe ratio measurements. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).

Incorporating downside risk into the metrics, we found that almost all rules have no predictive power, except for one rule in DASH. Discussion and related tables are shown in our appendix. We find there is only one significant rule for Dash, and there are no statistically significant rules after taking that into pre-selected rules. Neither the LF method nor SPA tests show that any tested rule is statistically significant. In other words, rules with high profitability do not grant them high predictive power. Although there is no significant rule, most of the statistics in the first period are much smaller than those in later periods, and the decline in statistical significance is remarkable. Since test statistics remain positive, we can state the augmented model has no improvement from our basic model. Even with negative test statistics, which means the technical rules have improved the predictive power of the basic model, we still cannot reject the null hypothesis that the augmented model has no forecasting ability. In short, good-performance rules do not give explanatory power. Our results prove that technical rules may not have explanatory power in predicting the return of cryptocurrencies.

3.4 Conclusions

To conclude, we summarize our findings and compare them to previous studies in this section. The profitability of technical indicators is much higher than the traditional buy-and-hold strategy. Align to prior studies, such as Elendner et al. (2018) and Bouri et al. (2018), and Dyhrberg (2017), we show that cryptocurrencies display low or negative daily returns. Compared to stocks markets, returns of cryptocurrencies are much lower, regardless of the application of technical rules. In other words, technical rules with daily or higher time-based constraints may not work well in the cryptocurrency market. Our investigation found that the explanatory ability of technical rules is not affected by measurement standards. Different measurement standards show the same results: technical rules barely have predictive power for the cross-section return of cryptocurrencies. Although a large number of rules are significant in the early periods (period one and period 2), only a few of them show persistence across the whole time. Furthermore, we find that MA rules perform much better than any other technical rules for all cryptocurrencies by our two measuring standards. Our investigation cannot find significant rules across the period, and we can say technical indicators have no explanatory power for cryptocurrencies' cross-sectional returns. Another interesting finding is the inverse relationship between the metrics in the cryptocurrency market. That is to say, the average rate of return and the Sortino ratio, as well as the average rate of return and the Sharpe ratio, all illustrate the cyclically inverse relationship in our sample.

In short, the profitability of technical rules is not as remarkable as their performance in stock markets. Nonetheless, technical rules still outperform buy-and-hold strategies. One reason could be attributed to the fact that cryptocurrencies are much more volatile than any other financial instrument. In addition, the predictive power of technical rules gradually disappears. According to our measurement standards, good performance rules are generally unable to predict the return of cryptocurrency. The stock market also shows this inverse relationship between technical rule forecasting capabilities (Bajgrowicz and Scaillet, 2012). Due to the large fluctuations in transaction costs of different cryptocurrency platforms, we cannot adopt a unique measure of agency fees. We thus hope standard regulation of cryptocurrencies exchange will be issued in the future. Meanwhile, mishaps in cryptocurrency online exchanges, like the frequent hacks, malignant manipulation, and things, can easily distort investors' expectations and development opportunities. Without stable, reliable and healthy investing environments, the cryptocurrency market's future may still be overgrown with brambles.

Chapter 4 Cryptocurrencies and Lucky Factors: the pathway towards the true value of technical and fundamental analysis

4.1 Introduction

The Financial Technology (FinTech) revolution is driven by valuable technological innovation applied in the financial industry. Chen et al. (2019) position the Bitcoin (BTC) and Blockchain (BCH) within FinTech's seven most innovatory drivers, while Choi et al. (2020) highlight that BCH technologies can positively affect firms' operations management and performance. This is not surprising as investment in cryptocurrencies has grown largely in the recent years and has brought BCH technology to the forefront of everyone's attention. The market capitalization of the BTC exceeds 420 billion US dollars, while the global market value of cryptocurrencies rises above 646 billion US dollars. BTC's ledger started in January 2009 and its approximate return on investment, if purchased at the time of launch, is above 9,000%. However, BTC, currently dominating the cryptocurrency market by more than 60%, suffered a price crash of around 65% in early 2018. Since then, it recovered and now BTC's price has broken the barrier of 22 thousand US dollars[5]. Similar booms, rapid downfalls and extreme volatility periods are commonly observed in alternative cryptocurrencies (cryptocoins) every year.

This poses a clear dilemma. On the one side, researchers, investors and policymakers discern the potential attractiveness of cryptocurrencies mainly due to their popularity and commercial expansion. On the other hand, they recognise that their risk management and lack of a clear underlying economic mechanism makes their utility controversial. For this reason, the cryptocurrency literature, although fast-growing, generally stands divided on the true value of cryptocoins. This originates from their conflicting results in terms of trading and investment diversification benefits, their unstable performance in terms of profitability and predictability through Technical and Fundamental Analysis (TA), and the high risk of data-snooping bias when analysing them. This study's contribution is to provide an answer to this dilemma by being the first one to offer a holistic evaluation of the genuine merit of Technical Analysis (TA) and Fundamental Analysis (FA) for cryptocurrencies. In doing so, we utilize a novel exercise for the cryptocurrency literature. The exercise combines studying a large universe of technical rules including the new momentum indicator, the log-Price Moving Average (PMA), along with a robust pool of traditional fundamental factors (e.g., commodities, stock indices, currencies) infused by BCH technology and BTC trend fundamentals. Additionally, we control for luck with some of the latest developments in the data snooping literature and capture the genuine forecasting and trading value of FA and TA in cryptocurrencies. To the best of our knowledge, our study offers an original and completely updated view compared to what other researchers do. More precisely,

[5] The reported figures are as of the 17th of December 2020 and are available from https://coinmarketcap.com/.

related research focuses on either TA or FA alone, uses strict and conservative measures that can distort the results of luck, or completely ignore data snooping.

Table 4. 1 Cryptocurrencies' literature summary

Research work	Dataset	Technical Analysis	Fundamental Analysis	Forecasting Ability Examination	Control of Luck
This study	BTC, XRP, ETH and CRIX	Yes (7,851)	Yes (57)	Empirical and Wild Bootstrap/Regression	k-Familywise Error Rate, Lucky factors
Liu and Tsyvinski	All cryptocurrencies are from Coinmarketcap	No	Yes	Regression	No
Nakano et al. (2018), Tiwari et al. (2018), Karalevicius et al. (2018), **Huang et al. (2019)**, Atsalakis et al. (2019)	BTC	Yes (124)	No	Empirical	No
Tzouvanas et al. (2020)	BTC, XRP, ETH, LTC, XLM, DSH, NEM, DOGE, BC, DB, BTS	Yes (6)	No	Empirical	No
Grobys et al. (2020)	BTC, ETH, XRP, BCC, EOS, LTC, ADA, XLM, TRX	Yes (5)	No	Empirical	No
Kristoufek (2013), Matta et al. (2015), Dyhrberg, (2016), Li and Wang (2017), **Baur et al. (2018)**, Ji et al. (2018), Koutmos (2018), Gandal et al. (2018), Bouri et al. (2018), Demir et al. (2018), Urquhart (2018), Salisu et al. (2019), Foley et al. (2019), Easley et al., (2019), Chan et al. (2020), Ciaian et al. (2020)	BTC	No	Yes (17)	Regression	No
Wang and Vergne (2017)	BTC, LTC, PPC, XRP, XLM	No	Yes (7)	Regression	No
Kraaijeveld and De Smedt (2020)	BTC, ETH, XRP, BCC, EOS, LTC, ADA, XLM, TRX	No	Yes (3)	Regression	No
Detzel et al. (2020)	BTC, ETH, XRP	Yes (5)	Yes (4)	Empirical / Regression	No
Bhambhwani et al. (2019)	BTC, ETH, LTC, DSH, XMR	Yes (1)	Yes (3)	Regression	No
Hudson and Urquhart (2021)	BTC, LTC, XRP, ETH	Yes (14,919)	No	Empirical	Familywise Error Rate, False Discovery Rate

Note: Bitcoin (BTC), Ripple (XRP), Ethereum (ETH), Litecoin (LTC), Stellar (XLM), Dash (DSH), Dogecoin (DOGE), Bytecoin (BC), Digibyte (DB), Bitshares (BTS), Peercoin (PPC), NEM (NEM), Nxt (NXT), MaidSafeCoing (MAID), NameCoin (NMC), Bitcoin Cash (BCC), EOS (EOS), Cardano (ADA), Tron (TRX). The value in the parenthesis of the third and fourth column represents the maximum number of TA and FA rules used within the studies cited in the first column. This number corresponds to the study highlighted in bold in each raw.

In order to better illustrate the above, we summarize in Table 4.1 the most recent studies in the field, their datasets and whether they focus on TA or FA, or control for luck. From this table, it becomes obvious that most of the studies offer only a snapshot of the TA and FA's predictability and profitability, unlike our complete, multi-dimensional approach. Expanding on Table 4.1, we continue to discuss the respective literature in order to offer the interested readers more insight on the current cryptocurrencies' research.

Recently, an increasing number of researchers delve deeper into the investment potentials of cryptocoins and their utility as digital assets (Elendner et al., 2018; Härdle et al. 2020). BTC exhibits the potential of cryptocurrencies as a new medium for future currencies, but there is still a long way until they can qualify as currencies. The interest remains hyped because cryptocurrency and BCH applications are expected to determine crucial technological and market developments for the future real economic activity. The extensive work of Yermack (2015, 2017) builds upon this argument. The author defines 'a *bona fide* currency function as a medium of exchange, a store of value, and a unit of account', which BTC largely fails to satisfy. Despite BTC's speculation vulnerability, it is used widely as an alternative to fiat money, and it is expected to affect both central banking and corporate governance (European

Central Bank, 2019). Cryptocurrencies' transactions and trading have some appealing properties. Most cryptocurrencies are traded on different online cryptocurrencies exchanges and the low transaction speed of cryptocoins does not affect the trading activity of these exchanges. Furthermore, when investors need to transfer the cryptocurrency stored in the exchange to their own digital wallet, some exchanges only use the cryptocurrency as the transaction cost to liquidate it. Unlike stock and other exchanges, cryptocurrencies exchanges are operating throughout the whole year. From a diversification perspective, several recent studies highlight the benefits associated with cryptocurrency investment (Liu, 2019; Platanakis and Urquhart, 2019; Demiralay and Bayraci, 2020; Tzouvanas et al., 2020). This increased interest in cryptocurrencies has led market participants, traders, regulators, investment institutions and government policy makers to study the predictability of these new financial assets. Technical rules and fundamental factors have been successfully employed in predicting the risk premium of stocks or stocks' indices (Bajgrowicz and Scaillet, 2012; Neely et al., 2014). Hence, they are the sensible contenders for this challenging task.

The cryptocurrency literature is also voluminous when it comes to investment and trading. Portfolio managers can use cryptocurrencies as a hedging tool for managing risk (Dyhrberg, 2016; Chan et al., 2019; Sebastião and Godinho, 2020). Other studies, such as Baur et al. (2018) and Klein et al. (2018), do not observe correlations between cryptocurrencies and financial assets, but Cagli (2018) states that bilateral co-moving activities exist between the possible pairs of cryptocurrency prices. Investigation into the efficiency of cryptocurrency market provides evidence that TA may possess both profitability and forecasting ability under the current circumstances. More specifically, several papers show that arbitrage opportunities and inefficiencies gradually appear after 2016 (Urquhart, 2016; Nadarajah and Chu, 2017; Tiwari et al., 2018) and mainly corroborate that weak efficiency conditions apply. Other studies, including Gandal et al. (2018), Almudhaf (2018) and Zargar and Kumar (2019), find evidence of market inefficiencies and random walk deviations (e.g., potential suspicious trading on Mt Gox or mispricing in the BTC Investment Trust). Shen, Urquhart and Wang (2020) focus on BTC volatility and explain that that the inclusion of structural breaks improves the predictability of volatility models in short forecasting horizons. Recent research papers also focus on the utility of TA and provide direct evidence of high profitability in the BTC market. Within a cryptocurrency framework, Detzel et al. (2020) employ an equilibrium model to show that BTC may follow an MA process. Nakano et al. (2018) show that the application of neural network techniques in intraday BTC improves a Buy-and-Hold (BH) strategy. Corbet et al. (2019) also provide evidence that a moving average strategy can generate high profitability in the cryptocurrency market. Huang et al (2019) apply price-based technical indicators for BTC return prediction and show that momentum indicators are powerful. Similar results of weekly momentum effects through regressions are also found to be significant in cryptocurrency returns (Liu and Tsyvinski, 2021). Hudson and Urquhart (2021) perform an extensive TA analysis and conclude that, after accounting for data-snooping bias, no genuine profitability is achieved in cryptocurrency markets. Atsalakis et al. (2019) propose a novel hybrid Neuro-Fuzzy controller incorporating momentum properties to forecast BTC prices and show that the trading performance is much higher than a BH strategy. Recently, Grobys et al. (2020) have investigated the profitability of technical rules in the cryptocurrency market and demonstrated that most rules, especially MA rules, perform better than a BH strategy.

There is also extensive literature that provides evidence in favour of the utility of FA for financial markets (see amongst others, Lev and Thiagarajan, 1993; Dechow et al., 2001; Kremer and Nautz, 2013; Yan and Zheng, 2017; Bartram and Grinblatt, 2018; Sloan, 2019). Unlike stocks, options or other financial assets, there are no underlying assets or firms supporting the intrinsic value of cryptocurrencies. That could be in a sense a short and logical argument against the use of fundamentals, like accounting factors from financial statements, when implementing fundamental analysis on cryptocurrencies. But this can also be a superficial argument, as many researchers advocate that cryptocurrency prices are influenced by comprehensive fundamental aspects related to factors endogenously or exogenously associated with cryptocurrencies. For example, BCH technology and its demand and/or supply should be considered endogenous and fundamental in the cryptocurrency domain. Changes of BTC prices can directly influence the whole cryptocurrency market and create cryptocurrency volatility spillovers (Yi et al., 2018; Antonakakis et al., 2019). Ciaian et al. (2016) show that BTC prices can be significantly influenced by demand and supply, while Koutmos (2018) indicates that BTC-related activities, such as the unique addresses and number of BTC transactions, are linked to BTC returns. Wang and Vergne (2017) and Bhambhwani et al. (2019) show that the technological development of BCH is the real driver of cryptocurrencies. Smart contracts, transparency, 'safe heaven property' and other BCH technology dimensions can provide investors with a '*crypto-raison d'être*', substituting direct monetary benefits (e.g., stock dividend) with time-effective and convenience yields (Yermack, 2015). Nonetheless, it is vital to pick up the factors in terms of BCH information, since not all production-based factors are found to be useful (Liu and Tsyvinski, 2021). Hence, BTC and BCH technology-based factors, such as the block size, transaction time between blocks, the Hashrate (HSH) and other factors related to computing power, should be considered[6].

Exogenous factors utilized in the literature are usually evolving around traditional macroeconomic, financial, sentiment and social media factors. Global equity, bonds and commodity prices can affect BTC movements; studies such as Bouri et al. (2018) and Fang et al. (2019) illustrate this. Demir et al. (2018) suggest that the Economic Policy Uncertainty (EPU) index is negatively related to BTC returns. Li and Wang (2017) suggest that short- and long-term BTC movements are sensitive to economic fundamentals, rather than technological factors, but mining is proved to be also influential. Salisu et al. (2019) show that macroeconomic variables, such as country-specific interest rates,

[6] For these and other related factors to BCH and cryptocurrencies, interested readers may refer to Blockchain.com and Bitcoinity.com.

can be used to predict BTC returns to a certain extent. Other studies (Ciaian et al., 2016; Karalevicius et al., 2018; Urquhart, 2018) suggest that the volume of keyword searching on Google and Wikipedia can explain the BTC's and other cryptocurrencies' return series. Matta et al. (2015) and Kraaijeveld and De Smedt (2020) show that online sentiment factors, such as searching numbers, online community posts, tweets and news, affect the prices of BTC and other cryptocurrencies. Researchers have also explored issues related to the usage, technological property, political and social influence (see amongst others, Reid and Harrigan, 2013; Yermack, 2015, 2017). Foley et al. (2019) demonstrate that cryptocurrency transactions make great contribution to the black market, although the share of illegal BTC transaction declines with the expansion of cryptocurrency interests. Recently, Easley et al. (2019) have modelled the equilibrium between transaction fees and BTC block size, indicating the importance of transaction fees in the BTC evolution. From the above it is clear that chartists and fundamentalists are quite segregated with regard to what drives cryptocurrency returns.

In terms of our empirical design, we focus on the three main cryptocurrencies and the main cryptocurrency index, namely the BTC, Ethereum (ETH), Ripple (XRP) and the CRIX index. First, we apply the traditional universe of trading rules of Sullivan et al. (1999) (STW) by generating a set of 7846 traditional technical rules consisting of the MA, Support and Resistance (SR), Channel Breakout (CB), On-Balance Volume (OBV) and Filter (FR) rules. Please refer to STW for specification of the TA universe. In addition, we employ a new MA-style indicator, the PMA proposed by Detzel et al. (2020), found to be successful in BTC prediction. Thus, we generate 7851 technical rules for each series under study. We estimate the trading performance of these rules in the in-sample, and we select the 15 out-performers. Then, we examine the predictability of these TA rules along with 57 FA indicators, that might have value in cryptocurrencies forecasting, through the regression framework of Neely et al. (2014). For the TA and FA rules and factors that have value in predicting our cryptocurrencies in-sample, we apply the Lucky Factors (LFs) framework of Harvey and Liu (2021) and the Superior Predictive Ability test (SPA) of Hansen (2005). Our aim now is to identify the rules and factors that also demonstrate genuine in-sample profitability. Finally, we examine in our out-of-sample periods the predictability of our selected TA and FA and their trading performance. Our empirical framework is implemented for three different forecasting horizons, each based on the 50%, 75% and 90% of our total sample as in-sample and the remainder as out-of-sample.

Our analysis suggests that only a small subset of TA rules (mostly MAs and FRs) have genuine predictive value in-sample for the cryptocurrencies under study. The same applies for a handful of the FA rules under study. From these rules and factors, only one TA rule (the short-term PMA) and the one FA factor (the HSH index) demonstrate also genuine profitability in the in-sample and predictability in the out-of-sample. Our findings indicate that traditional technical analysis rules have no value in cryptocurrencies and only the recently introduced short-term PMA seems valuable. HSH, which is a measure of the computing power used in mining BTC, seems the only fundamental factor that demonstrates predictability and profitability. This finding that opposes the literature which suggests that capturing BTC and BCH news can provide a solid FA framework for the cryptocurrency universe.

The rest of this paper is organized as follows. Section 2 describes the dataset and related factors utilized in this study, while section 3 summarizes our empirical design. The empirical results are provided in section 4. Finally, some concluding remarks are provided in section 5. Technical information relevant to our design are presented in the Appendix A.1, while further analysis and results are given in the Appendix.

4.2 Cryptocurrencies and relevant factors dataset

In this section, we provide a summary of the dataset used in this study. We focus on three main cryptocurrencies, namely, the BTC, ETH and XRP, and the CRIX index over the period 08/08/2015 to 08/12/2018. We acquire cryptocurrency prices from *Coinmarketcap.com*, which is usually used by professional publications such as the Wall Street Journal. For CRIX, the daily prices are obtained directly from *thecrix.de.* Our selection of cryptocurrencies is based on data availability, longevity and relatively large intraday transactions. Many cryptocurrencies introduced in earlier periods have dissolved, while other cryptocurrencies with large capitalization are only available after 2017. Our current selection is consistent across the time periods under study. BTC is the first cryptocurrency ever launched, taking up nearly half of the whole cryptocurrency market. BTC is considered the benchmark of coin-to-coin transactions against other cryptocurrencies in almost all online platforms. ETH is the so-called 2.0 version of cryptocurrency. Smart contracts and distributed applications can be built and used all the time through ETH, but this can also be traded as a digital currency. XRP is managed by several independent servers controlled by the Ripple network. XRP is the most efficient cryptocurrency for financial institutions as it has the fastest transaction confirmation. Finally, CRIX follows Laspeyres' derivation with each cryptocurrency being weighted by its market capitalization. The summary statistics of the cryptocurrency return series and the relevant fundamental factors are presented in Tables 4.2 and 4.3, respectively.

Table 4. 2 Summary statistics of cryptocurrency prices and returns.

Prices	BTC	ETH	XRP	CRIX	Returns	BTC	ETH	XRP	CRIX
Min	210	0.435	0.004	374	**Min**	-0.19	-0.27	-0.46	-0.22
Mean	3604	212	0.257	10163	**Mean**	0	0.01	0.01	0
Max	19497	1396	3.38	62895	**Max**	0.25	0.51	1.79	0.22
SD	3944	277	0.406	12340	**SD**	0.04	0.07	0.09	0.04
JB	411***	644***	1292***	681***	**JB**	133***	2355***	7908***	1110***
ADF	-2.358	-1.322	-3.514	-1.841	**ADF**	-33.6	-17.8	-15	--11
S	1.28	1.51	3.148	1.512	**S**	0.16	1.19	7.79	-0.28
K	4.242	4.889	17.657	5.064	**K**	5.27	6.59	127	4.78
LB (5)	5993***	5982***	5728***	5836***	**LB (5)**	2.31	15.23***	48.68***	4.33

Notes: This table reports the sample statistics of cryptocurrency prices and returns. SD is the standard deviation; S is the skewness; K is the excess kurtosis; and ADF is the Augmented Dickey-Fuller statistic. LB (5) are the Ljung–Box statistics with lag 5, respectively, distributed as χ^2 with n degrees of freedom, where n is the number of lags. Significance level: * 10%, ** 5%, *** 1%. JB is the Jarque-Bera test. The number of observations is 1218 for all series.

Table 4. 3 Summary of the cryptocurrency FA factors

Factors	Reference	Resources
Traditional Fundamental Factors		
Gold price (GLD)	Ji et al. (2018)	Federal Research Bank of St. Louis
CBOE Volatility Index price (VIX), CBOE DJIA Volatility Index price (VXD), CBOE NASDAQ-100 Volatility Index Price (VXN), 3-month treasury bill rate (3mBill), 10-year treasury bill rate(10yBill)	Detzel et al. (2020)	Wharton Research Data Services
S&P500 (SP500), Moody's Baa -bond index (MBaa), Moody's AAA-bond index (MAAA)	Detzel et al. (2020)	Federal Research Bank of St. Louis
Market Excess Return (MER)	Detzel et al. (2020)	Website of Kenneth French
Dow Jones Industrial Average (DJIA) and Nasdaq Composite Market index (NSQ), MSCI World Market index (MSCI)	Ciaian et al. (2016)	Federal Research Bank of St. Louis
Oil price (OIL)	Ciaian et al. (2016)	US Energy Information Administration
Currency Factors		
AUD/USD, EURO/USD, YEN/USD, CAD/USD, BRL/USD, RMB/USD, CHF/USD, IDR/USD, KRW/USD, VEF/USD, RUB/USD, TRY/USD	Baur et al. (2018)	Bloomberg
Stock Indices Factors		
Nikkei 225 Index (NI225), Caracas Stock Exchange Index (IBVC), Brazilian Bovespa Index (BRA), Canadian Composite Index (TSX), Korea Stock Index (KOSPI), S&P/ASX 200 index (ASX), Jakarta Stock Exchange Composite Index (JCI), Swiss Market Index (SMI), Shanghai Stock Exchange (SSE), Russian Trading System Stock Index (RTS)	Baur et al. (2018)	DataStream
Blockchain Technology-based Factors		
Daily Bitcoin Transactions (DBT), Hashrate (HSH), Mining Difficulty (MD)	Li and Wang (2017)	Blockchain.com
Block Size (BZ), Time between Transaction (TBT), Block Size Vote (BSV)	Besarabov and Kolev (2018)	Bitcoinity.com
Total Bitcoin Mined (TBM)	Kristoufek (2013)	Quandl
Days of Destroyed (DOD), Unique Bitcoin Address Used (UBA)	Ciaian et al. (2016)	Quandl
Economic Policy Uncertainty (EPU)	Demir et al (2018)	policyuncertainty.com
Bitcoin and Blockchain Trend-based Factors		
Search Number on Wikipedia (BTC-W, ETH-W, XRP-W)	Kristoufek (2013)	Wikipedia
Search Number on Google Trends (BTC-GT, ETH-GT, XRP-GT)	Kristoufek (2013)	Google
Number of New Topics (NTs), New Posts (NPs), New Users (NUs), Page views (PVs)	Ciaian et al. (2016)	bitcointalk.org

Note: The table summarizes all the relevant factors used in the regression specifications. There are 57 factors in total under consideration. The selection is based on studies that utilize similar factors to explain cryptocurrency returns. These studies are matched to each factor and the relevant data resource.

The Jarque-Bera (JB) statistic reported in Table 5.2 confirms that the return series under study are non-normal at the 99% confidence level. The Augmented Dickey-Fuller (ADF) suggests rejection of the null hypothesis of a unit root at the 99% confidence level for all the return series, hence the returns of BTC, ETH, XRP and CRIX are stationary. As shown in Table 4.3, we consider 57 factors, which are deemed relevant for cryptocurrency movements, and we split them into five categories. Each group of factors is used in separate regressions with their summary statistics presented in the Appendix B.1. Our factor selection is motivated by the TA and FA literature along with the growing literature on cryptocurrencies news and BCH technology. More specifically, the FA approach is initially built upon a set of 14 fundamental indicators, including commodity prices, volatility, main stock and volatility indices, along with market measures such as the excess returns, bond yields and risk-free rate proxies. Then, the influence of currency exchanges and stock indices on cryptocurrencies is investigated through 13 exchange rates and 10 stock indices respectively. In addition, we consider 10 factors measuring the demand and supply of the BTC, the BCH technology evolution and the related sentiment. Finally, prior studies suggest that social media or online communities impact cryptocurrency prices (Matta et al., 2016; Ciaian et al., 2016). We attempt to capture this with 10 trend factors based on search engine results, news, and discussion in crypto-forums.

4.3 Methodology

This section describes our methodology approach. Firstly, that TA approach is explained in short, along with the utility of the LF method for examining the true value of the top performing rules. Then, we discuss the equilibrium model that allow us to build our regression framework for the selected factors and examine their true importance in predicting crypto-movements.

4.3.1 Technical Analysis and Lucky Factors: A pure technical perspective

Regarding TA, we take the traditional approach following several studies such as Sullivan et al. (1999) (STW universe) and Bajgrowicz and Scaillet (2012). The STW universe includes around 8000 technical indicators including Moving Average (MA), Support and Resistance (SR), Channel Breakout (CB), On-Balance Volume (OBV) and Filter Rules (FR). In order to evaluate the performance of the trading strategies two traditional performance metrics are calculated, namely the Sharpe and Sortino ratio[7], based on cryptocurrency and CRIX returns. The performance of the technical strategies is benchmarked to a Buy-and-Hold (BH) strategy. We evaluate the trading performance of each technical indicator over three consecutive sub-periods of our whole sample. This design is following the principles of the Adaptive Market Hypothesis (AMH) (Lo, 2004), AMH suggests that arbitrage opportunities erode through time, hence the performance of trading strategies, especially in the numbers of the SWT universe, are expected to have short-term value, which is what we want to capture.

Once the trading performance for all rules is obtained, we rank the rules according to Sharpe and Sortino ratios. Given that rankings of 7864 trading rules per period and series under study, data-snooping issues arise. Considering the dimensionality issue, the LF framework of Harvey and Liu (2021) is ideal to reveal the genuine performance of the top fifteen rules based on each metric, compared to other Multiple Hypothesis Testing (MHT) approaches. For that reason, we setup LF MHT framework for variable selection. Mathematical details on this framework are presented in the section 3.2.1 to section 3.2.3 (Chapter 3). This step of our methodology will provide a pure technical analysis perspective for cryptocurrency returns.

4.3.2 Equilibrium Model and Lucky Factors: A further technical and fundamental perspective

Taking our first step further, we follow the design of Detzel et al. (2018). In other words, we build the rational continuous-time EM. The authors demonstrate that EM has robust predictive ability over risky assets such as BTC,

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[7] For the calculation of the Sharpe ratio, we employ the one-month fund management constant expiration rate in the Center for Research in Security Prices (CRSP) file based on monthly frequency and then we convert the monthly interest rate into a daily series as $r_d = \ln(1 + r_{mon}) / 30$, where r_d is the daily risk-free rate, r_{mon} is the monthly interest rate and 30 is the average number of trading days in a month. The Sortino ratio is a downward bias correction estimator for Sharpe ratio, as it focusses on the distribution of returns that are below the target or required return (in this case zero).

when it is combined with MA based ratios, identified as PMA factors. Following the three assumptions approach of Detzel et al. (2018), we build the EM model for each of our series as follows:

An equilibrium is set as follows:

$$dB_t = ((\beta + M_t^i)B_t - \delta_t)dt + \sigma_\delta B_t d\hat{Z}_{1t}^i \tag{13}$$

Where β is the discount rate, M_t^i is the conditional expectation of state variable X_t, B_t is BTC price at time t, $\hat{Z}_{1t}^i$ is an innovation process.

Detzel et al. (2018)'s first proposition poses some interesting implications as, the cryptocurrency returns are found to be predictable by MAs, best strategies are identified as linear functions of MAs and return movements are consistent with momentum effects. Under this proposition, the cryptocurrency returns can be approximated as a simple weighted average of the log prices of cryptocurrencies. Hence, for simplicity applying equal weighting in the moving averages can be adequate for predicting cryptocurrency returns. The PMA ratios are easy to calculate as follows:

$$PMA_t(L) = p_t - ma_t(L) \tag{14}$$

where p_t is the log price of the cryptocurrency, $ma_t(L) = (\frac{1}{n*L})\sum_{l=0}^{n*L-1} p_{t-l}$ and n is the number of days per week in L weeks and L = 1, 2, 4, 10, and 20 weeks. As cryptocurrency market always runs, we use n = 7 for PMAs and n = 5 for other factors. For detailed mathematical proofs and empirical design, we refer the interested reader to Detzel et al. (2018). More details about the EM approach are presented in Appendix B.1, while descriptive statistics for the PMA ratios are available in the Appendix B.2.

The EM models treats the PMA ratios as the central predictors of interest, as robust predictability is observed under different fundamentals and investors' preferences. Their true value is holds in short-term, making them a tool for capturing arbitrage in small horizons, which directly relates to AMH, and the TA analysis performed in the previous stage. It also motivates us to build upon a framework to test more fundamental factors for comparison. In order to achieve that we set up a regression framework with bivariate predictive regression regressions between cryptocurrency returns, PMA ratios and the remaining 57 factors. In a sense, we set a state variable X_t, capturing potentially unobservable factors influencing the convenience yield δ_t raised by investing in cryptocurrencies as in the following equation:

$$r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1} \tag{15}$$

where r_{t+1} is the log cryptocurrency returns and $X_{i,t}$ is one of relevant factors. where the r_{t+1} is denoted as the return on cryptocurrency on day (*t+1*); $X_{i,t}$ denotes a predictor at time *t*; and $\varepsilon_{i,t+1}$ denotes a zero-mean disturbance term. Our null hypothesis is that the predictor has no forecasting ability $(\beta_i = 0)$. Following Inoue and Kilian (2004), we set the alternative hypothesis as a one-side test in order to increase the predictive power during in-sample periods. In this way, we expect β_i to be positive for each $X_{i,t}$ under the alternative hypothesis. By using a heteroskedasticity-consistent t-statistic, we test $H_o : \beta_i = 0$ against $H_1 : \beta_i \geq 0$ for the Ordinary Least Squares (OLS) estimates of each β_i in above equation.

For testing a number of famous predictors, Stambaugh (1999) bias can potentially inflate the t-statistic for $\hat{\beta}_i$ in equation (3) and contort the test size for highly persistence $X_{i,t}$. In this way, we use the heteroskedasticity-robust test, for each bivariate model test. Taking the persistence in regressors and the correlations between cryptocurrency returns and innovation terms into account, we calculate p-values through a wild bootstrap procedure.

For the out-of-sample analysis, we calculate the statistics for each of the bivariate models by using one-day ahead expanding windows towards our whole sample. In this way, we split the whole data into several periods and apply two statistical measuring approaches. Hansen and Timmermann (2012) find that the predictive ability of out-of-sample tests can gain better size properties once the predictive measuring period is comparatively larger than the in-sample analysis period. Our design is based on a well-known benchmark, the historical average forecast which can have better performance than the selected statistical measure (Goyal and WeLFh, 2003 and Campbell and Thompson, 2008). This is estimated as:

$$\hat{r}_{t+1}^{HA} = (1/t)\sum_{s=1}^{t} r_s \tag{16}$$

Where $\hat{r}_{t+1}^{HA}$ is the expectation of average historical returns, r_s is the cryptocurrency return at times.

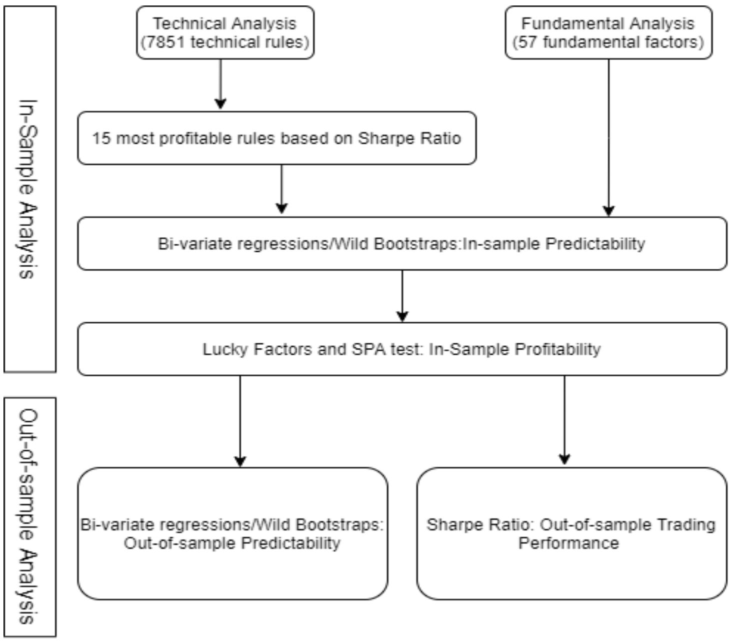
Following Campbell and Thompson (2008) and Clark and West (2007), we also apply the out-of-sample R^2 (R_{os}^2) and the adjusted Mean Square Forecast Error (MSFE-adj). The R_{os}^2 is used to gauge the difference of MSFE between our bivariate predictive model and the historical average and is specified as:

$$R_{os}^2 = 1 - (SSR_P / SST_T) \tag{17}$$

where SSR_P is the difference between cryptocurrency returns and predictive returns in the predictive set and SST_T is the difference between cryptocurrency returns and average returns in training set. Since the historical average model can be regarded as the reductive version of the predictive model, the comparison between these two models can also be treated as the test for the nested model. Following the method proposed by Diebold and Mariano (1995), MSFE-adj further ensures an approximately standard normal asymptotic distribution for the comparison between nested model and predictive forecast.

Following these procedure, predictive regressions are obtained based on the PMA ratios and the five sets of factors presented in Table 2, creating a rather more complete image in the value of TA and FA analysis in cryptocurrencies, taking under considerations the results of the previous section. Nonetheless, data-snooping issue can still be present under that setting. For that reason, as a last step we apply cross-sectional LF in order to identify which set of factors are genuinely performing and influencing the cryptocurrency returns. In this case, the dimensionality issue is not an issue as in the case of the STW universe. The numbers are manageable into 5 PMA, 14 traditional, 13 exchange rates, 10 indices, 10 BCH technology-based and 10 BTC and BTC trend-based factors. Figure 5.1 summarizes our empirical design.

Figure 4. 1Methodology Flowchart



Note: The figure presents the methodology flowchart of this study.

4.4 Empirical Results

4.5.1 In-sample Analysis

The first set of empirical findings relates to the profitability performance of the technical rules. We summarize the performance of the top fifteen performing rules based on their Sharpe ratios across all periods and series under study in Table 4.4 and Table 4.5. The table presents a mixed picture of the utility of different types of technical rules. Looking across periods and cryptocurrencies, there is no clear winner among different TA factors. There is a consistent presence of momentum rules (MAs and PMAs), while FR and CB are common in the rankings in terms of trading performance (the latter especially in the case of BTC). SR rules appear scarcely in the rankings. When evaluating the other cryptocurrencies across periods, momentum rules are usually the best or appear regularly in the top five ranking. FR have their share of success too, as they perform better in short days and with small value of multiplicative ban. This indicates that the multiplicative filter plays an important role in the best performing rules. In terms of momentum indicators, the short-term PMA (PMA1) indicator and other traditional MAs with a time delay filter or a multiplication ban tend to perform well in terms of profitability. PMAs of different lengths appear in all top five rankings, while PMA1 is consistently within the top three performing rules across periods and cryptocurrencies under study. Focusing on period 1 of BTC, the best rule (CB (5,0.075,5,0.001)) has the shortest length and the following rank of rules is constructed by the shortest time of channel in CB (5 days), PMA1 (one week) and MA (5 days).

Table 4. 4 Technical rules profitability (top 15 performing rules under the Sharpe ratio metric)

CRIX					
Technical Rule	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
MA(2,1,10)	0.452(0.010)	MA(2,1,0.001)	0.522(0.017)	MA(2,1,0.001)	0.427(0.016)
MA(2,1,0.001)	0.447(0.009)	MA(2,1,10)	0.518(0.017)	MA(2,1,2)	0.423(0.011)
FR(0.01,1)	0.429(0.009)	PMA1	0.512(0.017)	PMA1	0.414(0.015)
PMA1	0.404(0.009)	FR(0.01,1)	0.488(0.016)	FR(0.01,1)	0.412(0.015)
MA(2,1,0.005)	0.400(0.009)	MA(2,1,0.005)	0.484(0.016)	FR(0.015,1)	0.410(0.011)
FR(0.005,2)	0.389(0.008)	FR(0.015,1)	0.473(0.016)	FR(0.06,1)	0.402(0.014)
FR(0.01,2)	0.377(0.008)	FR(0.015,6)	0.458(0.015)	FR(0.005,1)	0.399(0.014)
FR(0.005,1)	0.370(0.010)	FR(0.06,1)	0.444(0.015)	SR(5,4,10)	0.398(0.011)
FR(0.01,3)	0.367(0.008)	MA(2,1,0.01)	0.439(0.014)	FR(0.01,1)	0.396(0.014)
FR(0.015,1)	0.362(0.008)	FR(0.005,2)	0.433(0.015)	FR(0.07,1)	0.395(0.014)
FR(0.005,3)	0.361(0.008)	FR(0.015,2)	0.424(0.015)	FR(0.015,6)	0.384(0.014)
FR(0.015,2)	0.350(0.008)	FR(0.01,2)	0.420(0.014)	MA(2,1,10)	0.382(0.014)
FR(0.015,3)	0.344(0.008)	FR(0.07,1)	0.416(0.014)	SR(10,2,5)	0.381(0.010)
FR(0.01,3)	0.343(0.008)	SR(5,2,10)	0.415(0.011)	FR(0.08,1)	0.380(0.014)
FR(0.015,7)	0.334(0.007)	SR(5,3,10)	0.411(0.011)	SR(10,3,5)	0.377(0.010)
Benchmark	0.105(0.003)		0.198(0.005)		0.162(0.004)

XRP					
Technical Rule	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
MA(5,2,5)	0.209(0.019)	FR(0.045,0.01)	0.281(0.027)	MA(2,1,0.01)	0.294(0.027)
PMA1	0.157(0.014)	PMA1	0.209(0.021)	MA(2,1,0.02)	0.211(0.020)
MA(5,2,2)	0.124(0.012)	FR(0.01,3)	0.170(0.017)	PMA1	0.181(0.010)
PMA2	0.096(0.009)	FR(0.045,0.01)	0.135(0.013)	MA(2,1,0.01)	0.169(0.016)
PMA4	0.083(0.008)	FR(0.14,10)	0.129(0.013)	MA(2,1,0.02)	0.163(0.008)
MA(5,2,5)	0.078(0.007)	FR(0.005,3)	0.123(0.012)	MA(2,1,0.015)	0.162(0.008)
MA(5,2,2)	0.075(0.007)	PMA20	0.122(0.012)	MA(2,1,0.005)	0.160(0.013)
FR(0.005,5)	0.074(0.007)	MA(40,25,0.05)	0.121(0.008)	MA(2,1,0.03)	0.157(0.005)
FR(0.045,5)	0.073(0.007)	FR(0.045,50)	0.118(0.012)	FR(0.005,3)	0.153(0.014)
FR(0.025,5)	0.072(0.007)	MA(40,25,0.01)	0.117(0.012)	MA(2,1,0.001)	0.152(0.014)
FR(0.045,25)	0.069(0.006)	FR(0.14,5)	0.116(0.011)	MA(2,1,5)	0.150(0.014)
FR(0.045,10)	0.067(0.006)	MA(40,25,0.04)	0.115(0.008)	FR(0.005,1)	0.148(0.014)
FR(0.14,1)	0.066(0.006)	FR(0.01,3)	0.114(0.011)	MA(5,1,0.04)	0.141(0.007)
FR(0.5,0.005)	0.065(0.006)	FR(0.12,0.005)	0.113(0.011)	FR(0.005,2)	0.140(0.013)
FR(0.01,5)	0.064(0.006)	FR(0.045,0.005)	0.112(0.011)	MA(2,1,0.04)	0.138(0.004)
Benchmark	0.055(0.005)		0.132(0.009)		0.117 0.007)

Note: This table presents the Sharpe ratios and mean returns (in parentheses) of the top 15 technical rules for the BTC, ETH, XRP and CRIX. PMA denotes the log-price to MAs ratio (e.g., PMA1 is the PMA ratio generated by one-week gap). MA are Moving Average rules (e.g., MA(5,1,5) denotes the MA rule with 5-day slow MA, 1-day fast MA and 5-day position held). FR represents the Filter Rule (e.g., FR(0.005,4) denotes a 0.005% change of price with 4 days of constant holding period). CB denotes the Channel-Break rule (e.g., CB(5,0.15,5,0) denotes the 5 days of channel, 0.15 difference between the high and low channel, 5 days of constant holding period and 0 percentage band). SR denotes the Support and Resistance rule (e.g., SR (2,2,1) means 2 days to generate extrema, 2 days for time delay of transaction and 1 day of constant holding period). As benchmark a BH strategy is used. 50%, 75% and 90% IS denotes that we use as in-sample the 50%, 75% and 90% of the total dataset in period 1, period 2 and period 3 respectively.

Table 4. 5 Technical rules profitability (top 15 performing rules under the Sharpe ratio metric)

Rank	Technical Rule	Period 1 (50%IS) 08/08/2015-05/04/2017	Technical Rule	Period 2 (75% IS) 08/08/2015-06/02/2018	Technical Rule	Period 3 (90% IS) 08/08/2015-03/08/2018
			BTC			
1	CB(5,0.075,5,0.001)	0.381(0.011)	CB(5,0.075,5,0)	0.427(0.016)	MA(5,1,5)	0.453(0.015)
2	CB(5,0.075,5,0)	0.338(0.006)	PMA1	0.421(0.014)	CB(5,0.075,5,0)	0.449(0.017)
3	PMA1	0.334(0.006)	MA(5,1,5)	0.403(0.010)	PMA1	0.433(0.011)
4	CB(5,0.075,5,0)	0.328(0.006)	CB(5,0.075,5,0.001)	0.399(0.010)	CB(5,0.075,5,0.001)	0.428(0.011)
5	CB(5,0.075,5,0.001)	0.323(0.006)	CB(5,0.075,5,0.005)	0.385(0.010)	CB(5,0.075,5,0.005)	0.415(0.011)
6	MA(5,1,5)	0.319(0.007)	MA(5,2,2)	0.368(0.011)	MA(5,1,2)	0.411(0.013)
7	CB(5,0.075,5,0.005)	0.318(0.006)	CB(5,0.075,5,0.01)	0.363(0.009)	CB(5,0.075,5,0.01)	0.392(0.010)
8	CB(5,0.075,5,0)	0.313(0.005)	MA(5,2,0)	0.359(0.013)	MA(5,2,2)	0.384(0.012)
9	CB(5,0.075,5,0.001)	0.308(0.005)	SR(250,2,5)	0.355(0.008)	CB(5,0.075,5,0)	0.378(0.009)
10	CB(5,0.075,5,0.005)	0.307(0.005)	MA(5,1,0.001)	0.354(0.013)	CB(5,0.075,5,0.001)	0.373(0.009)
11	CB(5,0.075,5,0.01)	0.293(0.006)	CB(5,0.075,5,0)	0.353(0.008)	CB(5,0.075,5,0.015)	0.372(0.010)
12	MA(5,2,2)	0.291(0.006)	MA(5,1,0.005)	0.352(0.012)	MA(5,2,0)	0.370(0.013)
13	CB(5,0.075,5,0.005)	0.290(0.005)	SR(250,3,5)	0.350(0.008)	MA(5,1,0.005)	0.369(0.013)
14	MA(5,2,0)	0.287(0.007)	CB(5,0.075,5,0.001)	0.348(0.008)	MA(5,1,0.05)	0.368(0.013)
15	MA(5,1,0.05)	0.285(0.007)	CB(5,0.075,5,0.015)	0.343(0.009)	MA(5,1,0.001)	0.367(0.013)
	Benchmark	0.091 (0.003)		0.164(0.005)		0.145(0.004)
			ETH			
Rank	**Technical Rule**	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
1	FR(0.015,5)	0.407(0.028)	MA(2,1,0.005)	0.432(0.029)	MA(2,1,0.005)	0.430(0.028)
2	PMA2	0.313(0.022)	FR (0.005,1)	0.330(0.023)	PMA1	0.324(0.021)
3	PMA1	0.221(0.016)	PMA1	0.236(0.017)	MA(2,1,0.001)	0.286(0.016)
4	FR(0.01,3)	0.163(0.011)	FR(0.01,1)	0.226(0.013)	PMA2	0.282(0.014)
5	MA(30,15,5)	0.157(0.010)	MA(2,1,0.01)	0.211(0.011)	PMA4	0.271(0.015)
6	PMA4	0.106(0.005)	PMA2	0.201(0.012)	FR(0.005,1)	0.268(0.015)
7	PMA10	0.105(0.005)	PMA4	0.200(0.010)	MA(2,1,0.01)	0.265(0.013)
8	PMA20	0.102(0.005)	FR(0.01,2)	0.197(0.012)	MA(2,1,5)	0.259(0.015)
9	FR (0.01,1)	0.100(0.005)	FR(0.06,1)	0.194(0.011)	FR(0.01,2)	0.255(0.014)
10	FR (0.05,1)	0.096(0.005)	FR(0.015,6)	0.192(0.011)	FR(0.015,1)	0.250(0.014)
11	MA(30,25,2)	0.095(0.005)	MA(2,1,5)	0.191(0.011)	MA(2,1,0.015)	0.248(0.011)
12	MA(25,5,5)	0.094(0.005)	FR(0.015,1)	0.190(0.011)	FR(0.015,6)	0.247(0.014)
13	FR (0.12,0.01)	0.093(0.005)	MA(2,1,0.015)	0.188(0.008)	FR(0.005,2)	0.245(0.014)
14	MA(30,25,5)	0.092(0.005)	FR(0.005,2)	0.186(0.011)	FR(0.06,1)	0.242(0.014)
15	FR (0.16,1)	0.091(0.004)	FR(0.015,2)	0.181(0.011)	FR(0.015,2)	0.238(0.013)
	Benchmark	0.125 (0.01)		0.209 (0.01)		0.187(0.008)

Note: This table presents the Sharpe ratios and mean returns (in parentheses) of the top 15 technical rules for the BTC, ETH, XRP and CRIX. PMA denotes the log-price to MAs ratio (e.g., PMA1 is the PMA ratio generated by one-week gap). MA are Moving Average rules (e.g., MA(5,1,5) denotes the MA rule with 5-day slow MA, 1-day fast MA and 5-day position held). FR represents the Filter Rule (e.g., FR(0.005,4) denotes a 0.005% change of price with 4 days of constant holding period). CB denotes the Channel-Break rule (e.g., CB(5,0.15,5,0) denotes the 5 days of channel, 0.15 difference between the high and low channel, 5 days of constant holding period and 0 percentage band). SR denotes the Support and Resistance rule (e.g., SR (2,2,1) means 2 days to generate extrema, 2 days for time delay of transaction and 1 day of constant holding period). As benchmark a BH strategy is used. 50%, 75% and 90% IS denotes that we use as in-sample the 50%, 75% and 90% of the total dataset in period 1, period 2 and period 3 respectively.

Similar results are found in CRIX and XRP where good performance rules are mainly constituted by short days of rules, i.e., 2-day or 5-day slow MA and 1-day or 2-day fast MA lines with fixed multiplicative band. Not surprisingly, the high volatility of the daily BTC prices is the most likely reason for the fixed percentage band filter performing better than the time delay filter. In all cases, the top performing rules beat the BH benchmark in terms of the Sharpe ratio and mean returns. Period 2 seems to have the best performance compared to periods 1 and 3 in terms of mean returns. To be more specific, we find mean returns of 0.016, 0.027, 0.029 and 0.017 for the BTC, XRP, ETH and CRIX respectively. Moreover, the highest observed Sharpe ratios are 0.522 (CRIX – period 2), 0.453 (BTC – period 3), 0.432 (ETH – period 2) and 0.294 (XRP – period 3). Technical rules consistently performing better than the BH strategy indicates that there is utility of TA in the cryptocurrency market.

We move to explore the predictability of the high-performing rules and the selected fundamental factors through the bivariate regression framework and the wild bootstrap. The in-sample examination and the corresponding results are given in Figures 4.2 to Figure 4.7. The figures present the in-sample analysis for the BTC and ETH, XRP and CRIX for three different lengths of forecasting exercises (F1, F2 and F3). Focusing on the BTC, we find that several TA factors have predictive power in all our samples. For example, in F1 (Panel A) CB rules with short periods of channels (CB (5,0.075,5,0.01) and CB (5,0.075,5,0.005)) and the shortest PMA ratio (PMA1) have better forecasting ability than other TA factors. Although different CB rules seem to be significant in F2 and F3, the only consistent performance across all cryptocurrencies and forecasting exercises is that of PMA1. This is in line with Detzel et al. (2020) where PMA ratios have both high trading performance and predictive power in cryptocurrencies. In the cases of ETH, XRP and CRIX, we observe PMA2, MAs and FRs with short periods having predictive power in cryptocurrency returns but this performance is not as consistent as it appears for PMA1. In terms of fundamental factors, the HSH (Figure 4.3) is notably robust across all cases within all forecasting exercises. RMB (Figure 4.4) is also found to be statistically significant in most cases in-sample. For BTC and ETH, another factor from BCH-related information, MD (Figure 4.3) is useful in prediction. Conventional financial indicators such as OIL (Figure 4.7) and GLD (Figure 4.7) also show forecasting ability in ETH. Popular online media factors, like Google Trends and Wikipedia search numbers of BTC (Btc-GT and Btc-W from Figure 4.2) seem to have forecasting ability only in F1. This can be explained by the fact that access to relevant information in the early stages of BCH is mainly narrative-based on online resources, therefore the online media can influence the cryptocurrency market (Ciaian et al., 2016). As suggested by Li and Wang (2017), this impact gradually erodes as practitioners become more knowledgeable with BCH-related information. This is also supported by our findings as neither F2 nor F3 provide significant statistics for online media factors. Eth-GT and Eth-W from Panel C seem to have predictability over BTC but not the other cryptocurrencies. Finally, the EPU factor (Figure 4.3) is found to be significant in terms of CRIX predictability. Overall, our in-sample analysis on the predictability of the factors employed shows that there is value in TA and FA when it comes to cryptocurrency prediction.

Figure 4. 2 In-sample Predictive Regression Estimation Results (Bitcoin and Blockchain Trend-based Factors)

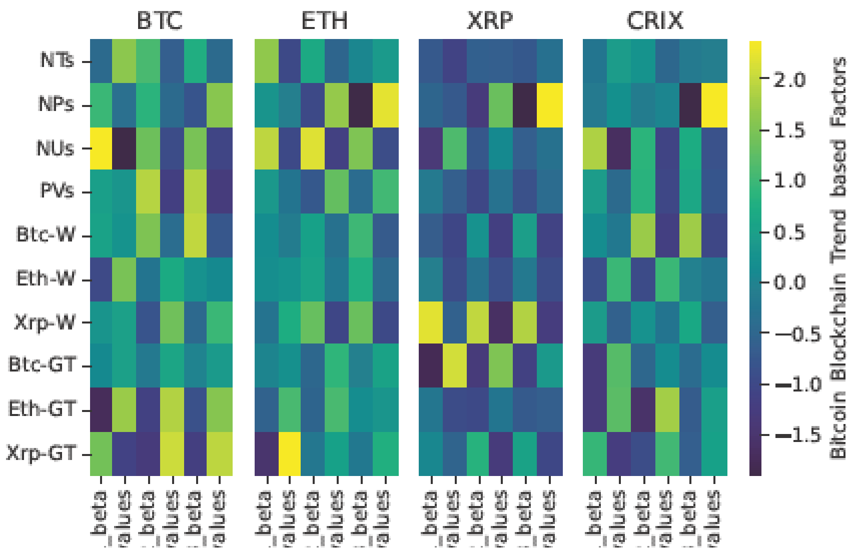


Figure 4. 3 In-sample Predictive Regression Estimation Results (Blockchain Technology based Factors)

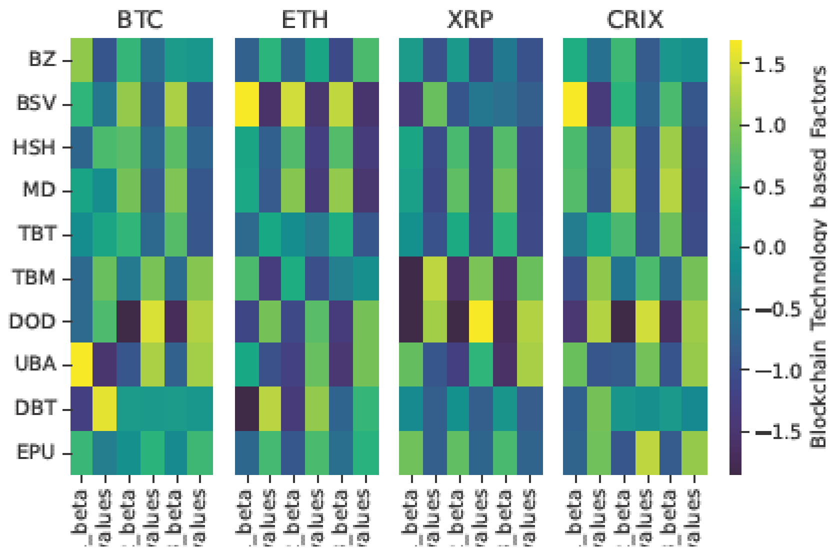


Figure 4. 4 In-sample Predictive Regression Estimation Results (Multiple Currency Factors)

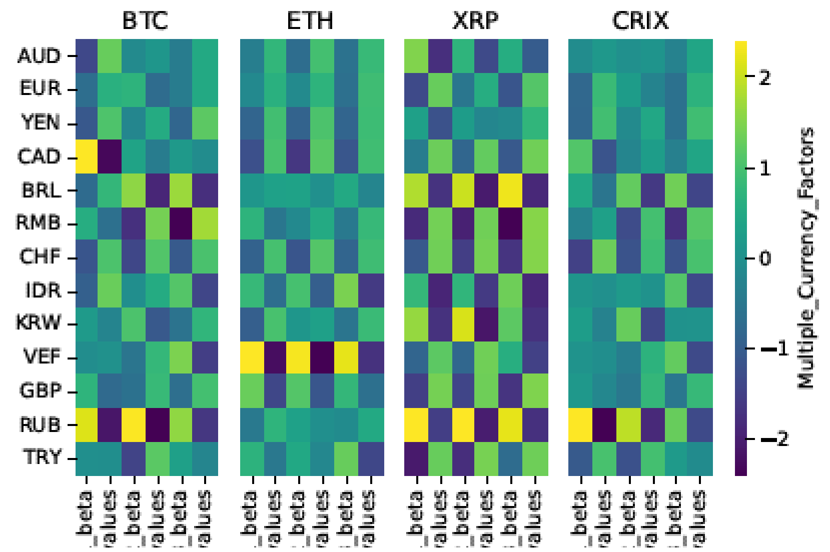


Figure 4. 5 In-sample Predictive Regression Estimation Results (Multiple Stock Factors)

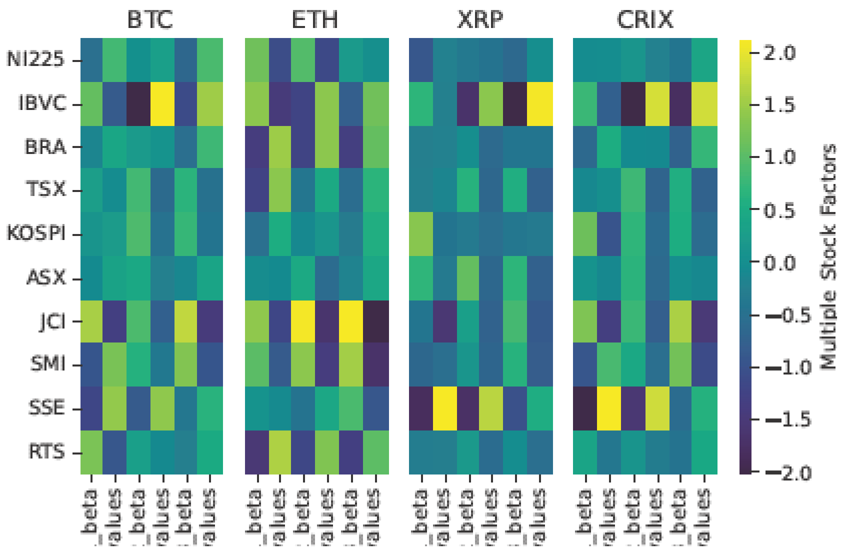
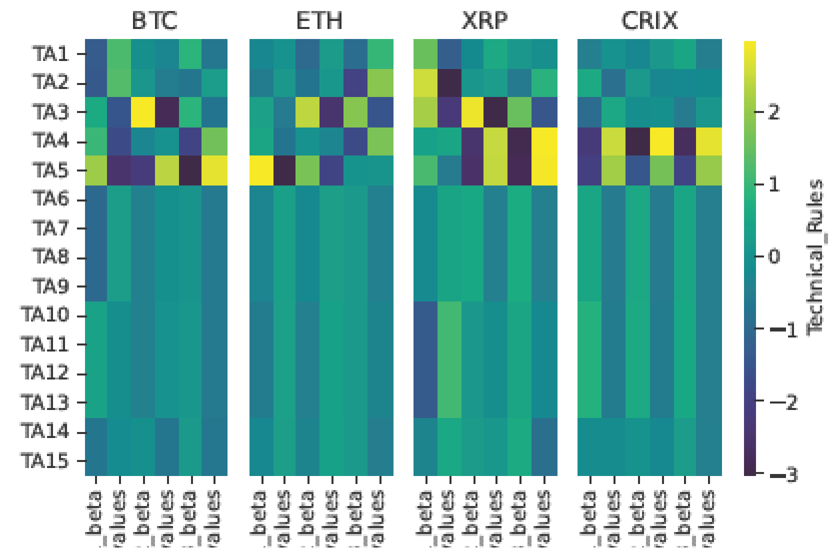
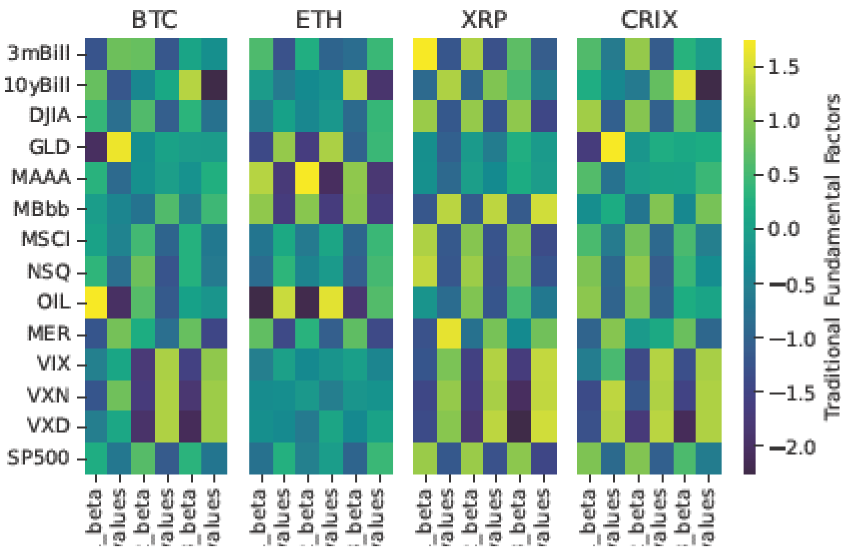


Figure 4. 6 In-sample Predictive Regression Estimation Results (Technical Rules)



Note: For illustration purpose, top fifteen technical rules are abbreviated as TA1 to TA15. Details of rules can be referred to Table 4.4 to Table 4.5.

Figure 4. 7 In-sample Predictive Regression Estimation Results (Traditional Fundamental Factors)



Given the largely utilized dataset and the several factors employed across the different horizons, serious questions of data-snooping bias are raised. Additionally, we want to test the in-sample profitability of the selected factors in an MHT framework. Hence, we further apply the LFs method and the SPA test to confirm our results. These findings are reported in Tables 4.10-4.12.

When interpreting these results, we focus on the R^2, the p-value of the LFs method and the p-value of the SPA test. These three elements summarize the utility of each factor individually and in an MHT setting. In each period, we collect all the factors that show predictability in the in-sample study into a factor pool and then apply the LFs and the SPA test to examine their statistical significance. For a factor to be genuinely significant, we expect the R^2 to be positive and the p-value as small as possible. Nonetheless, the hurdle rate of significance level is rather a subjective decision (Harvey et al., 2016), we apply 5% as cut-off point in this paper. In terms of the SPA test, we report the p-value by benchmarking each individual factor among all the significant factors in the pool. For example, in the case of the BTC and period 1, the largest R^2 (0.188) is matched to the PMA1 and the corresponding p-value of the LFs is 0.03. In addition, the p-value (0.002) of the SPA test further affirms our conclusion that the profitability of PMA1 is genuine and free from data-snooping bias. The second largest R^2 (0.158) is from the HSH factor and the corresponding LFs and SPA p-values are 0.04 and 0.004. Thus, we can declare both the HSH and PMA1 of BTC (period 1) as genuinely profitable in period 1. Having found two factors allows us to proceed with LF once more to explore the value of the remaining factors with PMA1 as the baseline. Unsurprisingly, HSH is the only significant factor in both the SPA and LFs at this stage. This process continues until no more factors are found to be significant in the third-round test, which is the case when PMA1 and HSH are used as baselines in Panel 3. We, thereby, can declare that only PMA1 and HSH have genuine profitability for BTC in period 1. Similar results are identified across different periods in all four series. Hence, we conclude confidently that the PMA1 and HSH have true value in cryptocurrency trading in a MHT setting and their profitability is genuine and not attributed to data-snooping bias. Combining these findings with those extracted earlier, we conclude that only one technical indicator (PMA1) and one fundamental factor (HSH) seem to be predicting consistently the cryptocurrency returns while having genuine profitability across all the cryptocurrencies and forecasting exercises in-sample. It is interesting to see whether this is confirmed also in our out-of-sample analysis that follows.

Table 4. 6 Lucky factors and SPA test summary (50% IS)

BTC

Panel 1: Baseline = No Factor (Period1)				Panel 2: Baseline = PMA1 Factor (Period1)				Panel 3: Baseline = PMA1 + HSH Factor (Period1)			
	R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)
Eth-W	0.005	0.54	0.7	**Eth-W**	0.055	0.47	0.7	**Eth-W**	0.004	0.51	0.926
Eth-GT	0.008	0.52	0.762	**Eth-GT**	0.005	0.5	0.762	**Eth-GT**	0.003	0.45	0.981
RMB	0.003	0.31	0.707	**RMB**	0.014	0.51	0.707	**RMB**	0.002	0.48	0.977
HSH	0.158	0.04	0.004	**HSH**	**0.178**	**0.035**	**0.004**	**MD**	0.024	0.48	0.893
MD	0.058	0.48	0.97	**MD**	0.005	0.16	0.97	**CB(5,0.075,5,0.01)**	0.019	0.5	0.91
PMA1	**0.188**	**0.03**	**0.002**	**CB(5,0.075,5,0.01)**	0.006	0.18	0.972	**CB(5,0.075,5,0.005)**	0.012	0.51	0.926
CB(5,0.075,5,0.01)	0.031	0.59	0.989	**CB(5,0.075,5,0.005)**	0.006	0.18	0.972		-		
CB(5,0.075,5,0.005)	0.082	0.58	0.999		-						

ETH

Panel 1: Baseline = No Factor (Period1)				Panel 2: Baseline = HSH Factor (Period1)				Panel 3: Baseline = PMA1 + HSH Factor (Period1)			
	R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)
GLD	0.036	0.43	1	**GLD**	0.031	0.52	0.876	**GLD**	0.039	0.59	0.996
OIL	0.042	0.51	0.867	**OIL**	0.024	0.56	0.938	**OIL**	0.079	0.57	0.895
HSH	**0.187**	**0.05**	**0.006**	**MD**	0.061	0.53	0.962	**MD**	0.076	0.53	1
MD	0.056	0.46	0.92	**RMB**	0.074	0.5	0.774	**RMB**	0.064	0.48	0.964
RMB	0.011	0.34	0.876	**PMA1**	**0.108**	**0.04**	**0.002**		-		
PMA1	0.181	0.05	0.007								

XRP

Panel 1: Baseline = No Factor (Period1)				Panel 2: Baseline = HSH Factor (Period1)				Panel 3: Baseline = PMA1 + HSH Factor (Period1)			
	R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)
RMB	0.004	0.566	0.859	**RMB**	0.005	0.705	0.96	**RMB**	0.019	0.46	0.93
HSH	**0.23**	**0.072**	**0.097**	**PMA1**	**0.196**	**0.045**	**0.998**	**PMA4**	0.071	0.45	0.993
PMA1	0.187	0.045	0.026	**PMA4**	0.033	0.46	0.986	**MA(5,2,5)**	0.073	0.46	0.981
PMA4	0.023	0.438	0.879	**MA(5,2,5)**	0.032	0.46	0.952	**FR(0.005,5)**	0.041	0.84	0.932
MA(5,2,5)	0.032	0.47	0.88	**FR(0.005,5)**	0.021	0.49	0.892				
FR(0.005,5)	0.004	0.566	0.659					-			

CRIX

Panel 1: Baseline = No Factor (Period1)				Panel 2: Baseline = HSH Factor (Period1)				Panel 3: Baseline = PMA1 + HSH Factor (Period1)			
	R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)
HSH	**0.17**	**0.025**	**0.051**	**RMB**	0.023	0.705	0.997	**RMB**	0.035	0.65	0.956
RMB	0.019	0.618	0.698	**EPU**	0.028	0.59	0.966	**EPU**	0.028	0.655	0.946
EPU	0.023	0.55	0.881	**MA(2,1,10)**	0.021	0.62	0.961	**MA(2,1,10)**	0.026	0.67	0.915
MA(2,1,10)	0.017	0.53	0.656	**PMA1**	**0.129**	**0.026**	**0.006**	**FR(0.005,2)**	0.023	0.645	0.817
PMA1	0.115	0.042	0.076	**FR(0.005,2)**	0.017	0.59	0.889				
FR(0.005,2)	0.013	0.516	0.97					**-**			

Note: This table reports the statistics (R^2) and the corresponding p-value using the LFs method and the p-value using SPA test. In boldface are the values corresponding to the factors that are found significant in each step of the process. 50% IS corresponds to period 1 as outlined in Table 5.4. The baseline model refers to the model that includes the pre-selected factors.

Table 4. 7 Lucky factors and SPA test summary (75% IS)

BTC

Panel 1: Baseline = No Factor (Period2)				Panel 2: Baseline = PMA1 Factor (Period2)				Panel 3: Baseline = PMA1 + HSH Factor (Period2)			
	R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)
Eth-W	0.020	0.556	0.700	**Eth-W**	0.043	0.560	0.700	**Eth-W**	0.063	0.575	0.926
Eth-GT	0.043	0.526	0.762	**Eth-GT**	0.028	0.680	0.762	**Eth-GT**	0.048	0.580	0.981
RMB	0.025	0.584	0.707	**RMB**	0.026	0.595	0.707	**RMB**	0.044	0.590	0.977
HSH	0.102	0.060	0.012	**HSH**	**0.112**	**0.045**	**0.002**	**MD**	0.044	0.600	0.893
MD	0.015	0.544	0.970	**MD**	0.020	0.650	0.97	**CB(5,0.075,5,0.01)**	0.019	0.499	0.910
PMA1	**0.115**	**0.045**	**0.007**	**CB(5,0.075,5,0.01)**	0.031	0.496	0.751	**CB(5,0.075,5,0)**	0.012	0.51	0.926
CB(5,0.075,5,0.01)	0.031	0.590	0.989	**CB(5,0.075,5,0)**	0.027	0.674	0.782		-		
CB(5,0.075,5,0)	0.082	0.580	0.999		-						

ETH

Panel 1: Baseline = No Factor (Period2)				Panel 2: Baseline = HSH Factor (Period2)				Panel 3: Baseline = PMA1 + HSH Factor (Period2)			
	R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)
GLD	0.025	0.580	1	**GLD**	0.027	0.505	0.876	**GLD**	0.032	0.685	0.996
OIL	0.027	0.584	0.867	**OIL**	0.027	0.54	0.938	**OIL**	0.027	0.655	0.895
HSH	**0.142**	**0.002**	**0.003**	**MD**	0.026	0.515	0.962	**MD**	0.031	0.679	1
MD	0.025	0.588	0.92	**RMB**	0.026	0.485	0.774	**RMB**	0.029	0.675	0.964
RMB	0.025	0.586	0.876	**PMA1**	**0.128**	**0.005**	**0.002**	**FR(0.01,1)**	0.037	0.538	0.748
PMA1	0.126	0.004	0.004	**FR(0.01,1)**	0.037	0.402	0.682				
FR(0.01,1)	0.039	0.427	0.721								

XRP

Panel 1: Baseline = No Factor (Period2)				Panel 2: Baseline = HSH Factor (Period2)				Panel 3: Baseline = PMA1 + HSH Factor (Period2)			
	R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)
RMB	0.012	0.614	0.859	**RMB**	0.012	0.695	0.96	**RMB**	0.039	0.505	0.93
HSH	**0.145**	**0.042**	**0.006**	**PMA1**	**0.139**	**0.004**	**0.001**	**FR(0.14,10)**	0.033	0.515	0.993
PMA1	0.132	0.048	0.007	**FR(0.14,10)**	0.033	0.42	0.986	**FR(0.005,3)**	0.043	0.465	0.981
FR(0.14,10)	0.023	0.44	0.879	**FR(0.005,3)**	0.043	0.415	0.952	**MA(40,25,0.05)**	0.043	0.475	0.932
FR(0.005,3)	0.037	0.438	0.88	**MA(40,25,0.05)**	0.043	0.41	0.892				
MA(40,25,0.05)	0.037	0.452	0.659					-			

CRIX

Panel 1: Baseline = No Factor (Period2)				Panel 2: Baseline = HSH Factor (Period2)				Panel 3: Baseline = PMA1 + HSH Factor (Period2)			
	R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)		R^2	LF (p-value)	SPA (p-value)
HSH	**0.132**	**0.008**	**0.015**	**RMB**	0.047	0.585	0.997	**RMB**	0.056	0.6	0.956
RMB	0.044	0.56	0.698	**EPU**	0.041	0.595	0.966	**EPU**	0.056	0.575	0.946
EPU	0.026	0.578	0.881	**MA(2,1,0.001)**	0.041	0.525	0.961	**MA(2,1,0.001)**	0.055	0.575	0.915
MA(2,1,0.001)	0.031	0.622	0.656	**PMA1**	**0.042**	**0.545**	**0.896**	**FR(0.015,1)**	0.048	0.605	0.817
PMA1	0.133	0.008	0.016	**FR(0.015,1)**	0.034	0.6	0.889				
FR(0.015,1)	0.024	0.586	0.97					**-**			

Note: This table reports the statistics (R^2) and the corresponding p-value using the LFs method and p-value using the SPA test. In boldface are the values corresponding to the factors that are found significant in each step of the process. 75% IS corresponds to period 2 as outlined in Table 5.4. The baseline model refers to the model that includes the pre-selected factors.

Table 4. 8 Lucky factors and SPA test summary (90% IS)

BTC											
Panel 1: Baseline = No Factor (Period3)				**Panel 2: Baseline = PMA1 Factor (Period3)**				**Panel 3: Baseline = PMA1 + HSH Factor (Period3)**			
	$\boldsymbol{R^2}$	**LF (p-value)**	**SPA (p-value)**		$\boldsymbol{R^2}$	**LF (p-value)**	**SPA (p-value)**		$\boldsymbol{R^2}$	**LF (p-value)**	**SPA (p-value)**
Eth-W	0.017	0.592	0.700	**Eth-W**	0.031	0.585	0.697	**Eth-W**	0.032	0.661	0.926
Eth-GT	0.029	0.554	0.762	**Eth-GT**	0.018	0.58	0.762	**Eth-GT**	0.035	0.655	0.981
RMB	0.014	0.600	0.707	**RMB**	0.021	0.600	0.707	**RMB**	0.033	0.662	0.977
HSH	0.016	0.606	0.004	**HSH**	**0.019**	**0.589**	**0.004**	**MD**	0.033	0.656	0.893
MD	0.013	0.572	0.970	**MD**	0.019	0.585	0.970	**CB(5,0.075,5,0.01)**	0.019	0.497	0.910
PMA1	**0.013**	**0.572**	**0.002**	**CB(5,0.075,5,0.01)**	0.006	0.179	0.972	**CB(5,0.075,5,0.015)**	0.012	0.510	0.926
CB(5,0.075,5,0.01)	0.031	0.590	0.989	**CB(5,0.075,5,0.015)**	0.006	0.178	0.972		-		
CB(5,0.075,5,0.015)	0.082	0.580	0.999	-							
ETH											
Panel 1: Baseline = No Factor (Period3)				**Panel 2: Baseline = HSH Factor (Period3)**				**Panel 3: Baseline = PMA1 + HSH Factor (Period3)**			
	$\boldsymbol{R^2}$	**LF (p-value)**	**SPA (p-value)**		$\boldsymbol{R^2}$	**LF (p-value)**	**SPA (p-value)**		$\boldsymbol{R^2}$	**LF (p-value)**	**SPA (p-value)**
GLD	0.021	0.551	1	**GLD**	0.026	0.621	0.876	**GLD**	0.028	0.545	0.996
OIL	0.026	0.532	0.867	**OIL**	0.025	0.555	0.938	**OIL**	0.026	0.551	0.895
HSH	**0.121**	**0.038**	**0.003**	**MD**	0.024	0.545	0.962	**MD**	0.029	0.575	1
MD	0.022	0.514	0.921	**RMB**	0.021	0.562	0.774	**RMB**	0.028	0.555	0.964
RMB	0.018	0.542	0.876	**PMA1**	0.123	0.005	0.001	**PMA2**	0.047	0.356	0.607
PMA1	0.119	0.054	0.004	**PMA2**	0.034	0.397	0.624				
PMA2	0.027	0.417	0.541								
XRP											
Panel 1: Baseline = No Factor (Period3)				**Panel 2: Baseline = HSH Factor (Period3)**				**Panel 3: Baseline = PMA1 + HSH Factor (Period3)**			
	$\boldsymbol{R^2}$	**LF (p-value)**	**SPA (p-value)**		$\boldsymbol{R^2}$	**LF (p-value)**	**SPA (p-value)**		$\boldsymbol{R^2}$	**LF (p-value)**	**SPA (p-value)**
RMB	0.011	0.578	0.859	**RMB**	0.011	0.635	0.96	**RMB**	0.032	0.545	0.931
HSH	**0.125**	**0.016**	**0.007**	**PMA1**	**0.132**	**0.005**	**0.002**	**MA(2,1,0.02)**	0.027	0.551	0.993
PMA1	0.106	0.007	0.003	**MA(2,1,0.02)**	0.027	0.425	0.986	**MA(2,1,0.015)**	0.035	0.512	0.981
MA(2,1,0.02)	0.017	0.471	0.879	**MA(2,1,0.015)**	0.034	0.411	0.952	**MA(2,1,0.02)**	0.031	0.508	0.932
MA(2,1,0.015)	0.031	0.468	0.883	**MA(2,1,0.02)**	0.031	0.417	0.892				
MA(2,1,0.02)	0.011	0.578	0.659					-			
CRIX											
Panel 1: Baseline = No Factor (Period3)				**Panel 2: Baseline = HSH Factor (Period3)**				**Panel 3: Baseline = PMA1 + HSH Factor (Period3)**			
	$\boldsymbol{R^2}$	**LF (p-value)**	**SPA (p-value)**		$\boldsymbol{R^2}$	**LF (p-value)**	**SPA (p-value)**		$\boldsymbol{R^2}$	**LF (p-value)**	**SPA (p-value)**
HSH	**0.124**	**0.042**	**0.025**	**RMB**	0.035	0.652	0.897	**RMB**	0.042	0.575	0.956
RMB	0.031	0.522	0.698	**EPU**	0.032	0.661	0.866	**EPU**	0.044	0.555	0.946
EPU	0.018	0.506	0.881	**MA(2,1,0.001)**	0.033	0.597	0.861	**MA(2,1,0.001)**	0.042	0.563	0.915
MA(2,1,0.001)	0.024	0.573	0.656	**PMA1**	**0.131**	**0.026**	**0.006**	**FR(0.06,1)**	0.041	0.542	0.817
PMA1	0.123	0.024	0.016	**FR(0.06,1)**	0.021	0.613	0.889				
FR(0.06,1)	0.024	0.542	0.972					**-**			

Note: This table reports the statistics (R^2) and the corresponding p-value using the LFs method and the p-value using the SPA test. In bold are the values corresponding to the factors that are found significant in each step of the process. 90% IS corresponds to period 1 as outlined in Table 5.4. The baseline model refers to the model that includes the pre-selected facto

4.5.2 Out-of-sample analysis

Our in-sample analysis revealed only 1 TA rule and 1 FA factor that possess both predictability and statistical significance in trading cryptocurrencies. In this section, we extend our analysis in the out-of-sample. Instead of focusing on only these two elements, we present our results for all the TA and FA elements that possess in-sample predictability (see Tables 5.13-5.16). We investigate the predictive power using the R_{OS}^2 and MSFE-adj statistics to test the null hypothesis that the historical average forecast MSFE is less than or equal to the computed MSFE. The R_{OS}^2 measures the proportional reduction in MSFE from the bivariate predictive model to the historical average (Campbell and Thompson, 2007). Positive (negative) R_{OS}^2 implies that the bivariate predictive model performs better (worse) than the historical average. We summarize our results in Tables 4.13-4.16. From the tables, we observe that in the selected out-of-sample periods, only HSH and PMA1 yield positive R_{OS}^2 with statistical significance across different horizons, hence possess predictability in the out-of-sample. Our in-sample and out-of-sample analysis confirms that only 1 out of 57 FA factors and 1 out of 15 top performing TA rules possess genuine forecasting ability in the cryptocurrency market that can be exploited in the out-of-sample. Our out-of-sample results highlight that traditional momentum rules are not robust in capturing cryptocurrency movements, as documented in the cryptocurrency literature, but the novel PMA1 can consistently do that.

In addition, previous studies have shown that BCH information (e.g., mining difficulty) causes price changes in the cryptocurrency market, especially in the BTC market, but its impact decreases gradually over time. We show that HSH, standing for the magnitude of the computational power towards mining BTC, has a positive relationship with the cryptocurrency returns. The major concerns in cryptocurrency investment are the security and regulation risks associated with hacking and shadow banking. BTC "attackers" must control more than 51% of the all the HSH capacity, hence HSH reflects the overall health of the cryptocurrency market. In other words, higher HSH insinuates a healthier BTC market, which in turns influences positively the cryptocurrency investment.

Table 4. 9 Out-of-sample Predictive Regression Estimation Results (F1: 50% IS)

	Panel A: Technical Rules								Panel B: Traditional Fundamental Factors			
	BTC		**ETH**		**XRP**		**CRIX**		**BTC**	**ETH**	**XRP**	**CRIX**
CB(5,0.075,5,0.001)	-0.009	**FR(0.015,5)**	0.007	**MA(5,2,5)**	0.224	**MA(2,1,10)**	0.002	**3mBill**	-0.011	-0.034	-0.069	-0.007
	(0.241)		(0.577)		(0.313)		(0.37)		(1.124)	(1.397)	(1.142)	(1.163)
CB(5,0.075,5,0)	-0.009	**PMA2**	-0.011	**PMA1**	**0.036***	**MA(2,1,0.001)**	-0.017	**10yBill**	-0.015	-0.029	-0.054	-0.006
	(0.357)		(0.583)		**(1.279)**		(0.346)		(0.9)	(1.242)	(1.468)	(1.04)
PMA1	**0.01***	**PMA1**	**0.424***	**MA(5,2,2)**	0.198	**FR(0.01,1)**	0.002	**DJIA**	-0.02	-0.033	-0.051	-0.014
	(1.412)		**(1.661)**		(0.288)		(0.248)		(1.085)	(1.342)	(1.209)	(1.107)
CB(5,0.075,5,0)	-0.001	**FR(0.01,3)**	-1.154	**PMA2**	0.355	**PMA1**	**0.002***	**GLD**	-0.011	-0.011	-0.055	-0.006
	(0.210)		(0.157)		(0.475)		**(1.427)**		(0.948)	(0.993)	(0.975)	(0.823)
CB(5,0.075,5,0.001)	0.001	**MA(30,15,5)**	-2.963	**PMA4**	-0.144	**MA(2,1,0.005)**	0.005	**MAAA**	-0.025	-0.026	-0.074	-0.004
	(0.209)		(0.157)		(0.169)		(0.124)		(0.756)	(1.176)	(0.861)	(0.935)
MA(5,1,5)	-0.010	**PMA4**	-0.425	**MA(5,2,5)**	-0.346	**FR(0.005,2)**	0.001	**MBaa**	-0.058	-0.046	-0.065	-0.009
	(0.338)		(0.161)		(0.226)		(0.262)		(0.546)	(1.005)	(0.892)	(0.995)
CB(5,0.075,5,0.005)	0.001	**PMA10**	0.025	**MA(5,2,2)**	-0.022	**FR(0.01,2)**	0.001	**MSCI**	-0.013	-0.028	-0.054	-0.005
	(0.197)		(0.241)		(0.382)		(0.254)		(1.178)	(1.317)	(1.201)	(1.106)
CB(5,0.075,5,0)	-0.009	**PMA20**	-0.852	**FR(0.005,5)**	-0.005	**FR(0.005,1)**	0.005	**NSQ**	-0.044	-0.038	-0.101	-0.005
	(0.325)		(0.159)		(0.273)		(0.128)		(0.998)	(1.408)	(1.046)	(1.225)
CB(5,0.075,5,0.001)	-0.001	**FR (0.01,1)**	-0.437	**FR(0.045,5)**	-0.038	**FR(0.01,3)**	0.001	**OIL**	-0.041	-0.058	-0.045	-0.013
	(0.175)		(0.160)		(0.342)		(0.258)		(0.69)	(1.178)	(1.451)	(0.98)
CB(5,0.075,5,0.005)	-0.001	**FR (0.05,1)**	-0.421	**FR(0.025,5)**	-0.026	**FR(0.015,1)**	-0.006	**MER**	-0.012	-0.006	-0.04	0.005
	(0.171)		(0.161)		(0.442)		(0.282)		(0.852)	(0.784)	(0.946)	(0.444)
CB(5,0.075,5,0.01)	0.001	**MA(30,25,2)**	0.009	**FR(0.045,25)**	-0.026	**FR(0.005,3)**	0.001	**VIX**	-0.104	-0.027	-0.081	0.008
	(0.202)		(0.196)		(0.42)		(0.287)		(0.585)	(0.758)	(0.912)	(0.651)
MA(5,2,2)	-0.009	**MA(25,5,5)**	-0.417	**FR(0.045,10)**	-0.043	**FR(0.015,2)**	-0.001	**VXN**	-0.014	-0.012	-0.036	0.007
	(0.35)		(0.162)		(0.354)		(0.263)		(0.871)	(1.086)	(1.308)	(0.951)
CB(5,0.075,5,0.005)	-0.011	**FR**	-0.438	**FR(0.14,1)**	-0.024	**FR(0.015,3)**	0.005	**VXD**	-0.025	-0.043	-0.05	0.009
	(0.37)	**(0.12,0.01)**	(0.161)		(0.319)		(0.179)		(1.013)	(0.918)	(1.261)	(0.739)
MA(5,2,0)	-0.015	**MA(30,25,5)**	-0.432	**FR(0.5,0.005)**	-0.042	**FR(0.01,3)**	-0.006	**SP500**	-0.020	-0.031	-0.058	-0.008
	(0.267)		(0.159)		(0.355)		(0.273)		(1.099)	(1.366)	(1.158)	(1.14)
MA(5,1,0.05)	-0.008	**FR (0.16,1)**	-0.436	**FR(0.01,5)**	-0.011	**FR(0.015,7)**	0.005	-				
	(0.348)		(0.160)		(0.322)		(0.179)					

	Panel C: Bitcoin and Blockchain Trend-based Factors				Panel D: Blockchain Technology-based Factors				
	BTC	**ETH**	**XRP**	**CRIX**		**BTC**	**ETH**	**XRP**	**CRIX**
NTs	0.004	-0.028	-0.063	0.018	**BZ**	-1.947	-1.354	-2.142	-4.614
	(0.531)	(1.092)	(1.321)	(0.383)		(0.423)	(0.423)	(0.424)	(0.423)
NPs	-0.038	-0.034	-0.024	-0.012	**BSV**	-0.013	-0.015	-0.041	0.001
	(0.78)	(1.24)	(0.962)	(1.108)		(0.853)	(1.049)	(1.458)	(0.731)
NUs	-0.016	-0.069	-0.064	-0.016	**HSH**	**0.295***	**0.173***	**0.132***	**0.058***
	(0.795)	(1.716)	(1.124)	(1.087)		**(1.472)**	**(1.572)**	**(1.498)**	**(1.635)**
PVs	-0.004	-0.04	-0.058	-0.006	**MD**	-0.035	-0.073	-0.157	-0.037
	(0.725)	(1.116)	(1.467)	(0.888)		(1.399)	(1.654)	(1.119)	(1.388)
Btc-W	-1.745	-0.46	-1.327	-1.87	**TBT**	-0.005	-0.003	-0.044	0.004
	(0.423)	(0.426)	(0.428)	(0.433)		(0.732)	(0.718)	(1.209)	(0.585)
Eth-W	0.005	-0.041	-0.177	0.011	**TBM**	-0.051	-0.049	-0.071	-0.009
	(0.888)	(0.995)	(0.599)	(0.799)		(0.692)	(1.315)	(1.191)	(1.272)
Xrp-W	-0.025	-0.016	0.005*	0.012	**DOD**	-0.014	-0.062	-0.025	-0.01
	(0.703)	(1.117)	(1.263)	(0.878)		(0.87)	(0.899)	(0.992)	(0.731)
Btc-GT	-0.014	-0.013	-0.109	0.001	**UBA**	-0.016	-0.015	-0.022	0.006
	(1.017)	(0.823)	(1.092)	(0.806)		(0.675)	(0.935)	(1.092)	(0.675)
Eth-GT	0.002	-0.034	-0.055	0.014	**DBT**	-0.016	-0.016	-0.016	0.009
	(0.813)	(1.09)	(0.655)	(0.556)		(0.647)	(0.959)	(0.983)	(0.772)
Xrp-GT	0.001	-0.067	0.019*	0.006	**EPU**	-0.022	-0.005	-0.028	0.007
	(0.772)	(0.654)	(1.316)	(0.808)		(0.579)	(0.630)	(0.817)	(0.547)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each one of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 respectively. We report the R^2_{OS} (%) and the MSFE-adj statistics from testing the null hypothesis that the historical average forecast MSFE is less than or equal to the actual forecast MSFE. The historical average (HA) forecast is given by $\hat{r}^{HA}_{t+1} = (1/t)\sum_{s=1}^{t} r_s$. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. 50% IS corresponds to period 1, as outlined in Table 5.4, keeping 50% of the total dataset out-of-sample.

Table 4. 10 Out-of-sample Predictive Regression Estimation Results (F2: 75% IS)

	Panel A: Technical Rules								Panel B: Traditional Fundamental Factors				
	BTC		ETH		XRP		CRIX		BTC	ETH	XRP	CRIX
CB(5,0.075,5,0)	-0.098	**MA(2,1,0.005)**	-0.034	**FR(0.045,0.01)**	-0.089	**MA(2,1,0.001)**	-0.113	**3mBill**	-0.121	-0.086	-0.144	-0.112
	(0.48)		(0.375)		(0.524)		(0.426)		(1.453)	(1.297)	(1.759)	(1.276)
PMA1	**0.081***	**FR (0.005,1)**	0.112	**PMA1**	**0.138****	**MA(2,1,10)**	-0.102	**10yBill**	-0.464	-0.433	-0.333	-0.589
	(1.474)		(0.234)		**(2.358)**		(0.494)		(0.995)	(0.838)	(0.822)	(0.862)
MA(5,1,5)	-0.105	**PMA1**	**0.221***	**FR(0.01,3)**	-0.139	**PMA1**	**0.133***	**DJIA**	-0.144	-0.141	-0.112	-0.184
	(0.543)		**(1.997)**		(0.618)		**(1.496)**		(1.211)	(1.224)	(1.316)	(1.197)
CB(5,0.075,5,0.001)	-0.08	**FR(0.01,1)**	-1.618	**FR(0.045,0.01)**	-0.134	**FR(0.01,1)**	-0.132	**GLD**	-0.130	-0.114	-0.119	-0.156
	(0.473)		(0.421)		(0.387)		(0.493)		(1.911)	(1.899)	(1.68)	(1.914)
CB(5,0.075,5,0.005)	-0.079	**MA(2,1,0.01)**	-1.612	**FR(0.14,10)**	-0.152	**MA(2,1,0.005)**	-0.123	**MAAA**	-0.239	-0.213	-0.237	-0.286
	(0.471)		(0.242)		(0.363)		(0.486)		(1.225)	(0.989)	(1.222)	(1.022)
MA(5,2,2)	-0.103	**PMA2**	-1.061	**FR(0.005,3)**	-0.141	**FR(0.015,1)**	-0.136	**MBaa**	-0.229	-0.212	-0.217	-0.27
	(0.571)		(0.325)		(0.358)		(0.499)		(1.291)	(1.082)	(1.256)	(1.045)
CB(5,0.075,5,0.01)	-0.078	**PMA4**	-2.010	**PMA20**	-0.389	**FR(0.015,6)**	-0.124	**MSCI**	-20.451	-23.152	-18.559	-28.516
	(0.471)		(0.228)		(0.261)		(0.517)		(0.599)	(0.599)	(0.602)	(0.599)
MA(5,2,0)	-0.099	**FR(0.01,2)**	-1.685	**MA(40,25,0.05)**	-0.090	**FR(0.06,1)**	-0.125	**NSQ**	-0.208	-0.169	-0.155	-0.242
	(0.553)		(0.277)		(0.687)		(0.489)		(1.472)	(1.33)	(1.342)	(1.394)
SR(250,2,5)	-0.068	**FR(0.06,1)**	-1.594	**FR(0.045,50)**	-0.388	**MA(2,1,0.01)**	-0.126	**OIL**	-1.266	-1.214	-1.05	-1.654
	(0.474)		(0.652)		(0.261)		(0.521)		(0.72)	(0.672)	(0.732)	(0.673)
MA(5,1,0.001)	-0.069	**FR(0.015,6)**	-2.380	**MA(40,25,0.01)**	-0.392	**FR(0.005,2)**	-0.133	**MER**	-0.187	-0.153	-0.192	-0.194
	(0.474)		(0.153)		(0.261)		(0.49)		(1.478)	(1.368)	(1.17)	(1.495)
CB(5,0.075,5,0)	-0.079	**MA(2,1,5)**	-2.119	**FR(0.14,5)**	-0.392	**FR(0.015,2)**	-0.296	**VIX**	-0.208	-0.172	-0.346	-0.235
	(0.472)		(0.222)		(0.261)		(0.353)		(1.163)	(1.056)	(0.942)	(1.11)
MA(5,1,0.005)	-0.621	**FR(0.015,1)**	-2.386	**MA(40,25,0.04)**	-0.389	**FR(0.01,2)**	-0.298	**VXN**	-0.521	-0.522	-0.486	-0.671
	(0.27)		(0.711)		(0.259)		(0.357)		(0.819)	(0.717)	(0.931)	(0.717)
SR(250,3,5)	-0.624	**MA(2,1,0.015)**	-1.594	**FR(0.01,3)**	-0.129	**FR(0.07,1)**	-0.121	**VXD**	-0.180	-0.141	-0.236	-0.187
	(0.269)		(0.984)		(0.406)		(0.406)		(1.167)	(1.016)	(1.093)	(1.055)
CB(5,0.075,5,0.001)	-0.084	**FR(0.005,2)**	-2.388	**FR(0.12,0.005)**	-0.388	**SR(5,2,10)**	-0.126	**SP500**	-0.193	-0.173	-0.152	-0.241
	(0.539)		(0.747)		(0.263)		(0.527)		(1.246)	(1.174)	(1.331)	(1.203)
CB(5,0.075,5,0.015)	-0.623	**FR(0.015,2)**	-2.387	**FR(0.045,0.005)**	-0.089	**SR(5,3,10)**	-0.123	**-**				
	(0.269)		(0.813)		(0.632)		(0.486)					

	Panel C: Bitcoin and Blockchain Trend-based Factors				Panel D: Blockchain Technology-based Factors				
	BTC	ETH	XRP	CRIX		BTC	ETH	XRP	CRIX
NTs	-0.259	-0.229	-0.253	-0.295	**BZ**	-1.314	-1.795	-2.696	-1.262
	(1.398)	(1.194)	(1.416)	(1.153)		(0.625)	(0.611)	(0.613)	(0.611)
NPs	-0.272	-0.239	-0.272	-0.308	**BSV**	-0.713	-0.663	-0.302	-0.836
	(1.462)	(1.259)	(1.495)	(1.203)		(0.697)	(0.675)	(0.91)	(0.686)
NUs	-0.251	-0.222	-0.243	-0.287	**HSH**	**0.146***	**0.286***	**0.363***	**0.134****
	(1.354)	(1.154)	(1.375)	(1.121)		**(1.652)**	**(1.801)**	**(1.477)**	**(2.343)**
PVs	-0.255	-0.226	-0.247	-0.291	**MD**	-0.258	-0.135	-0.279	-0.191
	(1.377)	(1.174)	(1.394)	(1.138)		(1.841)	(1.707)	(1.346)	(1.719)
Btc-W	-0.173	-0.133	-0.099	-0.162	**TBT**	-0.486	-0.453	-0.181	-0.555
	(1.523)	(1.554)	(1.657)	(1.567)		(0.749)	(0.713)	(1.18)	(0.733)
Eth-W	-0.569	-0.51	-0.411	-0.677	**TBM**	-0.263	-0.232	-0.264	-0.296
	(1.067)	(1.075)	(1.172)	(1.1)		(1.52)	(1.308)	(1.518)	(1.25)
Xrp-W	-0.386	-0.339	-0.331	-0.449	**DOD**	-0.086	-0.092	-0.093	-0.118
	(0.997)	(0.845)	(1.194)	(0.868)		(1.526)	(1.538)	(1.718)	(1.583)
Btc-GT	-0.23	-0.14	-0.157	-0.239	**UBA**	-0.157	-0.157	-0.169	-0.206
	(1.502)	(1.16)	(1.491)	(1.409)		(1.064)	(0.917)	(1.016)	(0.935)
Eth-GT	-0.252	-0.054	-0.152	-0.15	**DBT**	-0.222	-0.232	-0.243	-0.3
	(0.99)	(0.969)	(1.421)	(1.201)		(0.894)	(0.798)	(0.914)	(0.814)
Xrp-GT	-2.216	-2.034	-1.304	-2.704	**EPU**	-0.153	-0.104	-0.103	-0.147
	(0.634)	(0.629)	(0.658)	(0.629)		(1.275)	(1.358)	(1.388)	(1.418)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each one of the top fifteen technical rules selected in the previous step and the selected factors in Table 5.3 respectively. We report the R^2_{os} (%) and the MSFE-adj statistics from testing the null hypothesis that the historical average forecast MSFE is less than or equal to the actual forecast MSFE. The historical average (HA) forecast is given by $\hat{r}^{HA}_{t+1} = (1/t)\sum_{s=1}^{t} r_s$. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. 70% IS corresponds to period 2, as outlined in Table 5.4, keeping 25% of the total dataset out-of-sample.

Table 4. 11 Out-of-sample Predictive Regression Estimation Results (F3: 90% IS)

Panel A: Technical Rules								Panel B: Traditional Fundamental Factors				
	BTC		ETH		XRP		CRIX		BTC	ETH	XRP	CRIX
MA(5,1,5)	-0.541	**MA(2,1,0.005)**	-0.005	**MA(2,1,0.01)**	-0.248	**MA(2,1,0.001)**	-0.089	**3mBill**	-0.195	-0.191	-0.256	-0.201
	(0.466)		(0.388)		(0.473)		(0.451)		(2.213)	(2.431)	(1.698)	(1.957)
CB(5,0.075,5,0)	-0.523	**PMA1**	**0.09***	**MA(2,1,0.02)**	-0.346	**MA(2,1,2)**	-0.256	**10yBill**	-0.148	-0.169	-0.176	-0.169
	(0.462)		**(1.831)**		(0.5)		(0.67)		(3.425)	(1.854)	(1.831)	(2.073)
PMA1	**0.096***	**MA(2,1,0.001)**	0.487	**PMA1**	**0.037***	**PMA1**	**0.061***	**DJIA**	-0.32	-0.073	-0.131	-0.158
	(1.742)		(0.311)		**(1.469)**		**(1.729)**		(1.335)	(2.33)	(2.297)	(1.63)
CB(5,0.075,5,0.001)	-0.196	**PMA2**	-0.092	**MA(2,1,0.01)**	-0.498	**FR(0.01,1)**	-0.325	**GLD**	-0.208	-0.227	-0.258	-0.211
	(0.742)		(0.907)		(0.39)		(0.663)		(2.37)	(2.348)	(1.66)	(1.871)
CB(5,0.075,5,0.005)	-0.196	**PMA4**	-0.088	**MA(2,1,0.02)**	-0.197	**FR(0.015,1)**	-0.173	**MAAA**	-0.225	-0.118	-0.14	-0.142
	(0.762)		(1.076)		(0.617)		(0.762)		(2.434)	(2.382)	(2.666)	(2.611)
MA(5,1,2)	-0.528	**FR(0.005,1)**	-0.093	**MA(2,1,0.015)**	-0.365	**FR(0.06,1)**	-0.174	**MBaa**	-0.247	-0.139	-0.16	-0.161
	(0.461)		(1.034)		(0.468)		(0.705)		(1.732)	(2.549)	(2.744)	(2.688)
CB(5,0.075,5,0.01)	-0.198	**MA(2,1,0.01)**	-0.102	**MA(2,1,0.005)**	-0.32	**FR(0.005,1)**	-0.333	**MSCI**	-0.722	-0.192	-0.227	-0.223
	(0.757)		(0.977)		(0.473)		(0.658)		(1.171)	(2.334)	(2.089)	(1.998)
MA(5,2,2)	-0.522	**MA(2,1,5)**	-0.086	**MA(2,1,0.03)**	-0.202	**SR(5,4,10)**	-0.185	**NSQ**	-0.22	-0.139	-0.113	-0.138
	(0.459)		(1.077)		(0.605)		(0.789)		(2.381)	(2.187)	(1.768)	(2.11)
CB(5,0.075,5,0)	-0.151	**FR(0.01,2)**	-0.099	**FR(0.005,3)**	-0.232	**FR(0.01,1)**	-0.33	**OIL**	-1.599	-0.187	-0.605	-0.295
	(0.629)		(1.058)		(0.603)		(0.656)		(1.031)	(3.369)	(1.621)	(1.578)
CB(5,0.075,5,0.001)	-0.151	**FR(0.015,1)**	-0.089	**MA(2,1,0.001)**	-0.234	**FR(0.07,1)**	-0.149	**MER**	-0.194	-0.100	-0.15	-0.11
	(0.629)		(1.023)		(0.626)		(0.697)		(2.976)	(2.688)	(2.948)	(3.473)
CB(5,0.075,5,0.015)	-0.197	**MA(2,1,0.015)**	-0.103	**MA(2,1,5)**	-0.238	**FR(0.015,6)**	-0.341	**VIX**	-0.851	-0.142	-0.265	-0.23
	(0.757)		(0.996)		(0.632)		(0.79)		(1.245)	(2.588)	(1.499)	(2.243)
MA(5,2,0)	-0.523	**FR(0.015,6)**	-0.167	**FR(0.005,1)**	-0.188	**MA(2,1,10)**	-0.375	**VXN**	-1.282	-0.118	-0.377	-0.236
	(0.459)		(0.636)		(0.732)		(0.821)		(1.098)	(2.74)	(1.27)	(1.717)
MA(5,1,0.005)	-0.532	**FR(0.005,2)**	-0.101	**MA(5,1,0.04)**	-0.212	**SR(10,2,5)**	-0.107	**VXD**	-0.402	-0.126	-0.141	-0.175
	(0.461)		(1.059)		(0.643)		(0.077)		(2.02)	(2.2)	(2.484)	(2.716)
MA(5,1,0.05)	-0.262	**FR(0.06,1)**	-0.147	**FR(0.005,2)**	-0.200	**FR(0.08,1)**	-0.198	**SP500**	-0.542	-0.137	-0.143	-0.229
	(0.839)		(0.79)		(0.718)		(0.748)		(1.329)	(2.424)	(2.246)	(2.031)
MA(5,1,0.001)	-0.524	**FR(0.015,2)**	-0.091	**MA(2,1,0.04)**	-0.093	**SR(10,3,5)**	-0.176	-				
	(0.459)		(1.01)		(0.672)		(0.771)					

Panel C: Bitcoin and Blockchain Trend-based Factors					Panel D: Blockchain Technology-based Factors				
	BTC	ETH	XRP	CRIX		BTC	ETH	XRP	CRIX
NTs	-0.153	-0.193	-0.179	-0.149	**BZ**	-3.470	-0.157	-0.948	-0.8123
	(2.04)	(3.097)	(2.538)	(2.026)		(0.946)	(1.459)	(0.946)	(0.954)
NPs	-0.167	-0.205	-0.192	-0.158	**BSV**	-0.138	-0.115	-0.103	-0.115
	(2.106)	(3.202)	(2.605)	(2.115)		(1.942)	(2.113)	(1.481)	(2.116)
NUs	-0.145	-0.184	-0.169	-0.144	**HSH**	**0.308****	**0.219***	**0.235****	**0.248***
	(2.001)	(3.017)	(2.481)	(1.969)		**(1.976)**	**(1.563)**	**(2.309)**	**(1.537)**
PVs	-0.149	-0.189	-0.174	-0.146	**MD**	-0.08	-0.117	-0.130	-0.084
	(2.02)	(3.059)	(2.511)	(1.998)		(1.91)	(2.709)	(2.261)	(2.346)
Btc-W	-1.031	-0.092	-0.331	-0.166	**TBT**	-0.155	-0.109	-0.081	-0.117
	(1.053)	(2.724)	(1.252)	(1.495)		(1.895)	(2.323)	(1.565)	(1.915)
Eth-W	-0.158	-0.123	-0.121	-0.120	**TBM**	-0.179	-0.204	-0.191	-0.163
	(2.681)	(2.011)	(2.556)	(2.093)		(2.104)	(3.206)	(2.609)	(2.104)
Xrp-W	-0.434	-0.519	-0.664	-0.16	**DOD**	-0.347	-0.210	-0.149	-0.22
	(1.573)	(1.18)	(0.997)	(2.479)		(2.819)	(2.979)	(3.353)	(2.631)
Btc-GT	-0.619	0.094	-0.154	-0.045	**UBA**	-0.119	-0.104	-0.105	-0.097
	(1.06)	(1.42)	(1.61)	(1.432)		(2.371)	(2.642)	(2.479)	(1.994)
Eth-GT	-0.127	-0.004	-0.222	-0.074	**DBT**	-0.117	-0.117	-0.130	-0.098
	(1.645)	(1.071)	(1.182)	(1.566)		(2.15)	(2.55)	(2.477)	(1.854)
Xrp-GT	-0.245	-0.096	0.155	-0.092	**EPU**	-0.206	-0.101	-0.098	-0.143
	(2.109)	(2.531)	(0.856)	(2.387)		(1.703)	(2.247)	(2.251)	(1.667)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each one of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 respectively. We report the R^2_{os} (%) and the MSFE-adj statistics from testing the null hypothesis that the historical average forecast MSFE is less than or equal to the actual forecast MSFE. The historical average (HA) forecast is given by $\hat{r}^{HA}_{t+1} = (1/t)\sum_{s=1}^{t} r_s$. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. 90% IS corresponds to period 3, as outlined in Table 5.4, keeping 10% of the total dataset out-of-sample.

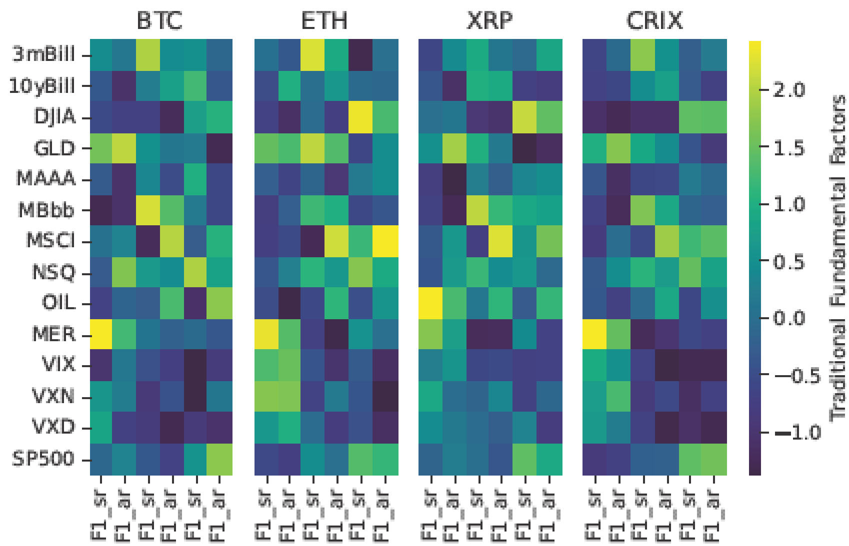
Table 4. 12 Out-of-sample Predictive Regression Estimation Results (F1, F2 and F3)

Panel E: Multiple Currency Factors													
	F1				F2					F3			
	BTC	**ETH**	**XRP**	**CRIX**	**BTC**	**ETH**	**XRP**	**CRIX**		**BTC**	**ETH**	**XRP**	**CRIX**
AUD	-0.536	-0.147	-0.123	-0.262	-0.171	-0.187	-0.141	-0.192	**AUD**	-0.022	-0.032	-0.062	-0.02
	(1.317)	(2.235)	(2.179)	(1.705)	(1.613)	(1.251)	(1.561)	(1.686)		(0.623)	(0.848)	(1.285)	(0.853)
EUR	-0.684	-0.103	-0.049	-0.202	-0.205	-0.263	-0.203	-0.245	**EUR**	-0.014	-0.027	-0.047	-0.001
	(1.193)	(2.251)	(1.323)	(1.646)	(1.624)	(0.809)	(1.304)	(1.67)		(0.951)	(1.282)	(1.154)	(0.907)
YEN	-8.603	-0.122	-2.293	-1.687	-0.279	-0.27	-0.141	-0.257	**YEN**	-0.071	-0.034	-0.035	-0.001
	(0.952)	(2.777)	(1.05)	(1.022)	(1.257)	(1.212)	(2.112)	(1.41)		(0.491)	(0.629)	(0.864)	(0.685)
CAD	-0.102	-0.027	-0.149	-0.079	-0.314	-0.122	-0.566	-0.467	**CAD**	-0.314	-0.195	-0.072	-0.06
	(2.05)	(1.934)	(1.523)	(1.992)	(1.144)	(1.725)	(0.672)	(0.818)		(0.452)	(0.54)	(1.365)	(0.758)
BRL	-0.27	-0.188	-0.192	-0.251	-0.331	-0.186	-0.177	-0.367	**BRL**	-0.033	-0.026	-0.075	-0.007
	(2.743)	(2.29)	(1.594)	(1.801)	(1.312)	(1.586)	(1.57)	(1.24)		(0.845)	(1.274)	(0.787)	(1.014)
RMB	-0.209	-0.218	-0.228	-0.192	-0.153	-0.151	-0.132	-0.168	**RMB**	-0.042	-0.059	-0.083	-0.041
	(2.405)	(1.754)	(1.258)	(1.726)	(1.84)	(1.584)	(2.341)	(1.782)		(1.289)	(1.521)	(1.096)	(1.35)
CHF	-0.271	-0.165	-0.088	-0.193	-0.23	-0.118	-0.148	-0.258	**CHF**	-0.013	-0.004	-0.04	0.009
	(2.278)	(1.85)	(1.189)	(2.141)	(1.62)	(1.325)	(1.406)	(1.464)		(0.864)	(0.958)	(1.312)	(0.778)
IDR	-0.282	-0.338	-0.424	-0.350	-0.173	-0.096	-0.17	-0.201	**IDR**	-0.022	-0.025	-0.039	-0.008
	(1.885)	(1.521)	(1.307)	(1.313)	(1.879)	(1.459)	(1.793)	(1.621)		(0.968)	(1.076)	(1.125)	(1.212)
KRW	-0.188	-0.087	-0.047	-0.107	-0.115	-0.164	-0.161	-0.158	**KRW**	0.002	0.001	-0.026	0.024
	(2.09)	(2.321)	(2.202)	(2.565)	(1.183)	(1.331)	(0.887)	(1.187)		(0.603)	(1.275)	(1.185)	(0.627)
VEF	-0.032	-0.001	-0.001	-0.018	-0.109	-0.125	-0.086	-0.124	**VEF**	-0.011	-0.013	-0.016	-0.008
	(1.801)	(-0.546)	(1.206)	(1.693)	(1.503)	(1.371)	(1.574)	(1.445)		(0.753)	(0.785)	(1.052)	(0.717)
GBP	-0.706	-0.15	-0.305	-0.210	-0.186	-0.186	-0.15	-0.225	**GBP**	-0.021	-0.012	-0.027	0.001
	(1.196)	(1.905)	(1.714)	(1.634)	(1.522)	(1.854)	(1.656)	(1.429)		(1.064)	(0.975)	(0.962)	(0.719)
RUB	-1.681	-0.111	-0.502	-0.308	-0.202	-0.187	-0.205	-0.191	**RUB**	-0.002	-0.01	-0.039	-0.001
	(1.037)	(2.48)	(1.259)	(1.449)	(1.449)	(1.251)	(0.999)	(1.404)		(0.844)	(1.136)	(1.104)	(0.828)
TRY	-0.654	-0.219	-0.410	-0.459	-0.238	-0.263	-0.235	-0.257	**TRY**	-0.012	-0.005	-0.03	0.010
	(1.612)	(1.993)	(1.504)	(1.239)	(1.837)	(0.809)	(1.095)	(1.817)		(1.165)	(1.269)	(1.285)	(1.112)
Panel F: Multiple Stock Indices													
	F1				F2					F3			
	BTC	**ETH**	**XRP**	**CRIX**	**BTC**	**ETH**	**XRP**	**CRIX**		**BTC**	**ETH**	**XRP**	**CRIX**
NI225	-0.479	-0.192	-0.281	-0.288	-0.162	-0.132	-0.151	-0.196	**NI225**	-0.016	-0.029	-0.042	0.008
	(1.546)	(1.872)	(1.871)	(1.605)	(1.179)	(0.956)	(1.427)	(1.064)		(0.667)	(1.137)	(0.97)	(0.808)
IBVC	-0.431	-0.333	-0.36	-0.338	-0.757	-0.695	-0.621	-0.943	**IBVC**	-0.066	-0.089	-0.088	-0.07
	(1.893)	(2.786)	(2.276)	(1.712)	(0.942)	(0.849)	(0.925)	(0.838)		(1.565)	(1.764)	(1.44)	(1.825)
BRA	-0.261	-0.164	-0.215	-0.216	-0.216	-0.188	-0.172	-0.254	**BRA**	-0.006	-0.031	-0.069	0.006
	(2.509)	(1.901)	(1.641)	(1.744)	(1.631)	(1.433)	(1.629)	(1.475)		(1.048)	(1.383)	(0.873)	(0.896)
TSX	-0.135	-0.154	-0.076	-0.104	-0.202	-0.162	-0.143	-0.231	**TSX**	-0.015	-0.007	-0.027	0.006
	(2.824)	(2.631)	(2.201)	(2.793)	(1.645)	(1.404)	(1.658)	(1.544)		(0.916)	(0.993)	(1.302)	(0.816)
KOSPI	-0.281	-0.316	-0.363	-0.317	-0.498	-0.573	-0.403	-0.737	**KOSPI**	-0.892	-0.520	-0.125	-0.123
	(1.914)	(1.722)	(1.466)	(1.405)	(0.741)	(0.694)	(0.801)	(0.717)		(0.424)	(0.464)	(0.979)	(0.506)
ASX	-0.077	-0.131	-0.127	-0.052	-0.512	-0.534	-0.385	-0.707	**ASX**	-0.219	-0.129	-0.062	-0.031
	(2.566)	(2.254)	(2.436)	(2.473)	(0.815)	(0.717)	(0.859)	(0.746)		(0.461)	(0.551)	(1.149)	(0.715)
JCI	-0.217	-0.073	-0.044	-0.07	-0.265	-0.204	-0.151	-0.263	**JCI**	-0.158	-0.009	-0.057	-0.031
	(2.152)	(1.749)	(2.372)	(1.71)	(1.682)	(1.546)	(1.759)	(1.623)		(0.489)	(0.692)	(1.18)	(0.831)
SMI	-0.564	-0.149	-0.165	-0.339	-0.113	-0.108	-0.114	-0.138	**SMI**	-0.163	-0.104	-0.029	-0.006
	(1.33)	(2.678)	(2.964)	(1.401)	(1.517)	(1.455)	(1.377)	(1.476)		(0.201)	(0.53)	(0.964)	(0.567)
SSE	-0.192	-0.11	-0.122	-0.127	-0.654	-0.639	-0.556	-0.872	**SSE**	-0.024	-0.03	-0.064	-0.008
	(2.716)	(2.611)	(2.241)	(2.552)	(0.742)	(0.695)	(0.734)	(0.704)		(0.814)	(1.383)	(1.092)	(1.066)
RTS	-0.521	-0.114	-0.291	-0.215	-0.165	-0.132	-0.154	-0.192	**RTS**	-0.008	-0.006	-0.028	0.006
	(1.388)	(1.969)	(2.05)	(1.722)	(1.265)	(1.032)	(1.162)	(1.088)		(0.691)	(0.858)	(1.160)	(0.510)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each one of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 respectively. We report the R^2_{os} (%) and the MSFE-adj statistics from testing the null hypothesis that the historical average forecast MSFE is less than or equal to the actual forecast MSFE. The historical average (HA) forecast is given by $\hat{r}^{HA}_{t+1} = (1/t)\sum_{s=1}^{t} r_s$. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. 90% IS corresponds to period 3, as outlined in Table 5.4, keeping 10% of the total dataset out-of-sam

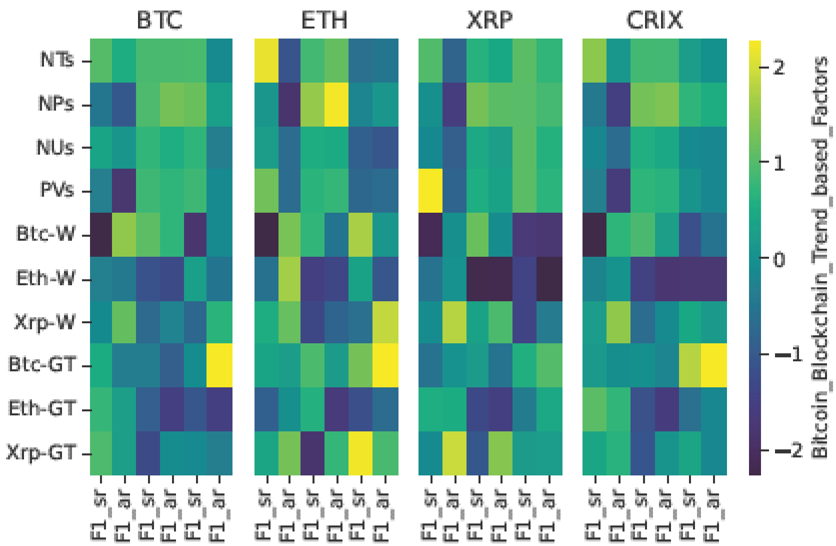
Finally, we report the profitability performance of the TA and FA factors in the out-of-sample periods. As in the previous sections, we report in Figures 4.8-4.13 both the Sharpe ratio and mean returns. With the BH strategy as the benchmark, the Sharpe ratio of the TA factors ranges from 0.504 to 1.398, while the mean returns from 0.013 to 0.033 in the case of the BTC (period 1). Comparing with the in-sample results, we have a dramatic upturn in each cryptocurrency. On the contrary, the performance of the two other forecasting exercises (periods 2 and 3) exhibits a great downturn. This is in line with our findings in the previous section, highlighting that good performance TA factors do not necessarily have high forecasting ability, hence their value in period 1 is not genuine. The FA factors show competitive performance against the TA factors. In period 1, the span of the Sharpe ratio using the BCH information factors is relatively large, ranging from 0.061 (BZ in Panel E) to 1.469 (TBT in Panel E). Other sets of FA factors perform similarly to the TA factors, for example, factors from conventional finance and economics yield Sharpe ratios in the range of 0.513 to 1.376. Nonetheless, the FA factors also fail to maintain the good performance in F2 and F3. Compared to F1, the FA factors sharply turn down like the TA factors. We note that further robustness results are presented in the Appendix B.4. We repeat the TA part of our methodology using the top 15 performing rules based on the Sortino Ratio as a starting point. Our results are consistent with those presented in the paper, extracting PMA1 as the only technical indicator that has significant predictability and profitability across all series and forecasting exercises.

Figure 4. 8 Out-of-sample profitability performance Results (Traditional Fundamental Factors)



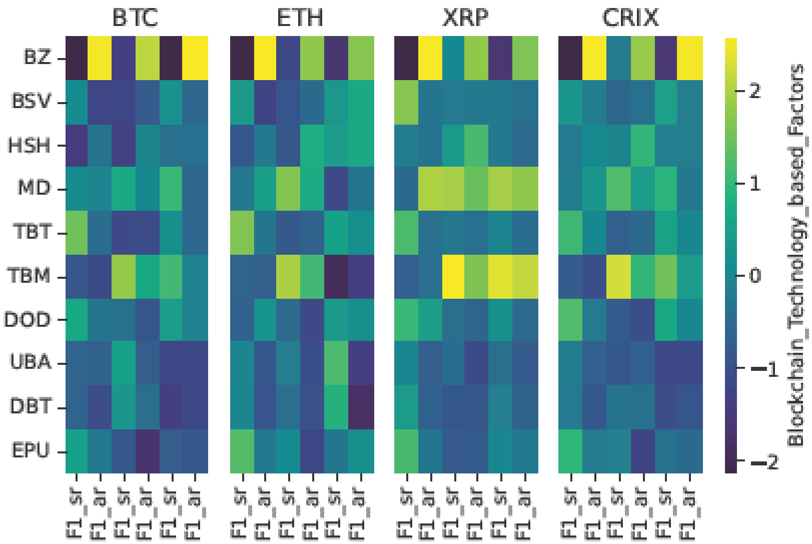
Note: This figure reports the Sharpe ratio (sr) and mean returns (ar) and the benchmark is the buy-and-hold strategy.

Figure 4. 9 Out-of-sample profitability performance Results (Bitcoin Blockchain Trend based Factors)



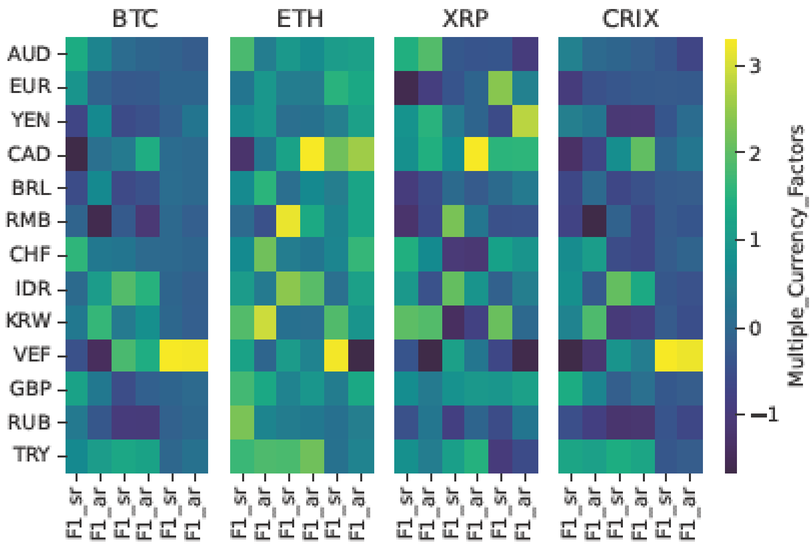
Note: This figure reports the Sharpe ratio (sr) and mean returns (ar) and the benchmark is the buy-and-hold strategy.

Figure 4. 10 Out-of-sample profitability performance Results (Blockchain Technology based Factors)



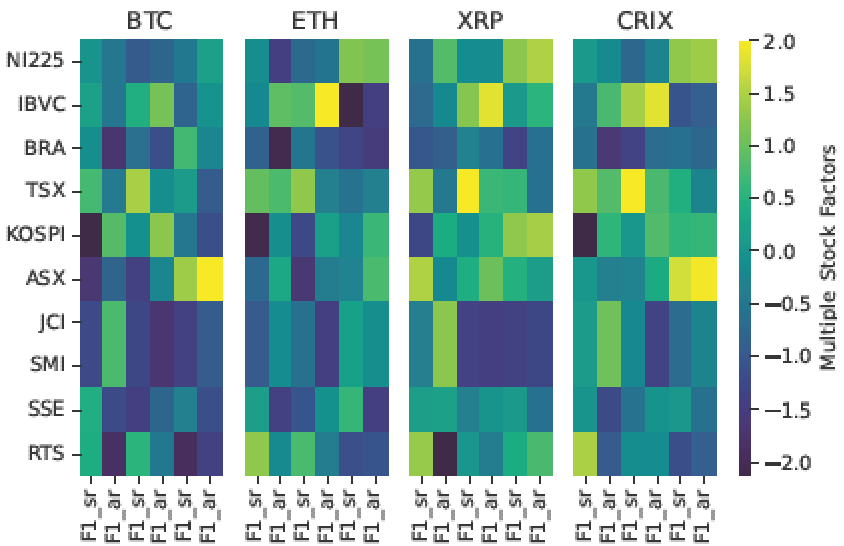
Note: This figure reports the Sharpe ratio (sr) and mean returns (ar) and the benchmark is the buy-and-hold strategy.

Figure 4. 11 Out-of-sample profitability performance Results (Multiple Currency Factors)



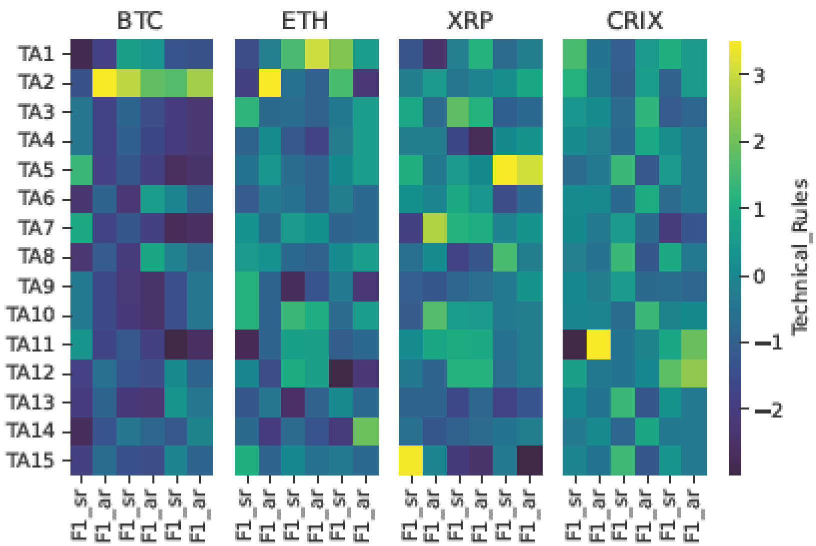
Note: This figure reports the Sharpe ratio (sr) and mean returns (ar) and the benchmark is the buy-and-hold strategy.

Figure 4. 12 Out-of-sample profitability performance Results (Multiple Stock Factors)



Note: This figure reports the Sharpe ratio (sr) and mean returns (ar) and the benchmark is the buy-and-hold strategy..

Figure 4. 13 Out-of-sample profitability performance Results (Technical Rules)



Note: This figure reports the Sharpe ratio (sr) and mean returns (ar) and the benchmark is the buy-and-hold strategy. For illustration purpose, top fifteen technical rules are abbreviated as TA1 to TA15. Details of rules can be referred to Table 4.4 to Table 4.5

Although previous studies state that the cryptocurrency market has a certain relationship with the financial markets (Li and Wang, 2017; Salisu et al., 2019), our results show that this is weak or nearly inexistent. Even other classes of fundamentals, such as BCH and BTC trend-based factors, are not found as important as other studies suggest (Matta et al., 2015; Ciaian et al., 2016; Kraaijeveld and De Smedt, 2020). Apart from the HSH, we are unable to identify other factors that possess explanatory power on the cryptocurrency returns. Investors in cryptocurrencies are mainly enjoying the process of chasing extreme high returns after a sudden drop from the peak. In addition, the lack of regulation from authorities and the collapse of exchanges due to continuous attack from cyber hackers might be able to explain the failure of the traditional FA factors. This implies that the cryptocurrency market is still young and isolated from other markets. On the other hand, we show that the PMA (1) ratio does have predictive power in cryptocurrency returns and significant profitability both in-sample and out-of-sample. Institutional investors, interested in the cryptocurrency market, can use the BTC or cryptocurrencies to diversify the total risk of their portfolio. Nonetheless, our results show that the TA benefits for cryptocurrency prediction erode quickly and are driven by momentum shifts. Hence, high cryptocurrency exposure of the investors' portfolio can lead to tail losses.

4.5 Conclusion

In this section, we present a thorough empirical framework to uncover the true value of TA and FA when it comes to cryptocurrency predictability and profitability. In order to achieve this, we utilize a novel exercise in the cryptocurrency literature. The exercise combines studying the large STW universe of technical rules and the PMA factors, along with the largest pool of factors related to cryptocurrencies found in the literature. Initially, we select the top 15 performing TA rules based on the Sharpe ratio and all the 57 FA factors and examine their in-sample predictability with bivariate regressions and wild bootstraps. Then, we test their genuine in-sample profitability by applying the LF method and the SPA test. The in-sample findings are further confirmed by out-of-sample bivariate regressions and trading performances.

In terms of our results, only short-term PMAs are found to have significant predictive ability across different horizons. This is confirmed consistently in both in-sample and out-of-sample tests across four cryptocurrencies (BTC, ETH, XRP and CRIX) and three forecasting exercises. This verifies that traditional momentum strategies cannot truly capture cryptocurrency movements, but novel ones like the one presented by Detzel et al. (2020) can. From the FA perspective, we investigate factors based on BTC information, economic and financial indices, and online sentiment indices. Although our results identify some FA factors with significant predictability in-sample, only HSH appears to have robust performance in the out-of-sample. This finding is particularly interesting, as HSH stands for the magnitude of the computational power towards mining and is a proxy of the healthiness of the BTC market. At the same time, HSH, being the only genuinely important factor, contradicts the common belief that crypto-news and crypto-sentiment are crucial factors of cryptocurrencies' volatility. Our findings further contribute to the literature that focuses on the utility of technical indicators for cryptocurrency trading, while we find that fundamentals related to financial and economic activity do not bring forward meaningful value. This is in line with many economists who believe that, as long as cryptocurrencies remain relatively unregulated, traditional FA will not serve any purpose in explaining them. Our empirical results are also showing the need for a rigorous testing of technical rules for luck and data snooping bias.

In conclusion, this study attempts to provide a holistic consolidation between TA and FA in the fast-growing cryptocurrency universe. We posit that investment and institutional attention needs to be steered towards PMA factors and factors capturing or proxying the computing power used for BTC mining, rather than cryptocurrency news and sentiment measures. It makes sense to contemplate the cryptocurrency market as still young and isolated from other conventional financial markets. This may be attributed to the decentralization of the BCH technology and the relatively small capitalization compared to the other financial (e.g., equity and exchange) markets. Although the recent boom of the BTC has attracted institutional investors, like Goldman Sachs, the whole cryptocurrency market is still immature and lacks regulation. This provides a welcome environment for speculators for possible market manipulation (Griffin and Shams, 2020; Dhawan and Putniņš, 2020) and dark-web illegal activity (Foley et al., 2019). Meanwhile, online exchanges remain the main pathway for the cryptocurrency investment, but they do not have full capacity for defense against hack attacks. The MT Gox and Quadriga examples make clear the need to reach an optimal balance between the safeguard of the store and convenience of the transaction for the investors. Large fluctuations in the transaction costs of different cryptocurrency platforms impede also extensive formal trading activity. These issues require further investigation if cryptocurrencies are to gain credibility as complete financial investment instruments.

Chapter 5 Explore Bitcoin Prediction with Leverage Trading and Sentiment

5.1 Introduction:

Along with the explosive growth in ML algorithms and hardware development, prosperity in Fin-tech, Big-data, Blockchain technology (BCH), and other high-tech fields is gradually changing the world. Carbonell, Michalski and Mitchell (1983) stated that ML methods' three primary research needs are task-oriented, cognitive-simulated and theoretical-analysed. Based on the required tasks, ML methods can be categorized into classification problems, regression problems, anomaly-detection problems, clustering problems, and reinforce-learning problems (Alzubi, Nayyar and Kumar, 2018). Compared to the classical ML algorithms, the modern-art neural networks (NNs), gradient boosting (GB), support vector regression (SVR) and other step-forward techniques strongly improve both computational efficiency and accuracy. The wide application of ML algorithms in stock, ETF and other conventional financial markets also motivates our hypothetical success in Bitcoin (BTC) market (Aguilar-Rivera, Valenzuela-Rendón, and Rodríguez-Ortiz, 2015; Oreski and Oreski, 2014; Sermpinis, Stasinakis and Hassanniakalager, 2017; Stasinakis et al. 2016).

Due to the highly volatile property of cryptocurrency and decentralization of BCH, prediction in BTC thereby becomes the most challenging task. Prior studies focus on the traditional statistical models (e.g., GARCH), and they are well documented (Katsiampa, 2017; Gourieroux, Hencic and Jasiak, 2020; Zhang et al., 2021). However, only limited work has been done in cryptocurrency prediction using ML algorithms. In terms of NNs techniques, McNally et al. (2018) perform empirical results that the benchmark model is less accurate than NNs in BTC prediction. Sun et al. (2020) display that SVR is more precise than benchmark models forecasting BTC prices. Ma et al. (2018) show GB styled methods are particularly efficient in P2P loan default prediction and the BTC market. A clear gap lies between past studies and recent exploration of ML applications in cryptocurrency, especially the BTC market.

Prior studies provide evidential results that the leverage trading strategy is profitable in the stock market (Sermpinis, Stasinakis and Dunis, (2014); Stasinakis et al. (2016)). A more recent work by Kahraman and Tookes (2017) shows that leverage trading has a causal effect on market liquidity in the stock market. Inspired by these studies, the authors argue that a leverage trading strategy can be a solver on such occasions, allowing transactions when volatility is relatively low but avoiding trading when volatility is relatively high. As proposed by Härdle, Harvey and Reule (2020), prices dispersion driven by sentiment in the cryptocurrency market could be larger than that in conventional financial markets. Unlike traditional leverage strategy, the authors adopt the sentiment index as our leverage because an analysis of the influence of sentiment indicates narratives and online media, like Twitter, Wikipedia and Google Trends, are associated with BTC prices (Ciaian et al., 2016; Garcia et al., 2014; Urquhart, 2018; Wang and Vergne, 2017). The literature shows that BTC prices can be affected or even predicted by social media sentiment. BTC is oriented and promoted through the internet; hence these results are not surprising. Online media play a significant role in influencing market behaviour (Majeed et al., 2020; Park and Park, 2020; Ramkissoon and Uysal, 2011). With the growth of BCH and cryptocurrency, other media sources, like narratives or publications, should influence the BTC market.

Karalevicius, Degrande and De Weerdt (2018) find intraday BTC prices follow the direction of sentiment extracted from expertise news while leaving a short time gap for traders to react. Online board discussion is associated with extremely high volatility and jumps in BTC prices (Ahn and Kim, 2019). Caviggioli et al. (2020) argue that the adoption of BTC technology improves corporate reputation by studying Twitter data. Yao, Xu & Li (2019) find news articles can influence BTC price in a certain level. Azqueta-Gavaldón (2020) further find bi-directional causal relationships between narrative sentiment and BTC prices by applying a dynamic system model, while Süssmuth (2021) explains that mutual causality exists between web search dynamic and BTC prices before 2018. These studies encourage the authors to employ a sentiment index constructed by narratives or formal publications as our leverages.

This chapter's objective is to explore the forecasting of BTC returns using a leverage trading strategy combined with sentiments. A two-step framework is set up. At first, a large pool of conventional models is applied, including Simple Moving Averages (SMA), Exponential Moving Averages (EMA), Autoregressions (AR), and Autoregressive Moving Averages (ARMA), Log prices to Moving Averages (PMA). Unlike traditional financial assets, conventional fundamental indicators (e.g., factors extracted from balance sheets) cannot be found in cryptocurrencies. Thus technical indicators could be one of the possible answers to the BTC prediction puzzle. Another reason should be attributed to the generalization and simplification of prediction. Our study seeks to examine whether the preliminary models have any predictive power in BTC prediction. To reduce the influence of over-fitting issues and possible data-snooping bias, we apply the two-dimensionality reduction techniques and extract a certain number of critical factors for succeeding experiments: principal component analysis (PCA) and recursive feature elimination random forest algorithm (RFE-RF). Finally, we use ML techniques, including Multi-Layer Perceptron (MLP), a Long-Short Term Memory (LSTM), Extreme Gradient Boost Decision (XGB), Light Gradient Boost Decision (LBM) and Support Vector Regression (SVR) sets as forecast combination models to improve the predictive ability of individual models. The best performing benchmark from the pool of individual models has been set as the benchmark to find the most accurate predictive model by applying multiple statistical measures, namely the Mean-Squared-Error (MSE), Root-of-Mean-Squared-Error (RMSE) and Mean-Absolutely-Error (MAE). To control the over-fitting issue and data-snooping bias, we apply the superior predictive ability test (SPA) of Hansen (2005), the modified Diebold and

Mariano (Harvey et al., 1997) and the model confidence set (MCS) of Hansen et al. (2011) to make robustness check for our results.
Secondly, we examine the usage of leverage trading strategy combined with sentiment and volatility. And the traditional strategy to explore the profitability of forecast models. Unlike other financial markets, it is rather tricky for investors to understand and analyse fundamental information without a certain level of knowledge. Thus, a trading strategy via technical analysis becomes a vitally important tool in the cryptocurrency market. Notably, we apply the time-varying leverage strategy in this chapter because of its outstanding performance in stock and exchange markets (see Sermpinis, Stasinakis and Dunis, (2014)). Past studies have mainly used polarity or sentiment scores to predict BTC prices (See Cician et al., 2016; Guégan and Renault (2020). This motivates us to take advantage of the causal relationship between BTC prices and sentiment. By benchmarking the buy-and-hold strategy, we start with two different leverage trading strategies: pure volatility and pure sentiment leverage strategy. Moreover, we further apply a hybrid strategy by combing sentiment and volatility leverage. Our results show that all leverage strategies significantly improve trading performance and that the hybrid strategy outperforms other strategies.

The motivations behind our framework are the characteristics of BTC prices along with the unique flaws and merits of each model. Takaishi (2018) suggested that the distribution of daily BTC returns is multifractal, with no volatility asymmetry. Like GARCH or ARIMA, traditional statistical models may not possess explanatory power on BTC prediction. Recent studies (e.g., Alessandretti et al., 2018; McNally., Roche and Caton, 2018; Ji., Kim and Im, 2019; Mallqui and Fernandes, 2019; Lahmiri and Bekiros, 2020; Mittal, Arora and Bhatia, 2020) show machine learning approaches are efficient and accurate in BTC or cryptocurrency-related predictions. Schapire (2003) suggested that it is easier to obtain many rough rules of thumb than a highly accurate forecasting rule. Therefore, selecting the most accurate and the best performing factor through the pool of individual models leads the combined forecast to a more accurate result.

The results show that XGB is the best predictor among all the applied forecast combination models. Our investigation finds that all forecast combination models perform better than the best individual model in terms of forecasting accuracy. Our results are free of data-snooping bias based on the application of the previous three tests. In terms of the overall trading performance, we show that all forecast combination models are more profitable than the benchmark model, especially for XGB. Their performances are consistent with applying both the traditional trading strategy and the hybrid trading strategy. Notably, our hybrid trading strategy generates much higher returns than the traditional trading strategy. Unlike previous papers, we consider the semantic definition of sentiment indices and extract reliable information sources from narratives.

5.2 Data

5.2.1 BTC

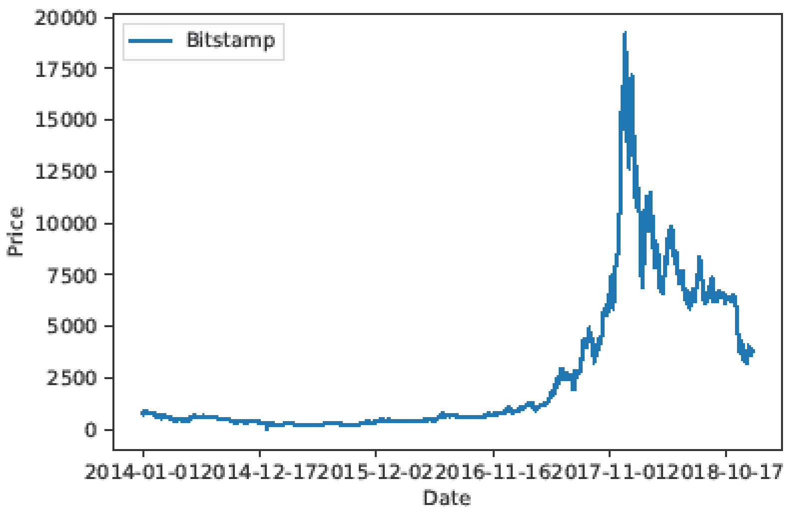
We have collected a total number of 1749 daily prices of BTC from 2014/01/01 to 2019/01/01 in three rolling forecasting exercises (F1, F2, and F3). The original data source can be found in Bitstamp. The data structure of this study is presented as Table 5.1 below.

Table 5. 1 Summary of dataset

Forecasting Exercise	Data Split	Number of Observation	Start Date	End Date
F1	Total Dataset	1232	01/01/2014	31/06/2017
	In-sample Dataset	1132	01/01/2014	01/03/2017
	Out-of-sample Dataset	110	02/03/2017	31/06/2017
F2	Total Dataset	1395	01/07/2014	30/06/2018
	In-sample Dataset	1255	01/07/2014	04/02/2018
	Out-of-sample Dataset	140	05/02/2018	30/06/2018
F3	Total Dataset	1389	01/01/2015	01/01/2019
	In-sample Dataset	1250	01/01/2015	07/08/2018
	Out-of-sample Dataset	139	08/08/2018	01/01/2019

Note: F2 is organized by rolling the dataset of F1six months ahead and F3 is rolling forward six months ahead of F2. The different length in each period is caused by missing values or zero.

Figure 5. 1BTC price series.



We then obtain the daily series of returns in the following way:

$$R_t = \left(\frac{P_t}{P_{t-1}}\right) - 1 \quad \textbf{(18)}$$

Table 5. 2 Summary statistics of each exchange BTC returns.

Return	Min	Mean	Max	SD	JB	ADF	S	K	LB (5)
BSP	**-1**	**0.001**	**0.269**	**0.047**	**108*** **	**0*** **	**-5.51**	**122**	**0.33**

Notes: This table reports the sample statistics of cryptocurrency prices and returns. SD is the standard deviation; S is the skewness; K is the excess kurtosis; and ADF is the Augmented Dickey-Fuller statistic. LB (5) are the Ljung–Box statistics with lag 5, respectively, distributed as χ^2 with n degrees of freedom, where n is the number of lags. Significance level: * 10%, ** 5%, *** 1%. JB is the Jarque-Bera test. The number of observations is 1749 for all series.

Table 5.2 reflects the summary of descriptive statistics for BTC returns. We rescale data to fit the forecasting models by transforming prices into return series while not causing estimation bias. Although BTC returns remain non-normally distributed, the transformed series becomes less volatile. The Jarque-Bera and ADF tests also provide confirmative results and further justification for our statements. Meanwhile, the return series follows non-normal distribution and does not have a unit root at the 99% confidence level.

5.2.2 Sentiment Index

To construct the sentiment index, we have collected publications and news articles describing BTC from Factiva, containing massive reports, news, and other kinds of narratives from the worldwide business press, such as *The Financial Time*s, *The Economist*, and things. Our main aim was to extract daily sentiment scores from these documents to generate a time-series sentiment index as the measure of leverage. In the current study, we collect a total number of 31436 articles from 2014/01/01 to 209/01/01. We first ran an ML algorithm for every article; this method is called *Latent Dirichlet Allocation (LDA)*, developed by Blei et al. (2003). We have provided a brief introduction to LDA and the implementation process in the Appendix section. LDA is a widely used topic modelling technique (Chen et al. 2019: Feuerriegel and Prollochs, 2018) with the distributions of word and topic, respectively, where documents are generated accordingly to these two distributions. Following Gavaldón (2020), Table 5.3 reports our results of LDA and average sentiment scores.

We obtain the sentiment of each article and further augment sentiments of articles belonging to the top 10 topics on a daily basis. To generate time series of sentiment, we use a public library in the natural language process called *TextBlob*. *TextBlob* considers negation and modified words, measuring words with their adjectives (see Gavaldón, 2020 for more details). To illustrate as an example, *very good* will be given a higher weight when calibrating the sentiment score of *bad* and *not* before *good* or *bad* will be assessed rightly as to their original meaning. Moreover, we can measure the sentiment from two aspects: the polarity (positive vs negative, ranging from 1 to -1) and subjectivity (ranging from 0 to 1). Obviously, polarity scores reflect the sentimental attitude towards studied topics. When polarity scores are above zero, we believe the sentiment is positive and negative polarity scores vice versa.

Table 5. 3 Summary of overall LDA results

Topic	Label	Score	Percentage (%)	Words
1	Finance and Economy (I)	0.038	21.4	bitcoin, financial, company, bond, business, bank, currency, money, market, capital, investors, payments, transaction, industry, dollar, security, exchange, trading, investment, deal
2	Finance and Economy (II)	0.040	14.5	mt, gox, people, cash, wsj, stock, earnings, fund, firm, customer, oil, online, asset, buy, growth, price, gold, federal, economy, sale
3	Technology	0.109	15.3	digit, ethereum, blockchain, system, document, coin, technology, future, times, cryptocurrency, data, government, platform, global, virtual, tech, online, reserve, update
4	Media	0.027	12.1	press, state, including, public, percent, chief, media, president, label, low, forward, report, day, power, right, journal, read, real, fell, magazine
5	Politics	0.029	9.70	trump, government, America, China, UK, tax, power, rise, European, nation, English, north, inflation, Korea, top, move, base, regulator, service
6	Crime	0.009	7.97	crucial, position, stan, standout, poker, giant, cop, approximate, telegraph, illegal, credit, operative, knight, group, garage, hostage, terminate, wall, court, drug
7	Accountancy	0.010	6.58	ledger, information, atmosphere, statement, tax, load, decentralize, distance, stall, carrie, week, year, puzzle, ring, sign, inception, ltd, number, story, version, men
8	Corporation	0.022	6.44	adopt, book, start, conference, web, piece, ltd, centre, mail, wide, kind, electronic, body, road, tip, sense, entrepreneur, city, origination, team
9	Tech-related	0.033	3.27	ebay, yahoo, web, publication, artist, crowdfund, minute, let, accountant, ross
10	Unidentified	0.031	2.75	poker, bowl, forest, high, gmt, copyright, cryptographic, anyone, ny, vs

Note: This table reports the key words extracted for each topic based on LDA algorithm. For the corpus, Score denotes the sentiment score (polarity) of each topic and percentage (%) denotes the proportion of each topic. All the country names should in lower case (we use capital letters for a better view).

5.3 Forecasting Models

In this section, we summarize our predictive models. Intuitively, we start with an individual forecast through conventional predictive models. Prior studies show theoretical and practical results that combining forecasts or models can generate higher power over single predictive models (e.g., Altavilla and De Grauwe, 2010; Hendry and Hubrich, 2011; Yang, 2004;). Hence, we start by selecting from the individual pool and then pour into our combination forecast techniques.

5.3.1 Individual Prediction Models

As the first step, we apply a large number of single forecast models. As discussed in the earlier sections, quite a few cases focus on BTC prediction, and the majority of studies provide successful answers with high complexity models. This study starts with a pool of linear models, including SMA, EMA, AR, ARMA and PMA, in case of missing trials with easy models. Moreover, we take PMA ratios extended from the equilibrium model proposed by Deztel et al.

(2018) into our model pool as the nonlinear component. PMA ratio is the difference between log prices and moving averages. In an economy like the cryptocurrency market, fundaments and other sources of information are difficult to find or trust. Under such circumstances, technical indicators constructed by past prices may become a unique weapon for investors. A detailed description of the models is provided in Table 5.4.

Table 5. 4 Summary of individual forecast models

Linear Models	Description	Total Individual Forecasts
SMA(q)	$E(R_t) = (R_t + ... + R_t)\big/ q, q = 3...30$	28
EMA(q')	$E(R_t) = \frac{R_{t-1} + (1-\alpha')R_{t-2} + ... + (1-\alpha')^{q'-1} R_{t-q'}}{\alpha' + (1-\alpha') + ... + (1-\alpha')^{q'-1}},$ $q' = 3...30, \quad \alpha' = 2/(1+N_{days}), N_{days}$ *is the number of trading days*	28
AR(q'')	$E(R_t) = \beta_0 + \sum_{i'=1}^{q''} \beta_{i'} R_{t-i'}, \quad q'' = 1,...,24, \beta_0, \beta_{i'}$ *are the regression coefficients*	24
ARMA (m, n)	$E(R_t) = \bar{\varphi}_0 + \sum_{j'=1}^{m'} \bar{\varphi}_{j'} R_{t-j'} + \bar{\alpha}_0 + \sum_{k'=1}^{n'} \bar{w}_{k'} \bar{\alpha}_{t-k'}$ $m', n' = 1...15, \bar{\varphi}_0, \bar{\varphi}_{j'}$ *are the regression coefficients,* $\bar{\alpha}_0, \bar{\alpha}_{t-k'}$ *are the residual terms,* $\bar{w}_{k'}$ *is the weights of the residual terms*	210
PMA(L)	$PMA_t(L) = p_t - ma_t(L), where\ ma_t(L) = \frac{1}{nL}\sum_{l=0}^{nL-1} p_{t-l}$	5

Notes: *The total number of individual inputs calculated is 290. In all the specifications above, Rt is the factor return at time t.* P_t is the log-price of the bitcoin and n *is* the number of days per week in L = 1, 2, 4, 10, and 20 weeks

The total number of individual models is 295. To avoid possible over-fitting issues caused by dimensionality issues, we apply the PCA technique to extract the best set of predictors and discard high-correlated variables. PCA components account for 95% of the total variance, and only the selected components are used as inputs for all the remaining models. In total, we have 30 principal components selected from the linear pool of predictors. Previous studies, for instance, Tsai and Hsiao (2011) and Conn et al. (2019), show the RF algorithm performs good feature selectivity. We have provided a general description of the RFE-RF process in the Appendix section. To make the factor comparison with PCA more explanatory, we selected the best 30 factors based on individual feature importance. By applying RFE-RF, we have ranked predictors based on the order of their importance. Similar to PCA, RFE-RF also avoids the occurrence of over-fitting issues. We set the best individual model as our benchmark model.

Table 5. 5 Summary of best individual predictor set

Forecasting Exercise	MAE	MSE	RMSE
F1	EMA (3)	EMA (3)	EMA (3)
F2	SMA (1)	EMA (2)	PMA (2)
F3	PMA (1)	PMA (2)	PMA (1)

Notes *The numbers in the parenthesis correspond to the lags in the individual model.*

Table 5.5 provides the summary of best predicator selected from the pool of individual models. From the above table, we find short-term lags may have better predictive power than longer lags, except the AR model. In this way, we use machine learning algorithms to further improve the predictive ability of individual models.

5.3.2 Combination Forecast Techniques

5.3.2.1 Multi-Layer Perceptron Model

MLP has been used in different fields since 1950s (Murtagh, 1991; Nassif, Ho and Capretz, 2013; Zhu and Wang, 2010). Prior studies also show the predictive power of MLP in BTC as well as conventional financial areas (Jang and Lee, 2017; Naeini and Taremian, 2010; Sin and Wang, 2017). The training process of MLP is quite straightforward, that is, a perceptron with more than one set of layers. Input layer is generally considered as the first step, which is used to feed the training data into the model. The way from input layer to output layer is indirect, which shall go through an intermediary layer, called hidden layer. Output is regarded as the last step, producing the estimated value. Training process can be referred to Murtagh (1991) and Shapiro (2000).

5.3.2.2 Long-Short Term Memory

Similar to the recurrent Neural Network (RNN), LSTM has the chain of repeating neural models with above layers. In order to solve the long-term dependency issues, LSTM have added control gates, that is, the input gate, forget gate and output gate. The main difference between RNN and LSTM is the cell state, which is used to control the information regulated by three gates. Intuitively, sigmoid layers are used to determine how much information to be restored, that is the range of [0,1] represents the kept information from nothing to all. Prior studies have shown the success of LSTM in many fields, we here focus on the time-series prediction (e.g., Duan, Lv and Wang, 2016; Nelson, Pereira and de Oliveira, 2017; Phaladisailoed and Numnonda, 2018). Compared to simple MLPs or other feed forward NNs, LSTM has bi-directional neural connections. The latter implies that is current data can be passed to previous or the same layer. LSTM can thus keep the short-term memory as well as the long-term memory by control gates.

5.3.2.3 Support Vector Regression

Support Vector Regression (SVR) has been widely used in time-series prediction, for example stock prices and extreme streamflow (Cao and Tay 2001; Matos et al. 2018; Zhao et al. 2019). For a given set of training data $\{(\mathrm{x}_1, y_1),...,(\mathrm{x}_n, y_n)\}$ where $X \subset \Re$ and total number of n observations, the general function of ν-SVR can be set as:

$$f(x) = w^T \phi(x) + b \tag{19}$$

To demonstrate the linearity of training data, we project the nonlinear function ϕ(x) onto a feature space. A regularized risk function must be minimized to obtain w and b as follows:

$$\left\{ for\varepsilon \geq 0, R(C) = C\frac{1}{n}\sum_{i=1}^{n} L_\varepsilon(y_i, f(x_i)) + \frac{1}{2}\|w\|^2, L_\varepsilon(y_i, f(x_i)) = \begin{cases} 0, \text{if } |y_i - f(x_i)| \leq \varepsilon \\ |y_i - f(x_i)| - \varepsilon, otherelse \end{cases} \right\} \quad \textbf{(20)}$$

Where y_i is the observed value at time i, parameters C and ε can be adjusted by practitioner, f(x_i) is the forecasted value at the same period, and L_ε is the ε-sensitive loss function. We can hence control the upper bound and lower bound of predicted value by adjusting parameter ε, which is also known as "tube" in prior studies (Bartlett, Smola, and Williamson, 1999; Vapnik, 1995). Given a parameter ν ∈ (0,1), the SVR problem can then be transformed into a νSVR optimization problem as follows:

$$\begin{gathered} Minimize\; C(\nu\varepsilon + \frac{1}{n}\sum_{i=1}^{n}(\xi_i + \xi_i^*)) + \frac{1}{2}\|w\|^2 \\ subject\ to \begin{Bmatrix} \xi_i \geq 0 \\ \xi_i^* \geq 0 \\ C \geq 0 \end{Bmatrix} and \begin{Bmatrix} y_i - w^T\phi(x_i) - b \leq +\varepsilon + \xi_i \\ w^T\phi(x_i) + b - y_i \leq +\varepsilon + \xi_i^* \end{Bmatrix} \end{gathered} \quad \textbf{(21)}$$

This then becomes a dual problem. The solution is based on two Lagrange multipliers a_i, a_i^* and the kernel function K(x_i, x):

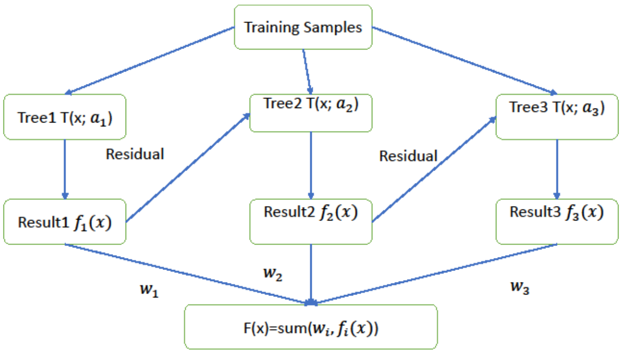
$$f(x) = \sum_{i=1}^{n}(a_i - a_i^*)K(x_i, x) + b,\ \ where\, 0 \leq a_i, a_i^* \leq \frac{C}{n} \quad \textbf{(22)}$$

The transformation process is solved by Gaussian radial basis function (RBF) for all the SVR models applied.

5.3.2.4 GBDT family: XGBoost (XGB) and LightGBM (LBM)

As one important branch of Ensemble Learning algorithms in machine learning field, gradient boost decision tree (GBDT) developed by Friedman (2001) is a multiple-task solver used in a myriad of aspects. According to the statistics of Kaggle, GBDT based algorithms win the championship for more than half of ML competitions and are widely used in computer visualization, medicine, biology and finance (Chen, Wang and Pan, 2019; Nobre and Neves 2019; Rao et al, 2019; Wang and Gribskov, 2019; Zhang et al, 2019). Intuitively, GBDT is the combination of gradient boost (GB) and decision tree (DT). The former algorithm focuses on finding a strong learner $F(x)$ by aggregating a bunch of weak learners $T(x)$, while the later algorithm is used to construct the judgement condition for learning power through iteration. Therefore, the training process of GBDT is additive, that is, the final prediction is based on the sum of previous predictions ($F(x) = F_1(x) + F_2(x) + ... + F_m(x)$).

Figure 5. 2 Flowchart of GBDT structure



Note: The residuals obtained from previous base learner is fed into the following base learner as training data (instance).

Figure 5.2 illustrates a flowchart of GBDT structure, and the training process is described as follows (Friedman, 2001; Rao et al, 2019):

Input: Denote $\{x_i, y_i\}_{i=1}^{n}$ as training instances, where $x_i = (x_{1i}, x_{2i}, ..., x_{ki})$ denotes the features, k denotes the number of features and y_i denotes the target value.

Step 1: Denote the initial constant value w and initialize the predictors as follows:

$$F_0(x) = \arg\min_c \sum_{i=1}^{n} L(y_i, w) \quad \textbf{(23)}$$

where $L(y_i, w)$ denotes the loss function.

Step 2: For data $i = 1, 2, ..., n$, we have the negative gradient or the residual along the gradient direction as follows:

$$r_{im} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{f(x)=f_{m-1}(x)} \quad \textbf{(24)}$$

where m denotes the number of iterations.

Step 3: We fit sample instances into the initial tree $T(x_i; a_n)$ and obtain the parameter a_n through the least square method as:

$$a_m \arg\min_{a,w} \sum_{i=1}^{n} (r_{im} - wT(x_i; a))^2 \quad \textbf{(25)}$$

Step 4: To acquire the minimal loss function, the current weight of each base learner is described as

$$w_m = \arg\min_w \sum_{i=1}^{n} L(y_i, F_{m-1}(x) + wT(x_i; a_m)) \quad \textbf{(26)}$$

Step 5: The current prediction based on strong learner is given as follows.

$$F_m(x) = F_{m-1}(x) + w_m T(x_i; a_n) \quad \textbf{(27)}$$

The above steps will keep running until the convergence condition or the specified iteration times are met.

5.3.2.5 XGBoost

Based on the structure of GBDT, Chen and Guestrin (2016) propose a scalable end-to-end gradient tree boosting model, XGB system, standing for 'Extremely Gradient Boosting'. Similar to other machine learning algorithms, XGB is designed to find a predictive model that fits best the training set (x_i) and target values (y_i). To measure how good of the predictive model is, the following objective function needs to be minimized:

$$OBJ(\theta) = L(\theta) + \Omega(\theta), \begin{Bmatrix} L(\theta) = \sum_{i=1}^{I} (y_i - \hat{y}_i)^2, \\ \Omega(\theta) = \sum_{m=1}^{M} \Omega(f_m), \end{Bmatrix} \quad \textbf{(28)}$$

where $L(\theta)$ denotes training loss function[8], $\Omega(\theta)$ denotes regularization terms, $\hat{y}_i$ is the prediction value and m denotes the number of trees. The upper function ($L(\theta)$) is used to measure the forecasting ability of tested model and the below function ($\Omega(\theta)$) is used to control the model complexity. Particularly, the regularization term Ω is a function of the total number of leaves in the tree (N) and leaf weights (ω), which can be described as follows:

$$\Omega = \alpha \mathrm{N} + \frac{1}{2} \beta \|\omega\|^2 \quad \textbf{(29)}$$

where α denotes the complexity of leaves and β denotes the penalty parameter. Apparently, the regularization term thus reducing the overfitting probability by leading to a predictive model with simple structure. Intuitively, traditional optimization algorithms cannot be used for the objective function above.

For the tree ensemble model like XGB, the final prediction is the sum of scores of each tree. Denote $\hat{y}_i$ as the prediction in i-th instance (x_i) and f_m denotes a tree structure to mostly improve our model in m-th iteration, we

[8] This is a common mean-squared-error function. XGB is a high compatible algorithm, allowing to employ a variety of metrics based on specific task.

therefore have the prediction score as follows:

$$\hat{y}_i = \sum_{m=1}^{M} f_m(x_i) \textbf{ for } x_i \tag{30}$$

Then, second-order Taylor expanding is used to optimize the objective function as follows:

$$Obj = \sum_{j=1}^{N}[(G_j\omega_j + \frac{1}{2}(H_j + \beta\omega_j^2)] + \alpha N \tag{31}$$

where I_j denotes the instance set for j-th leaf, $G_j = \sum_{i \in I_j} g_i$ is a constant, denoting the sum of first order partial derivation of all samples in j-th leaf and $H_j = \sum_{i \in I_j} h_i$ is a constant, denoting the sum of second order partial derivation of all samples in j-th leaf. Therefore, optimization of objective function is transferred into a minimum determination problem of quadratic function.

Based on the definition of loss function, XGB is capable of solving both classification and regression tasks. In general, XGB is an improved version of GBDT, optimizing the objective function by adding the regularization terms and increasing the prediction accuracy by using the second-order Taylor expansion. Moreover, two more techniques are applied to tackle the overfitting issue during the tree growth, which are shrinkage and column subsampling (see Chen and Guestrin (2016) and Friedman et al. (2000) for a detailed discussion).

5.3.2.6 LightGBM

Similar to XGB, LBM is an open-source framework developed by Microsoft Research Asia in 2016 (Ke et al. 2016). Generally, LBM is designed to solve the lack of computation efficiency in mass data without losing much accuracy. Compared with XGB, LBM mainly have two advantages in terms of time complexity reduction, finding the optimal splitting node and trees growth strategy. In terms of first side, LBM have three aspects of improvement, that is, reducing number of splitting nodes, size of training data and number of features. At first, LBM applies histogram-based DT algorithm instead of presorted approach in splitting points to reduce the number of splitting nodes. The principal of histogram algorithm is discretizing the continuous floating-point eigenvalues into k number of small bins and construct k-width histograms. The accumulation of histogram is indexed by the discrete values in each bin. Then, the sum of gradients and number of samples in each bin, as required statistics, are gradually stored in histogram. With the necessary statistics in histograms after the first traverse of data, it is possible to find the optimal segment point based on the discrete value indices. Comparing with presorted method, histogram algorithm reduces the memory cost by storing only the discrete values.[9] Abundant discussion of both pre-sorted method and histogram-based method is well documented already (Jin and Agrawal, 2003; Ke et al. 2016; Li et al. 2007; Mehta, Agrawal and Rissanen, 1996; Ranka and Singh, 1998; Shafer, Agrawal and Mehta, 1996). Secondly, LBM develops the Gradient-based One Side Sampling (GOSS) technique to control the size of training instances. Unlike AdaBoost, no sample weights are given in GBDT, but gradient of instances are also good indicators for searching for the optimal split point. Intuitively, training instances with small gradient have relatively smaller training error, indicating these parts of data are well-trained and should be abandoned. This is similar to GBDT that large deviations from target value will be penalized harder. In AdaBoost, the sample weight serves as a good indicator to determine the importance of samples. However, the data distribution may be distorted by the loss of instances and influence the accuracy of trained models. In order to keep the balance between reduction of data size and accuracy of learning decision trees, GOSS applies a constant multiplier to instances with low gradient when computing information gains. Exclusive Feature Bundling (EFB), as the approach of feature number reduction technique, is another key technique in LBM. This method is inspired by the sparsity of high dimension data and is designed to reduce the feature numbers by combining mutually exclusive features (values are simultaneously nonzero). Detailed explanation of algorithms is given in Ke et al. (2017).

LBM applies a leaf-wise growth strategy with depth controller, which searches for the maximum profit from leaf-splitting while level-wise strategy splits every leaf. Unavoidably, level-wise strategy used in XGB may generate a lot of redundant data and reduce computing efficiency. On the contrary, leaf-wise growth strategy only focuses on the leaf with greatest information gain on the same layer, thereby enhancing algorithm speed. This method needs to manually set and tune the max depth of trees and minimum data in each leaf to control the possible overfitting issue.

[9] Practically, int 8 type is adequate for memorizing discrete data, as only numerical type of data is used in research.

5.3.2.7. Hyperparameter Optimization

Due to the complexity of most ML algorithms, tuning hyperparameters is a crucial step to convincible results. In this study, we apply grid search which is one of the most popular approaches in terms of hyperparameters search methods. Grid search method is designed to find the optimal value by exhaustively searching in a specified hyperparameters space. In Table 5.6, we give brief introduction and the optimal value of our critical hyperparameters used in GBDT family models.

Table 5. 6 Main hyperparameters and optimal value of GBDT family models (XGB and LBM)

XGB model						
Symbol	**RFE(F1)**	**RFE(F2)**	**RFE(F3)**	**PCA(F1)**	**PCA(F2)**	**PCA(F3)**
N_estimators	500	500	500	500	500	500
Eval_metrics	rmse	rmse	rmse	rmse	rmse	rmse
Subsample	1	1	1	1	1	1
Min_child_weight	1	1	1	1	1	1
Max_depth_	4	6	6	3	6	4
Gamma	0	0	0	0	0	0
Colsample_bytree	1	1	1	1	1	1
Alpha	0	0	0.01	0	0.01	0
Lambda	0	0	0	0	0	0
Eta	0.041	0.045	0.024	0.046	0.055	0.050
XGB model						
Symbol	**Symbol**	**Symbol**	**Symbol**	**Symbol**	**Symbol**	**Symbol**
N_estimators	500	500	500	500	500	500
Max_depth	6	3	6	7	4	8
Num_leaves	32	16	32	32	16	64
Colsample_bytree	1	1	1	1	1	1
Reg_alpha	0.01	0	0	0.01	0.01	0
Reg_lambda	0	0	0	0	0	0
Learning_rate	0.045	0.039	0.041	0.055	0.051	0.047

Note: N_estimators denotes Number of boosted trees to fit, Eval_metrics denotes Evaluation metrics, Subsample denotes Subsample ratio of training data, Min_child_weight denotes Minimum sum of data weight needed in a child, Max_depth denotes Maximum depth of a tree, Gamma denotes Minimum loss reduction required to make a further partition of a leaf node of the tree, Colsample_bytree denotes Subsample ratio of columns for construction of each tree, Alpha denotes L1 regularization term on weights, Lambda denotes L2 regularization term on weights, and Eta denotes Learning rate. N_estimators denote Number of boosting iterations, Max_depth denotes Maximum depth of a tree, Num_leaves denotes Maximum number of leaves in one tree, Colsample_bytree denotes Subsample ratio of instances for construction of each tree, Reg_alpha denotes L1 regularization term on weights, Reg_lambda denotes L2 regularization term on weights, Learning_rate denotes Learning rate

5.4 Statistical Performance

In order to examine the statistical significance of each predictor, we employ three popular metrics, MSE, RMSE and MAE. Instinctively, lower statistics indicate more accurate prediction of examined model. Table 5.7 reports the summary of out-of-sample statistical performance.

Table 5. 7 Summary of out-of-sample statistical performance

				Panel A Set of Selected Factors based on RFE-RF				
Metrics	**Forecasting Exercise**	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**XGB**	**LBM**
MAE	**F1**	0.0334	0.0185	0.0089	0.0080	0.0059	**0.0042**	0.0050
	F2	0.0416	0.0202	0.0083	0.0068	0.0057	**0.0050**	0.0347
	F3	0.0369	0.0093	0.0043	0.0087	0.0084	**0.0034**	0.0042
MSE	**F1**	0.00185	0.0011	0.00014	0.00011	0.00006	**0.00003**	0.00006
	F2	0.0025	0.0016	0.00037	0.00028	0.00027	**0.00006**	0.00092
	F3	0.00235	0.0013	0.00007	0.00017	0.00009	**0.00002**	0.00008
RMSE	**F1**	0.0430	0.0333	0.0119	0.0105	0.0079	**0.0056**	0.0075
	F2	0.0450	0.0403	0.0611	0.0167	0.0163	**0.0075**	0.0303
	F3	0.0484	0.0362	0.0087	0.0132	0.0095	**0.0042**	0.0089
				Panel B Selected Principal Components				
Metrics	**Forecasting Exercise**	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**XGB**	**LBM**
MAE	**F1**	0.0334	0.0284	0.0173	0.0195	0.0179	**0.0056**	0.01925
	F2	0.0416	0.0304	0.0198	0.02129	0.02134	**0.01007**	0.02234
	F3	0.0369	0.0291	0.0256	0.03226	0.02809	**0.00702**	0.01735
MSE	**F1**	0.00185	0.00113	0.00050	0.00158	0.00064	**0.00005**	0.00028
	F2	0.0025	0.00162	0.00063	0.00089	0.00085	**0.00021**	0.00079
	F3	0.00235	0.00213	0.00062	0.00062	0.00072	**0.00035**	0.00072
RMSE	**F1**	0.0430	0.0334	0.02231	0.03978	0.02521	**0.00564**	0.0235
	F2	0.0450	0.0392	0.02506	0.02978	0.02914	**0.01457**	0.02804
	F3	0.0484	0.0462	0.02494	0.02495	0.02683	**0.01875**	0.02689

Note: numbers in bold style denote the lowest statistics under corresponding metric.

The above results show that the models' statistical ranking is consistent across three forecasting exercise periods and two sets of factors. Unsurprisingly, Table 5.7 provides the summary of best predicator selected from the pool of individual models., the most accurate predictor selected from the pool of individual models is beaten by all machine learning models. In terms of forecasting performance of ML algorithms, XGB provides the best statistical accuracy among the forecasting combination models. Although SVR sets are inferior to XGB in terms of out-of-sample performance, their predictive power is better than other models. The result is in line with several studies that suggest SVR can be a robust prediction tool with the support of individual predictors (Sermpinis et al., 2014; Zhao et al., 2019). Although LSTM falls short to GBDT family, it has more accurate results than Table 6.5 provides the summary of best predicator selected from the pool of individual models.. This is in line with recent experiments in BTC prediction (Ji, Kim and Im., 2019; McNally, Roche and Caton, 2018). One possible reason could be the relatively short sample period in our study. By grid search, we also try a number of parameters and several approaches of data pre-processing to seek for a beautiful prediction, but the final result suggests LSTM cannot give a better result based on our sample. We do not deny the predictive ability of LSTM since its main usage is in NLP and recommendation algorithms where sufficient data are provided. Due to the length of our sample data is relatively short (1719 observations in total), LSTM may not acquire adequate learning ability through training process.

In order to formally validate the consistence of forecasting ability rank in the above results, we perform the Modified Diebold and Mariano (MDM) test suggested by Harvey (1997). The MDM test statistic is calculated as follows:

$$MDM = T^{-1/2}[T + 1 - 2k + T^{-1}k(k-1)]^{1/2} DM \quad \textbf{(32)}$$

where T denotes the number of observations in out-of-sample period, k denotes the number of step-ahead forecasts. Based on the forecasting performance of XGB, we apply MDM by benchmarking XGB and comparing with rest models one by one. A negative realization of the MDM test statistic implies XGB performs better than the second forecast model in prediction accuracy. The results of MDM tests are summarized in Table 5.8. Unsurprisingly, the statistical outcomes of MDM from Table 5.9 confirms the consistence of statistical ranking presented in Table 5.9. For both two sets of factors (RFE-RF and PCA), we shed light of the predictive power of GBDT family (XGB and LBM), because of all negative statistics of MDM test. As suggested by Zhao et al (2019), when the superiority of forecasting models suffers from data-snooping bias, the predictive performance may be attributed to luck.

To further validate the superiority of the XGB model, we then apply two statistical tools: the SPA test and the MCS test. The results are given in Table 5.9.SPA test focuses on comparing the predictive abilities of multiple methods within a full set of models. High SPA p-values imply that at least one of the compared models may outperform the benchmark model. In our case, we examine the superior predictive power by benchmarking each model and comparing it with the bundle of rest forecasting models. Based on the null hypothesis of SPA (no model is more accurate than the benchmark model), we declare the predictive ability of XGB is superior to alternative models. All models from Tables 5.9 are also used as benchmarks in turn in our second test (MCS). As suggested by Hansen et al. (2011), MCS is a data-driven statistic that the more informative the data are, the less models are chosen. By controlling the family-wise error, MCS determines the statistically insignificant set compared with the alternative model. High p-values indicate that the benchmark model should belong to the most accurate model set. The consistent results of both SPA and MCS across three forecasting exercises suggest the superior performance of XGB in terms of two sets of factors, which follows the logic of model forecasting performance. This goes towards the recent literature that indicates the GBDT family has superior forecasting performance than classical ML algorithms (e.g., SVR and Random Forecast (RF)). Moreover, the overall performance of predictive algorithms also suggests that encompassing robust forecasts can boost forecasting accuracy (Diebold and Pauly, 1990). In a nutshell, the outperformance of the XGB in the out-of-sample is genuine by controlling the data-snooping bias

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Table 5. 8 Summary results of modified Diebold-Mariano (MDM) statistics for MSE and MAE loss functions

F1	Panel A Set of Selected Factors based on RFE-RF						
Metrics	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
MDM_1	-16.513***	-11.028***	-10.865 ***	-9.632***	-3.675***	-2.750**	-
MDM_2	-15.980***	-12.414***	-10.268***	-8.869***	-5.293***	-5.899***	-
F1	**Panel B Selected Principal Components**						
Metrics	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
MDM_1	-15.423***	-12.028***	-10.865 ***	-9.632***	-3.675***	-2.750**	-
MDM_2	-15.165***	-12.414***	-10.268***	-8.869***	-8.293***	-8.899***	-
F2	**Panel A Set of Selected Factors based on RFE-RF**						
Metrics	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
MDM_1	-17.416***	-11.325***	-8.816***	-4.858***	-3.330***	-10.709***	-
MDM_2	-19.413***	-11.144***	-7708***.	-4.329***	-3.223***	-9.291***	-
F2	**Panel B Selected Principal Components**						
Metrics	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
MDM_1	-20.471***	-11.437***	-13.620***	-14.725***	-14.808***	-13.651***	-
MDM_2	-17.527***	-11.267***	-11.830***	-11.011***	-10.987***	-9.845***	-
F3	**Panel A Set of Selected Factors based on RFE-RF**						
Metrics	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
MDM_1	-17.970***	-11.489***	-3.304***	-7.097***	-9.171***	-2.982**	-
MDM_2	-23.822***	-20.282***	-4.781***	-14.677***	-6.311***	-3.782***	-
F3	**Panel B Selected Principal Components**						
Metrics	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
MDM_1	-22.417***	-20.604***	-11.780***	-18.627***	-15.524***	-10.834***	-
MDM_2	-22.527***	-18.255***	-6.493***	-6.505***	-6.618***	-6.632***	-

Notes: *MDM_1 MDM_2 are the statistics computed for MAE and MSE loss function, respectively. Significance level: * 10%, ** 5%, *** 1%. Missing sections represent the benchmark model.*

Based on three metrics, we provide evidence that machine learning techniques improve the predictive power of individual models, which is in line with our proposed hypothesis. Particularly, GBDT family has the best performance among forecasting model pool without data-snooping bias.

Table 5. 9 Summary results of MCS and SPA statistics

F1	Panel A Set of Selected Factors based on RFE-RF						
Metrics	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
MCS	0	0	0.001	0.001	0.001	0.007	**1**
SPA	0	0	0	0.001	0.002	0.042	**0.522**
F1	**Panel B Selected Principal Components**						
Metrics	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
MCS	0	0	0	0	0	0	**0.564**
SPA	0	0	0	0	0	0	**0.758**
F2	**Panel A Set of Selected Factors based on RFE-RF**						
Metrics	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
MCS	0	0	0	0	0	0	**1**
SPA	0	0	0	0	0	0	**0.622**
F2	**Panel B Selected Principal Components**						
Metrics	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
MCS	0	0	0	0	0	0	**1**
SPA	0	0	0.001	0	0	0	**0.928**
F3	**Panel A Set of Selected Factors based on RFE-RF**						
Metrics	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
MCS	0	0	0	0	0	0	**1**
SPA	0	0	0	0	0	0	**0.868**
F3	**Panel B Selected Principal Components**						
Metrics	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
MCS	0	0	0	0	0	0	**1**
SPA	0	0	0.005	0.001	0.001	0.002	**0.613**

Notes: *MCS and SPA are the statistics computed for the* model confidence set (MCS) of Hansen et al. (2011) *and* superior predictive ability test (SPA) of Hansen (2005)*, respectively. This table reports the p-value of aforementioned two statistics, high value of SPA indicates the benchmark model is superior to at least one of the other models and high value of MCS implies the benchmark model belongs to the set of best models.*

5.5 Trading Performance

In order to examine the trading efficiency, we apply two approaches to our forecasting models. In section 5.5.1, we apply the traditional trading strategy and a hybrid leverage trading strategy combining sentiment and volatility in section 5.5.2. In addition, we provide results using pure volatility leverage and pure sentiment leverage in Appendix section.

5.5.1 Trading performance of traditional trading strategy (L_T)

Intuitively, we choose to stay '*long*' when the forecast return at day *t* is above zero and stay '*short*' when the forecast return at day *t* is below zero. That is, the '*long*' position is defined as buying BTC/USD at the current price and the '*short*' position is defined as selling BTC/USD at the current price. Due to the lack of regulation in cryptocurrency market, no unified trading cost is defined across different cryptocurrency exchanges. Particularly, exchanges set variable standards of trading fees based on the payment area, payment type and payment amount. For example, most cryptocurrency exchanges like Huobi or OKCoin used to charge no trading fees until the intense talk with Peoples Bank of China in 2017. Nonetheless, some exchanges preserve such rules and even set free costs for deposit and withdrawal fees, like SIMPLEFX and Coinfloor. Therefore, we do not consider the trading costs in our strategies. In Table 5.10, we present the out-of-sample trading performances of our models and NNs techniques.

Table 5. 10 Summary results of out-of-sample traditional trading performance

Panel A Set of Selected Factors based on RFE-RF								
Forecasting Exercise	**Metrics**	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
F1	**Sharpe ratio**	0.0945	0.3665	0.3756	0.3873	0.4053	0.4189	0.5164
	Annualized return	0.0111	0.021	0.0214	0.0221	0.0224	0.0228	0.0229
	Sortino ratio	0.1774	1.7485	1.9477	2.0374	2.099	2.1321	2.2788
	Maximum drawdown	-0.2679	-0.3179	-0.3351	-0.349	-0.4063	-0.4087	-0.4505
	Information ratio	0.1571	0.5795	0.5939	0.6123	0.6409	0.6624	0.8164
F2	**Sharpe ratio**	0.1031	0.2395	0.2489	0.297	0.3632	0.4047	0.481
	Annualized return	0.0125	0.0219	0.0223	0.0241	0.031	0.0373	0.0378
	Sortino ratio	0.1998	1.7409	2.1774	2.4479	3.8398	4.9542	5.7908
	Maximum drawdown	-0.4464	-0.526	-0.5454	-0.5493	-0.6349	-0.6938	-0.7633
	Information ratio	0.163	0.3786	0.3935	0.4696	0.5742	0.6399	0.7605
F3	**Sharpe ratio**	0.0865	0.3472	0.3473	0.3567	0.3596	0.363	0.4664
	Annualized return	0.0104	0.0216	0.0224	0.0228	0.0229	0.023	0.0231
	Sortino ratio	0.1741	1.8199	1.836	1.8549	1.8858	2.03	2.045
	Maximum drawdown	-0.5377	-0.492	-0.5377	-0.5417	-0.5594	-0.5595	-0.5991
	Information ratio	0.131	0.549	0.5492	0.564	0.5686	0.574	0.7374
Panel B Selected Principal Components								
Forecasting Exercise	**Metrics**	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
F1	**Sharpe ratio**	0.0945	0.3552	0.3691	0.3707	0.3821	0.4063	0.4945
	Annualized return	0.0111	0.0183	0.0192	0.0196	0.02	0.0219	0.0238
	Sortino ratio	0.1774	1.2744	1.54	1.6322	1.708	2.0238	2.7958
	Maximum drawdown	-0.2679	-0.4064	-0.4124	-0.4319	-0.4363	-0.4367	-0.5317
	Information ratio	0.1571	0.5617	0.5836	0.5862	0.6041	0.6424	0.7819
F2	**Sharpe ratio**	0.1031	0.3808	0.3854	0.4098	0.4126	0.4143	0.4468
	Annualized return	0.0125	0.021	0.0212	0.0223	0.0225	0.0226	0.0241
	Sortino ratio	0.1998	1.6755	1.6796	1.7388	1.8399	1.8557	2.1192
	Maximum drawdown	-0.4898	-0.5454	-0.5631	-0.6009	-0.6305	-0.6321	-0.7307
	Information ratio	0.163	0.6022	0.6093	0.6479	0.6524	0.6551	0.7064
F3	**Sharpe ratio**	0.0865	0.3208	0.3401	0.3461	0.3531	0.3648	0.4134
	Annualized return	0.0104	0.0189	0.0194	0.0194	0.0196	0.0201	0.0226
	Sortino ratio	0.1741	1.189	1.2938	1.3033	1.3527	1.4823	2.0439
	Maximum drawdown	-0.5377	-0.5383	-0.6155	-0.6247	-0.641	-0.6519	-0.6745
	Information ratio	0.131	0.5072	0.5377	0.5472	0.5583	0.5767	0.6537

Note: Benchmark rates used in metrics are the annualized returns of buy-and-hold strategy in each forecasting exercise, which are 0.01826, 0.01185 and 0.01881.

From Table 5.10, all the forecasting models display positive trading performance for two sets of factors. Taking a look at the general ranking, the overall profitability performance of our models coincides with their forecasting performance. In terms of model comparison, forecasting combination techniques outperform the best predicator selected from the pool of individual models. under all metrics. XGB is the best model under most trading measures, which are annualized return (2.29%), Sharpe ratio (51.64%), Sortino ratio (2.2788) and information ratio (81.64%). Nonetheless, we can see Maximum Drawdown (MDD) of XGB is also the highest, which is -45.05%. This is because models with high returns come from high risk. We note MDD of all forecasting models is roughly ranging from 26%

(Best) to 45% (XGB), indicating investors may lose nearly half of their funding for extreme cases. Compared with the performance of ML algorithms in exchange market (-15%), the average MDD in BTC market (-35%) is much higher (Sermpinis et al. 2014). Nonetheless, the average Sortino ratio is higher than 2 for all machine learning techniques, implying investment in BTC is operating efficiently by taking those high risks. Across three forecasting exercise, F2 has the best performance while the worst sub-period is F1. As a matter of fact, the profits in BTC can be high, while it is also undeniable that investment in BTC should be cautious with its intensive volatility.

5.5.2 Trading performance of volatility leverage and hybrid leverage strategy

Due to the dramatic volatile property of BTC, we apply a hybrid leverage based on two time-varying parameters, the first leverage based on daily volatility forecasts (L_V) and a leverage based on sentiment (L_P). Detailed explanation of our strategy is given in the following section.

5.5.2.1 Volatility leverage ($\mathbf{L_V}$)

The principals of the volatility forecasts (L_V) is exploiting transaction days when volatility of the return is relatively low, while trying to reduce transaction days with extremely or relatively high volatility. Meanwhile, we further take sentiment as our leverage reference from market. In this way, we can easily achieve the time-varying leverage by assigning inversely scale size of position to recent risk measures, while maintaining the information from market behaviour.

At first, we employ a GJR (1,1) in the out-of-sample periods and forecast the one day ahead realized volatility of BTC returns. We further split the total test period into six sub-periods., ranging from days with significantly low volatility to days with extremely high volatility. Based on the different volatility level of each day we set up two parameters to classify our sub-periods. The first parameter is the average (μ), which is the difference between the actual volatility in day *t* and the predicted for day (*t+1*) and its corresponding standard deviation as the measure of volatility. The parameters of our strategy are updated ($\mu + \sigma$) every three days by rolling forward the estimation period. That is, we classify periods when the difference is between μ plus one σ as ‘Lower High Volatility’. Similarly, we define periods with volatility larger than ($\mu + 2\sigma$) as ‘Extremely High Volatility’ and periods with volatility between ($\mu + \sigma$) and $\mu + 2\sigma$ as ‘Medium High Volatility.’ Following the same method, we denote periods with volatility ranging from ($\mu - \sigma$) to $\mu - 2\sigma$ as ‘Medium Low Volatility’ and periods with volatility below $\mu - 2\sigma$ as ‘Extremely Low Volatility.’ As for the leverages (L_V) assigned for each period, we give 0 for periods with extremely high volatility and 2 for periods of extremely low volatility. Both parameters (μ and σ) used in our method are updated every month by rolling forward the estimation period. For robustness check, we then assign the leverages for each trading day based on the sign of the daily forecast. We expect to exaggerate positive returns while shrinking negative returns.

1) If the sign of the forecast is positive (we are 'long'), we apply a leverage (L_V^+) of more than 1.
2) If the sign of the forecast is negative (we are 'short'), we apply a leverage (L_V^-) of less than 1.

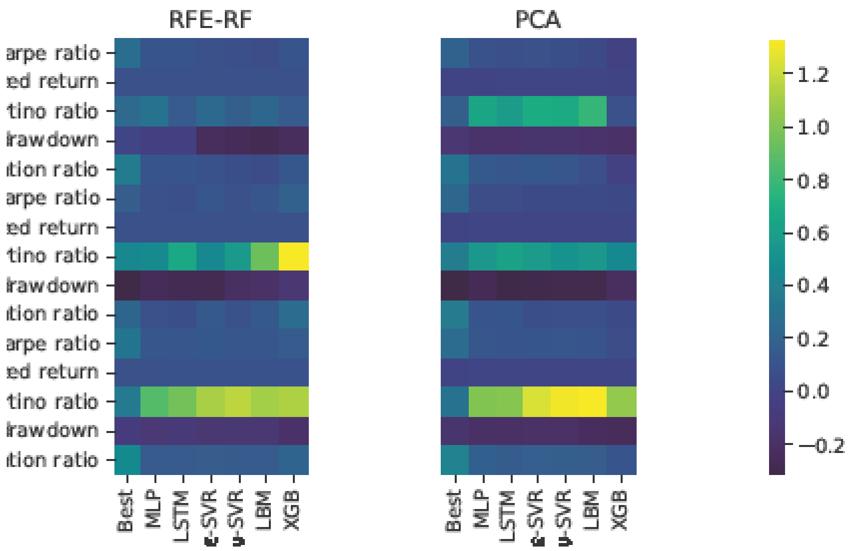
L_V is available for each trading day. We apply L_V to each model and examine their trading performance follow previous metrics. For better understanding, we also illustrate the comparison between volatility strategy and traditional strategy in terms of each ratio. The results are given in Table 5.11.

Table 5. 11 Summary results of out-of-sample volatility (L_V) leveraged trading performance

Panel A Set of Selected Factors based on RFE-RF								
Forecasting Exercise	**Metrics**	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
F1	**Sharpe ratio**	0.2964	0.3837	0.394	0.3951	0.4019	0.4033	0.5443
	Annualized return	0.0143	0.0262	0.0264	0.0278	0.028	0.028	0.0285
	Sortino ratio	0.3617	1.9878	2.0253	2.2054	2.2054	2.2926	2.3613
	Maximum drawdown	-0.3936	-0.4427	-0.4692	-0.6898	-0.7684	-0.7843	-0.7877
	Information ratio	0.4687	0.6067	0.623	0.6248	0.6355	0.6377	0.8607
F2	**Sharpe ratio**	0.1983	0.2419	0.2444	0.3386	0.3673	0.4455	0.6042
	Annualized return	0.0163	0.0256	0.0268	0.0294	0.0388	0.0452	0.0462
	Sortino ratio	0.5821	2.144	2.8063	2.8396	4.3663	5.8737	7.1256
	Maximum drawdown	-0.8703	-0.8818	-0.9243	-0.9322	-0.9539	-0.9936	-0.9942
	Information ratio	0.3135	0.3825	0.3865	0.5355	0.5807	0.7044	0.9553
F3	**Sharpe ratio**	0.3441	0.398	0.3984	0.4154	0.4161	0.4162	0.5562
	Annualized return	0.0146	0.0296	0.0318	0.0326	0.0327	0.0327	0.0328
	Sortino ratio	0.4782	2.6665	2.7737	2.9582	3.043	3.1201	3.1601
	Maximum drawdown	-0.6954	-0.6999	-0.7337	-0.7644	-0.7776	-0.7819	-0.8875
	Information ratio	0.5441	0.6293	0.6299	0.6569	0.6579	0.658	0.8794
Panel B Selected Principal Components								
Forecasting Exercise	**Metrics**	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
F1	**Sharpe ratio**	0.2964	0.4466	0.451	0.4581	0.4584	0.4591	0.4797
	Annualized return	0.0143	0.0247	0.0259	0.0267	0.0269	0.0296	0.0303
	Sortino ratio	0.3617	1.9268	2.1219	2.3214	2.3913	2.8035	2.8818
	Maximum drawdown	-0.4427	-0.5847	-0.5864	-0.5894	-0.5947	-0.6153	-0.7235
	Information ratio	0.4687	0.7062	0.7132	0.7243	0.7247	0.7258	0.7585
F2	**Sharpe ratio**	0.3386	0.4484	0.4547	0.4553	0.4646	0.4658	0.4802
	Annualized return	0.0163	0.0293	0.0303	0.0305	0.0306	0.0306	0.0328
	Sortino ratio	0.5821	2.2314	2.3158	2.3238	2.3613	2.4116	2.5739
	Maximum drawdown	-0.8044	-0.8095	-0.8703	-0.9002	-0.9214	-0.9223	-0.9554
	Information ratio	0.5355	0.709	0.7189	0.72	0.7346	0.7366	0.7592
F3	**Sharpe ratio**	0.3441	0.4414	0.4438	0.4595	0.4696	0.4713	0.4819
	Annualized return	0.0146	0.0259	0.0272	0.0274	0.0277	0.0283	0.0315
	Sortino ratio	0.4782	2.2043	2.3159	2.5488	2.6624	2.814	3.1049
	Maximum drawdown	-0.6999	-0.7389	-0.818	-0.8233	-0.8339	-0.877	-0.9125
	Information ratio	0.5441	0.6978	0.7017	0.7265	0.7424	0.7452	0.762

Note: Benchmark rates used in metrics are the annualized returns of buy-and-hold strategy in each forecasting exercise, which are 0.01826, 0.01185 and 0.01881.

Figure 5. 3 Comparison between traditional strategy and volatility (L_V) leveraged strategy



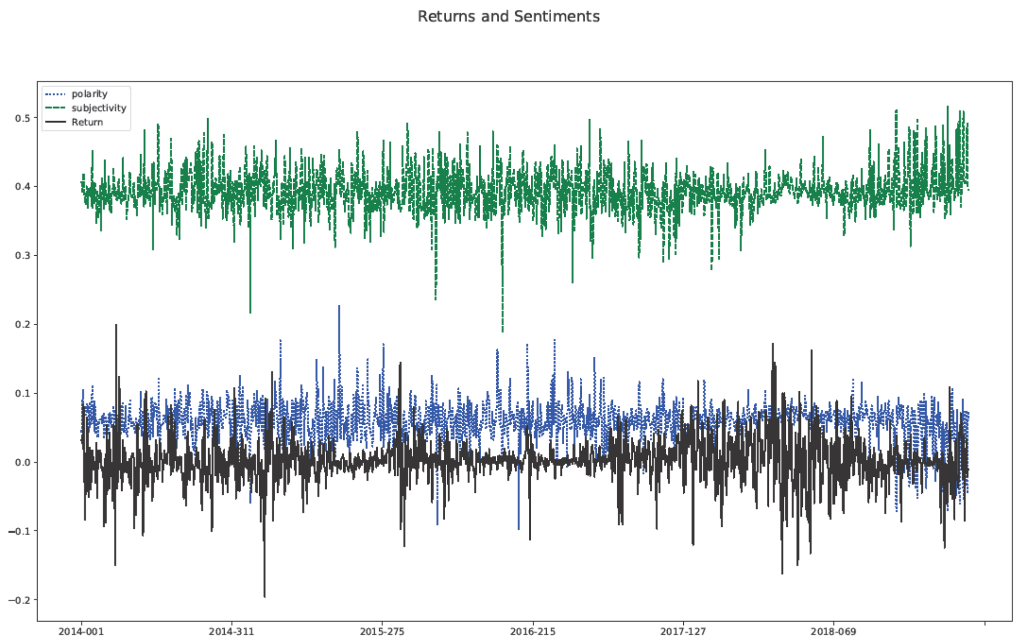
Note: This table reports the variations between volatility leverage strategy and traditional strategy, in terms of each profitability measure.

Table 5.11 summarizes profitability performance for volatility leveraged strategy and Figure 5.3 illustrates the comparison between L_T and L_V. Firstly, the trading performance of L_V is positive and the ranking is consistent with its performance in L_T. Across three forecasting exercises, F2 still takes the first place while F1 is the worst period. For model comparison, XGB still has the best performance under each profitable measure, except for MDD (-78.77% in F1). For set of RFE-RF factor, the overall risk grows higher because MDD of L_V ranges from -39% to -78% for F1. Similar results can be found in F2 and F3. From Table 5.12, we can see volatility leverage strategy amplifies the returns from high returns while it fails to shorten the corresponding risk. One possible reason could be attributed to the daily volatility variations. Although volatility leverage strategy decreases the extreme negative returns, the variations from lowest returns to highest returns still grow much larger because of the significant increase of positive returns. In terms of ratio comparison between L_T and L_V, annualized returns increase above 0.2 times, while Sortino ratio and Sharpe ratio at least increase above 0.04 times. In conclusion, the general performance of L_V is better than L_T.

5.5.2.2 Sentiment leverage (L_P)

Sentiment has been widely used in financial areas (e.g., Kearney and Liu, 2014; McLean and Zhao, 2014), moreover, prior studies show cryptocurrency market (Chen and Hafner, 2019) has a certain level of relationship with news-driven sentiment. Hence, we apply a hybrid leverage strategy (L_H) combined with sentiment (L_P)and volatility to further improve the profitability of our strategy. We also demonstrate sentiments (polarity and subjectivity) in Figure 5.4.

Figure 5. 4 Sentiments and BTC returns



Note: The x-axis denotes the number of days in a year.

In order to generate L_H, we introduce two sentiment indices, polarity and subjectivity indices.[10] Polarity index is a prevalent indicator in sentiment analysis, commonly treated as a classifier for the trend moving by labelling either 'positive' or 'negative'.[11] However, some relatively recent articles do not notice the reliability of their information sources (e.g., Chhatwani, 2019: Kilimci, 2020; Kinderis, Bezbradica and Crane, 2018; Raju and Tarif, 2020). Nonetheless, it is important to put the subjectivity of comment or news into consideration when analysing the sentiment (Subirats et al., 2018). In the present study, we employ two sentiment indices and use their literal definition as well as mathematical variations in our strategy. The first index can be interpreted as the different levels of attitude variation, while the second index is used to describe the subjectivity of collected documents. Naturally, we will only proceed to polarity measurement once the corresponding subjectivity score is above the threshold because measurement of the credibility of information source into consideration is essential (Ghose and Ipeirotis, 2011). Thus, subjectivity index is regarded as the reliability measure of narratives, representing how much investors can trust (Nunkoo and Ramkissoon, 2012) the sentiment score. Previous studies show polarity index has been widely used in

[10] We use TextBlob, which is a Python library to generate sentiment indices. Prior studies, like Singh, Gupta and Singh (2017) and Sohangir, Petty and Wang (2018) have shown the usage of Textblob is a popular and accurate python library in NLP field, which motivates us to apply this tool to generate sentiment in our strategy.

[11] That is, researchers always focus on the direction of changes, thus neglecting the magnitude.

Big Data fields, such as business analysis and public health observation (Micu at al., 2017; Subirats et al., 2018). As mentioned earlier, polarity gauges the sentiment from two sides, one for negative sentiment and the other is for positive sentiment. Investors are thereby aware of the attitude variations from public recognition in cryptocurrency market and catch possible leverage opportunities. Nonetheless, it is possible to have unreliable sentiment source, that is, narratives are organized by too subjective description or meaningless hypothesis. Under such circumstances, volatility leverage becomes the best option instead of sentiment leverage. Considering the range of subjectivity, we use the moving average of one month as threshold for subjectivity and employed volatility leverage when the subjectivity score is above the threshold.

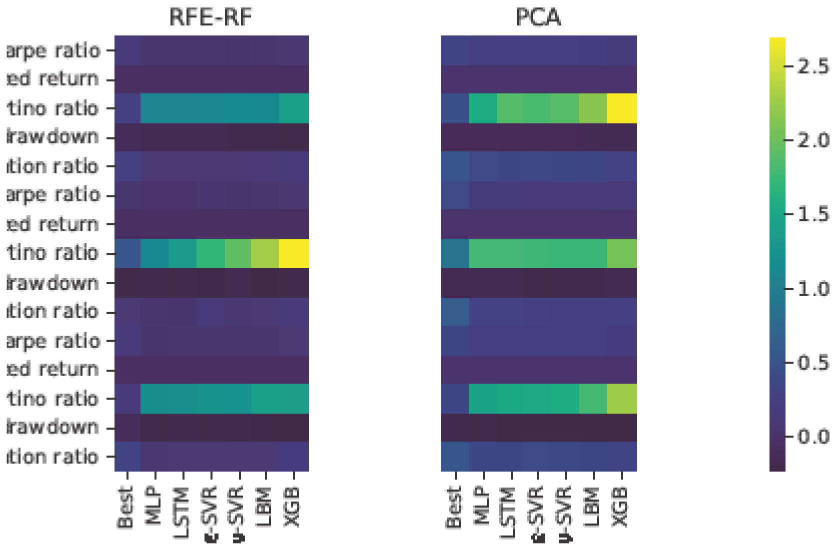
Following the same approach of L_V, we firstly obtain the mean of polarity index (μ') and its standard deviation (σ') to construct sentiment leverage (L_P). Thus, based on (μ') and (σ'), we split the total test period into six sub-periods, ranging from days with significantly low volatility to days with extremely high volatility. Based on the different volatility level of each days we again set up two parameters to classify our sub-periods. The parameters of our strategy are update (μ') and (σ') every month by rolling forward the estimation period. We classify periods when polarity score is between μ plus one σ as 'Lower High Volatility'. Similarly, we define periods with volatility larger than ($\mu' + 2\sigma'$) as 'Extremely High Volatility' and periods with volatility between ($\mu' + \sigma'$) and ($\mu' + 2\sigma'$) as 'Medium High Volatility.' Following the same method, we denote periods with volatility ranging from ($\mu' - \sigma'$) to ($\mu' - 2\sigma'$) as 'Medium Low Volatility' and periods with volatility below ($\mu' - 2\sigma'$) as 'Extremely Low Volatility.' As for the sentiment leverages (L_P) of each period, we assign 0 for periods with extremely high volatility and 2 for periods of extremely low volatility. For robustness check, we provide the performance of sentiment leverage (L_P) strategy before proceeding to the hybrid leverage strategy. Following the same procedure of L_V, we then assign the leverages for each trading day based on the sign of the daily forecast. The trading performance of L_P and the comparison between sentiment leverage strategy and traditional strategy are summarized in Table 5.12 and Figure 5.5, respectively.

Table 5. 12 Summary results of out-of-sample sentiment (L_P) leveraged trading performance

Forecasting Exercise	Metrics	Best	MLP	LSTM	ε-SVR	ν-SVR	LBM	XGB
Panel A Set of Selected Factors based on RFE-RF								
F1	**Sharpe ratio**	0.4208	0.5321	0.5468	0.5473	0.5589	0.5949	0.7427
	Annualized return	0.0157	0.0295	0.0298	0.0307	0.0312	0.0319	0.0323
	Sortino ratio	0.6425	3.4612	3.6569	3.7646	3.9059	3.9153	4.457
	Maximum drawdown	-0.4321	-0.4769	-0.5184	-0.5186	-0.6058	-0.6096	-0.6608
	Information ratio	0.6653	0.8414	0.8646	0.8654	0.8837	0.9406	1.1743
F2	**Sharpe ratio**	0.2765	0.3441	0.346	0.4978	0.502	0.5668	0.6974
	Annualized return	0.0181	0.0308	0.0312	0.0342	0.0438	0.052	0.0525
	Sortino ratio	1.0624	3.4922	4.2986	5.0811	6.815	8.4348	9.9046
	Maximum drawdown	-0.6511	-0.7275	-0.76	-0.789	-0.8197	-0.9525	-0.968
	Information ratio	0.4371	0.544	0.5471	0.7871	0.7937	0.8962	1.1027
F3	**Sharpe ratio**	0.4331	0.4996	0.5122	0.516	0.5222	0.5242	0.7089
	Annualized return	0.0145	0.0302	0.0309	0.0316	0.0316	0.0319	0.032
	Sortino ratio	0.5234	3.69	3.7381	3.8228	3.8382	4.2082	4.218
	Maximum drawdown	-0.631	-0.7174	-0.7263	-0.7504	-0.7893	-0.8001	-0.8713
	Information ratio	0.6848	0.7899	0.8099	0.8159	0.8257	0.8289	1.1209
Panel B Selected Principal Components								
Forecasting Exercise	**Metrics**	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
F1	**Sharpe ratio**	0.4208	0.606	0.6068	0.615	0.6168	0.6208	0.6837
	Annualized return	0.0157	0.0261	0.0276	0.028	0.0286	0.0313	0.0339
	Sortino ratio	0.6425	2.8291	3.4197	3.4654	3.6127	4.1762	5.4981
	Maximum drawdown	-0.4769	-0.5583	-0.574	-0.5924	-0.5972	-0.5994	-0.712
	Information ratio	0.6653	0.9581	0.9594	0.9724	0.9753	0.9816	1.081
F2	**Sharpe ratio**	0.4978	0.5715	0.5775	0.5857	0.5864	0.5868	0.6175
	Annualized return	0.0181	0.0295	0.0298	0.0313	0.0315	0.0316	0.034
	Sortino ratio	1.0624	3.451	3.458	3.4993	3.5783	3.5947	4.1888
	Maximum drawdown	-0.6667	-0.7275	-0.7383	-0.8037	-0.8232	-0.8258	-0.8953
	Information ratio	0.7871	0.9036	0.9131	0.9261	0.9271	0.9279	0.9764
F3	**Sharpe ratio**	0.4331	0.5505	0.5715	0.5935	0.5965	0.6003	0.6195
	Annualized return	0.0145	0.0262	0.0269	0.0269	0.027	0.0278	0.0313
	Sortino ratio	0.5234	2.6373	2.8021	2.8386	2.9215	3.2667	4.2978
	Maximum drawdown	-0.7263	-0.7493	-0.8571	-0.8603	-0.8833	-0.8914	-0.9155
	Information ratio	0.6848	0.8704	0.9037	0.9384	0.9432	0.9491	0.9794

Note: Benchmark rates used in metrics are the annualized returns of buy-and-hold strategy in each forecasting exercise, which are 0.01826, 0.01185 and 0.01881.

Figure 5. 5 Comparison between traditional strategy and sentiment (L_P) leveraged strategy



Note: This table reports the variations between sentiment leverage strategy and traditional strategy, in terms of each profitability measure.

Based on above tables, we note the trading performance of L_P stays positive and the general ranking is consistent with L_V and L_T. F2 is the best period out of three forecasting exercises, while F3 remains the worst period. As for model comparison, all ML models overperform than Best and XGB is the best model among all forecasting combination techniques. Similar to the performance of L_V, L_P improves the overall trading performance for most profitability metrics. Taking F1 as example, annualized returns of XGB increases from 2.29% (L_T) to 3.23 (L_P), Sharpe ratio increases from 51.64% (L_T) to 74.27% (L_P), Sortino ratio increases from 2.2788 (L_T) to 4.457 (L_P) and information ratio increases from 81.64% (L_T) to 1.1743 (L_P). Although L_P still amplifies the general volatility, it seems to work better than L_V in solving extreme cases, since MDD decreases from -78% (L_V) to -66% (L_P). Figure 5.5 also provides evidence that L_P performs better than L_V, since XGB at least increases by 39% across three forecasting exercises under each profitability metric. In conclusion, we state the success of sentiment leverage strategy.

5.5.2.3 Hybrid leverage (L_H)

With both L_P and L_V, we describe the approach of hybrid strategy as follows:

$$L_H = 1_{S_{sub}} * L_H \begin{Bmatrix} L_H = L_P, when\ S_{sub} \geq MA_{sub}(30); \\ L_H = L_V, otherwise \end{Bmatrix} \quad \textbf{(33)}$$

where $MA_{sub}(30)$ denotes the 30 days moving average of subjectivity scores, S_{sub} denotes the daily subjectivity and L_P denotes leverage based on polarity. Once S_{sub} is lower than the threshold (a rejection to usage of sentiment), we should depend on the volatility indicator. Similar to volatility and sentiment leverage strategy, we then assign the leverages for each trading day based on the sign of the daily forecast. We demonstrate leverage for RFE-RF factor set in Figures 5.6-5.8. For robustness check, we also provide leverage for PCA factor set in Appendix.

Figure 5. 6 Hybrid strategy leverages of RFE-RF factors (F1)

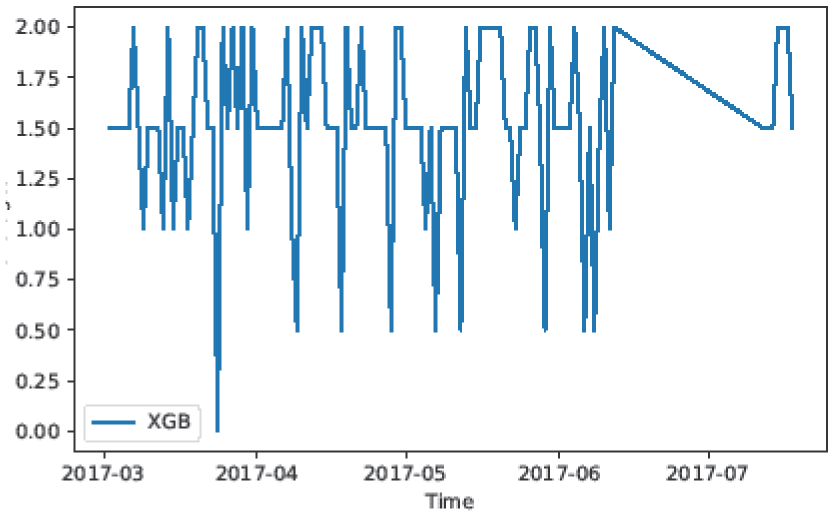


Figure 5. 7 Hybrid strategy leverages of RFE-RF factors (F2)

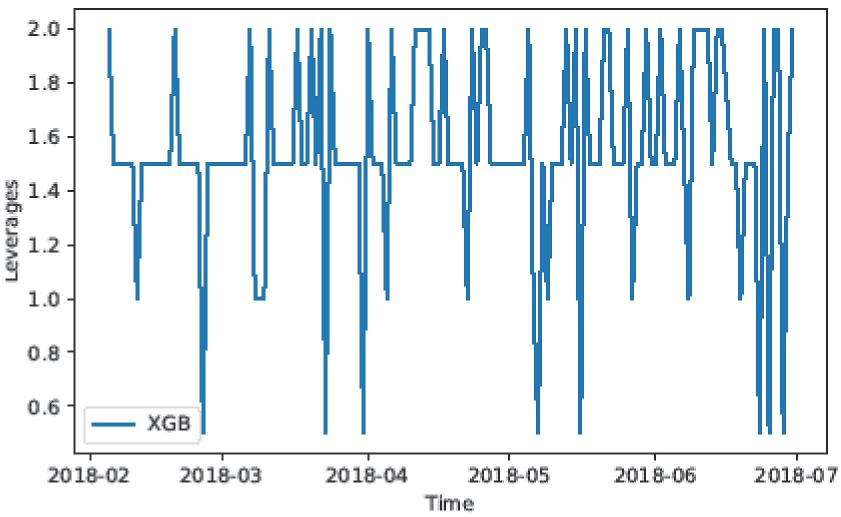
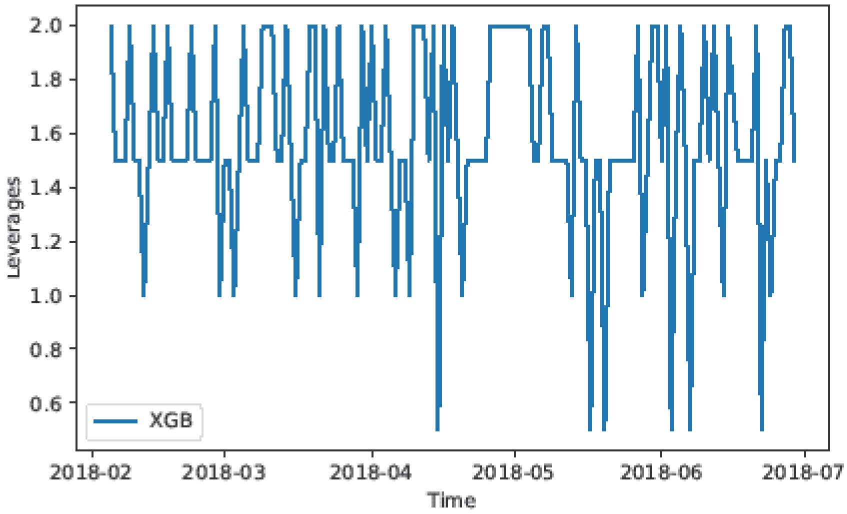
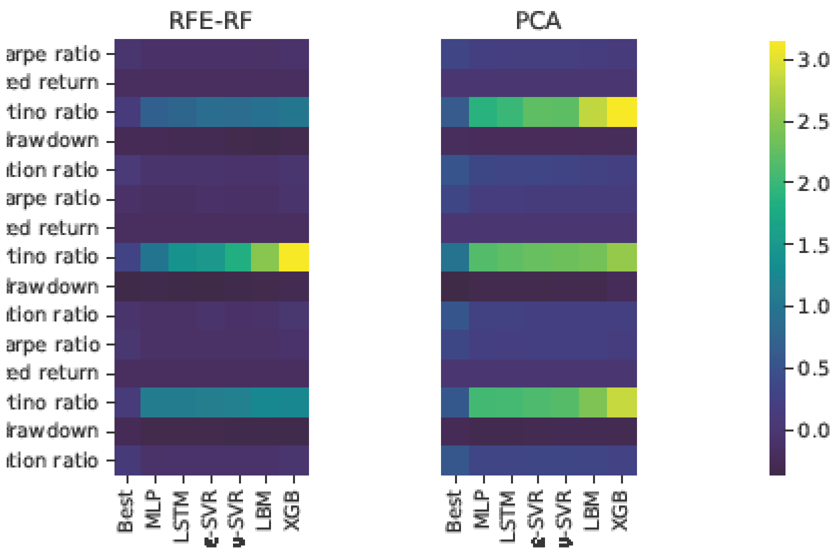


Figure 5. 8 Hybrid strategy leverages of RFE-RF factors (F3)



We apply the hybrid trading strategy to each model and examine their trading performance follow previous metrics. The results are given in Table 5.13.

Figure 5. 9 Comparison between traditional strategy and hybrid leveraged strategy



Note: This table reports the variations between hybrid leverage strategy and traditional strategy, in terms of each profitability measure.

Table 5. 13 Summary results of out-of-sample hybrid leveraged trading performance

Panel A Set of Selected Factors based on RFE-RF								
Forecasting Exercise	**Metrics**	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
F1	**Sharpe ratio**	0.4286	0.526	0.5288	0.5399	0.5475	0.5493	0.7229
	Annualized return	0.0171	0.0317	0.0329	0.0339	0.034	0.0343	0.0379
	Sortino ratio	0.8201	3.573	3.9301	4.2511	4.2646	4.4093	4.737
	Maximum drawdown	-0.4849	-0.5109	-0.5603	-0.5608	-0.7123	-0.727	-0.7287
	Information ratio	0.6776	0.8317	0.8362	0.8537	0.8657	0.8685	1.143
F2	**Sharpe ratio**	0.2484	0.3134	0.3211	0.4491	0.464	0.5125	0.7115
	Annualized return	0.0193	0.0336	0.0343	0.0376	0.0482	0.0569	0.0578
	Sortino ratio	1.172	4.1639	5.5072	5.9065	7.9759	10.5002	12.6815
	Maximum drawdown	-0.8027	-0.8632	-0.906	-0.9494	-0.9571	-0.9961	-0.9969
	Information ratio	0.3927	0.4956	0.5077	0.71	0.7337	0.8104	1.125
F3	**Sharpe ratio**	0.4433	0.4717	0.4826	0.4922	0.4953	0.4976	0.6778
	Annualized return	0.0162	0.0338	0.0351	0.0359	0.036	0.0361	0.0362
	Sortino ratio	0.7814	4.4916	4.503	4.5694	4.6788	4.992	5.0014
	Maximum drawdown	-0.7298	-0.7846	-0.8268	-0.8522	-0.8785	-0.887	-0.9414
	Information ratio	0.7009	0.7458	0.7631	0.7783	0.7832	0.7867	1.0717
Panel B Selected Principal Components								
Forecasting Exercise	**Metrics**	**Best**	**MLP**	**LSTM**	**ε-SVR**	**ν-SVR**	**LBM**	**XGB**
F1	**Sharpe ratio**	0.4286	0.5778	0.5783	0.5784	0.581	0.5814	0.6304
	Annualized return	0.0171	0.0288	0.0303	0.0311	0.0316	0.0347	0.0373
	Sortino ratio	0.8201	3.1777	3.5642	3.8757	3.9319	4.8625	5.9532
	Maximum drawdown	-0.5109	-0.6171	-0.6194	-0.6448	-0.6492	-0.6515	-0.7557
	Information ratio	0.6776	0.9135	0.9143	0.9145	0.9186	0.9193	0.9967
F2	**Sharpe ratio**	0.4491	0.5536	0.5555	0.5556	0.5564	0.5666	0.5927
	Annualized return	0.0193	0.0327	0.0332	0.0346	0.0348	0.035	0.0376
	Sortino ratio	1.172	3.8486	3.9254	4.0158	4.1704	4.2243	4.711
	Maximum drawdown	-0.8579	-0.8632	-0.8823	-0.9154	-0.9351	-0.9354	-0.9618
	Information ratio	0.71	0.8753	0.8783	0.8784	0.8798	0.8958	0.9371
F3	**Sharpe ratio**	0.4433	0.5321	0.5476	0.5638	0.5724	0.5759	0.5909
	Annualized return	0.0162	0.0295	0.0303	0.0304	0.0304	0.0312	0.0353
	Sortino ratio	0.7814	3.2532	3.3726	3.4429	3.5415	3.9141	4.8992
	Maximum drawdown	-0.7846	-0.8416	-0.9193	-0.921	-0.9258	-0.9326	-0.9645
	Information ratio	0.7009	0.8414	0.8659	0.8915	0.905	0.9106	0.9343

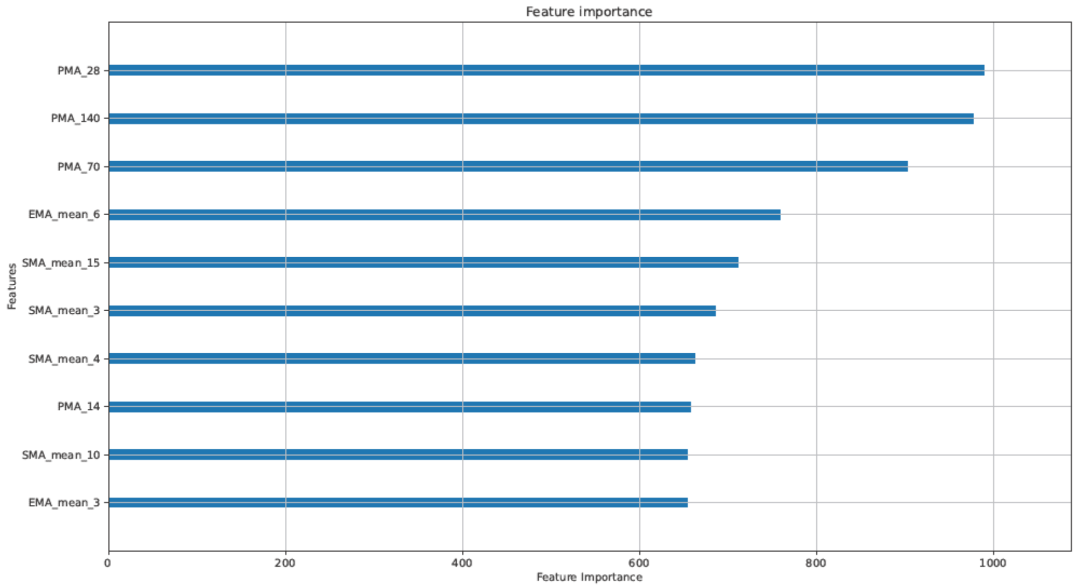
Note: Benchmark rates used in metrics are the annualized returns of buy-and-hold strategy in each forecasting exercise, which are 0.01826, 0.01185 and 0.01881.

Figure 5.9 shows the comparison between the trading performance of traditional strategy and hybrid leverage strategy. Based on our study findings above, we conclude the hybrid trading strategy was successful. Compared to the traditional trading strategy, the annualized return of hybrid strategy for each model is at least 1.4 times larger for both RFE-RF and PCA factors in all three forecasting exercises. For RFE-RF factors, XGB has the highest Annualized return, Sharpe ratio and Information ratio, consistent with its performance in traditional strategy ranking for all three forecasting exercises. Similar results can be found in other machine learning techniques. This provides strong evidence that the application of sentiment levs significantly improves the profitability of forecasting techniques. Our findings are in line with the previous studies (Azqueta-Gavaldón 2020; Karalevicius, Degrande and De Weerdt, 2018; Yao, Xu and Li, 2019) that an interactive relationship exists between BTC and narratives, thus leading to the extraordinary profitability of hybrid trading strategy. Based on our results, we state the application of sentiment indices was successfully.

5.6 Factor Importance Ranking

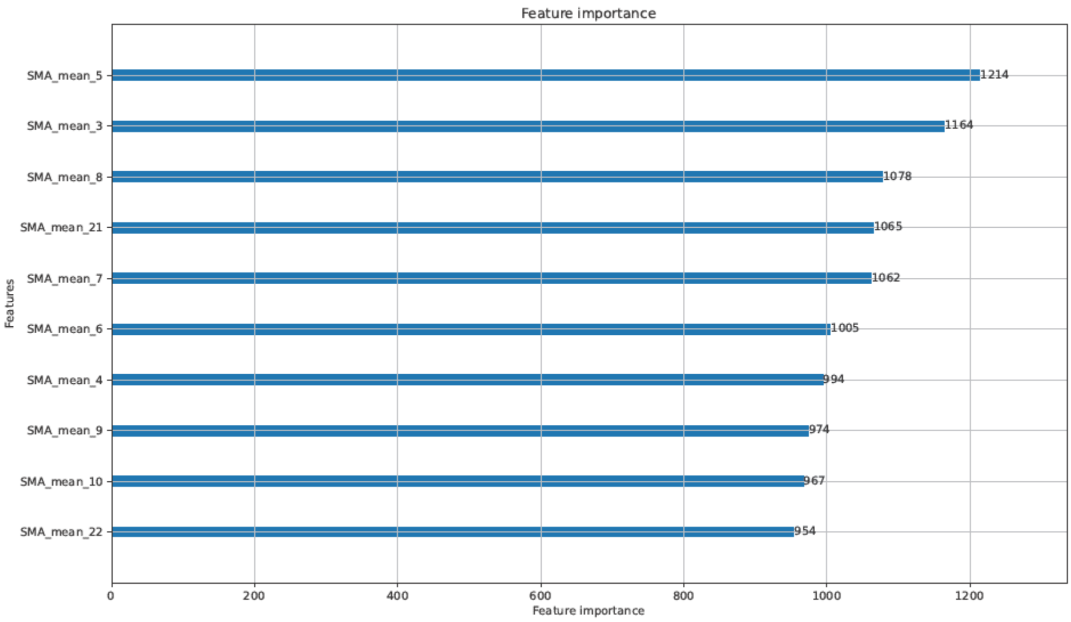
From both forecasting ability and trading performance, we find GBDT family has better performance than other models. This encourages us to further explore the significance of input factors in our best model. Figures 5.10 and 5.11 provide the top 10 features' (RFE-RF factors) contribution to the building of XGB and LBM, respectively (from the most important to the least important) in F1 forecasting exercise period. Additional figures of PCA factors are given in Appendix. Detailed explanation of importance scores can be referred to (Elith, Leathwick and Hastie, 2008; Hastie, Tibshirani and Friedman, 2016).

Figure 5. 10 Top 10 features' contribution of RFE-RF factors in the construction of XGB



Note: Factors are named by their models with specific parameter. For example, PMA_28 denotes the 28 lag of PMA ratio and SMA_mean_3 denotes the simple moving average model with parameter 3.

Figure 5. 11 Top 10 features' contribution of RFE-RF factors in the construction of LBM



Note: Factors are named by their models with specific parameter. For example, PMA_28 denotes the 28 lagged days of PMA ratio and SMA_mean_3 denotes the simple moving average model with parameter 3.

Unlike other ML algorithms, GBDT family is good at interpretation of feature selection by retrieving important score during tree construction. The highest score indicates that specific attribute is used most frequently in tree split. From above figures, PMA ratios outperform other selected factors and occupy a large proportion in the construction of GBDT family. That is, PMA ratios make the greatest contribution to the forecasting accuracy of our model.

5.7 Conclusion

This study proposes a hybrid trading strategy combining sentiment and volatility. We have examined the predictive power of forecast combination techniques and individual models. Through our investigation, we find the overall performance of forecast combination techniques has a better performance than the individual model in terms of prediction accuracy. These results are roughly consistent with our hypothesis that machine learning techniques can improve the accuracy of simple models. Particularly, XGB has the best performance among all the machine learning techniques. Moreover, our results are free of data-snooping bias through examining SPA, MCS and MDM.

As for our examination of profitability, we apply two trading strategies: the traditional and hybrid trading strategies. Unsurprisingly, the annualized returns of machine learning techniques, especially for XGB, perform much better than other models for the conventional strategy. However, by applying a hybrid trading strategy, we find that the profitability performance of all our forecasting models increases. These findings are in line with our hypothesis that strategies combined with sentiment indices can exaggerate the profitability of BTC.

In conclusion, XGB is the optimal forecast model based on remarkable trading performance and significant predictive accuracy. Furthermore, the success of our hybrid trading strategy indicates the importance of volatility and narrative sentiment in the cryptocurrency market. Although former research has suggested the usage of sentiment in the cryptocurrency market, the impact of online sentiment sources is not significant in recent years (Urquart, 2018). Prior studies showing sentiment as either a significant predictor or related factor applies their empirical results from 2010 to 2017 (Garcia and Schweitzer, 2015). Considering cryptocurrency's temporal influence and public recognition, exploring the sentiment indicator using a more recent period instead of a large scale or entirely early period data is essential. Due to limited information sources and uncertainty of new technology, preliminary indicators, such as Google Trends or post numbers on the website, may directly influence the early cryptocurrency market. With the development of blockchain technology in the cryptocurrency market, we believe the sentiments of narratives will considerably impact the cryptocurrency market.

Chapter 6 General Conclusion

6.1 Summary

This chapter will wrap up the thesis by summarising key findings concerning the research objectives, refining the validity of the findings, and reviewing contributions to the current literature. It will also show the limitations and challenges identified throughout the study and how they might be improved in future work and suggest future work prospects. With the increasing demand for low costs, high speed, and a high level of privacy in transactions, payments, and other financial services, the development of Fin-tech, BCH and other advanced techniques will be astonishing, thus promoting the growth and prosperity of the cryptocurrency market. Moreover, the attention from media, governments and the public contributes to the healthy proliferation of this thriving but young market. However, the negative influence brought by cryptocurrency trading, such as money laundry, financial frauds and hacking, and climate change caused by high energy consumption, cannot be neglected. In light of the above discussion, useful factors and functioning models that can forecast the returns of cryptocurrencies are worthy of extensive efforts.

This thesis purported to find a generalised, efficient, and reliable forecasting toolbox that anticipates future movements in the cryptocurrency market by employing different ML algorithms combined with statistical models. In addition, a pool of factors from both TA and FA aspects are applied and examined. However, the more a data set is scrutinised, the more likely spurious patterns will emerge. Moreover, empirical results can differ substantially from their natural properties. Therefore, a bundle of formal tests is used to test the validity of results to control for the data-snooping bias and reduce the influence of luck. Based on the accurate models and factors with forecasting abilities, it is crucial to explore the profitability of trading strategies further. In general, the forecasting ability of ML algorithms outperforms tested statistical models in the cryptocurrency market by controlling for the data-mining bias. The proposed hybrid leverage strategy also has the best trading performance by benchmarking to the traditional buy-and-hold strategy. A summary of each chapter is shown as follows.

Chapter 3 employs a new framework of MHT proposed by Harvey and Liu (2021) to examine TA's forecasting ability and profitability in cross-section returns on the cryptocurrency market. From 2013 to 2018, both BTC and six mainstream altercoins were used to establish the universe of trading rules proposed by STW. One interesting finding is that the returns of sampled cryptocurrencies are not as expected but lower than the returns on the stock market based on the buy-and-hold strategy. MA rules outperform other technical rules in trading performance within the trading rule universe. However, good-performance rules built upon the selected cryptocurrencies appear insignificant in forecasting cryptocurrencies' cross-section returns. This result is in line with the finding given by Bajgrowicz and

Scaillet (2012) in the stock market that the profitability of technical rules may not be genuine but come from data-snooping bias. This finding provides supportive evidence that the cryptocurrency market is currently not efficient but moving towards efficiency (Urquart,2018; Zhang et al., 2018; Kyriazis, 2019).

Chapter 4 selects factors from both TA and FA in time-series returns on the cryptocurrency market. Fifteen cryptocurrencies were investigated from 2015 to 2018. According to my result, only short-term PMAs have considerable predictive capacity across multiple periods. The result is proven consistently across four cryptocurrencies (BTC, ETH, XRP, and CRIX) and three forecasting exercises. This finding demonstrates that while conventional momentum techniques cannot accurately capture cryptocurrency changes, innovative ones such as the one provided by Detzel et al. (2020) are. This chapter studies aspect from an FA viewpoint using BTC data, economic and financial indicators, and online sentiment indices. While tested data indicate that several FA factors exhibit strong prediction in-sample, only HSH appears to perform well out-of-sample. This conclusion is particularly intriguing because HSH represents the quantity of processing power dedicated to mining and serves as a proxy for the BTC market's health. Simultaneously, as the sole genuinely significant component, HSH challenges the widely held idea that crypto-news and sentiment are critical drivers of volatility in cryptocurrencies. The result adds to the body of knowledge that emphasises the relevance of technical indicators for cryptocurrency trading, despite the fact that fundamentals relating to financial and economic activities do not add considerable value. Consistent with the view of many economists that, as long as cryptocurrencies remain relatively uncontrolled, classical FA will be unable to adequately explain them, which further highlights the importance of rigorously verifying technical rules for chance and data snooping bias. The results suggest that investment and institutional focus should be shifted away from cryptocurrency news and sentiment measurements and toward PMA variables and indicators that capture or proxy the computer power required for BTC mining. It makes it reasonable to think of the cryptocurrency market as being in its infancy and isolated from other traditional financial markets. The reason could be ascribed to the decentralised nature of the BCH technology and its low capitalisation in comparison to other financial markets (e.g., equities and exchange). Although Bitcoin's recent surge has attracted institutional investors such as Goldman Sachs, the entire cryptocurrency business remains immature and unregulated. This creates an ideal setting for market manipulation (Griffin and Shams, 2020; Dhawan and Putni, 2020) and dark-web illicit behaviour (Griffin and Shams, 2020). (Foley et al., 2019). Meanwhile, online exchanges continue to be the primary channel for bitcoin investment, but they lack the necessary defences against cyber-attacks. The MT Gox and Quadriga examples demonstrate the importance of striking an appropriate balance between security and investor convenience. Large swings also hamper extensive formal trading activity in the transaction costs of different cryptocurrency platforms. These issues must be investigated further if cryptocurrencies are to earn legitimacy as financial instruments.

In Chapter 5, a hybrid trading technique that incorporates both sentiment and volatility is proposed in this research. In addition, the predictive power of forecast combining strategies as well as individual models is tested in this study. This chapter uses BTC prices and narratives from 2014 to 2019. According to the results, the overall performance of forecast combining techniques is superior to individual models in terms of predictability. These findings are generally in line with prior studies that machine learning approaches can increase the accuracy of simple models. Specifically, XGB outperforms all other machine learning techniques in overall performance. Furthermore, by studying SPA, MCS, and MDM, the results control for the data-snooping bias. When determining profitability, four trading strategies are used: the classic trading strategy, the volatility leverage strategy, the sentiment leverage strategy, and the hybrid trading strategy. Surprisingly, the annualised returns of machine learning techniques, particularly for XGB, outperform other models for traditional strategy by a significant margin. However, by implementing a hybrid trading strategy, the profitability performance of all forecasting models improves significantly. These findings are consistent with the initial expectation that trading tactics paired with sentiment indices can inflate the profitability of BTC trading. Finally, based on its exceptional trading performance and high predictive accuracy, it can be concluded that XGB is the best forecast model available. The success of the hybrid trading technique also demonstrates the importance of volatility and narrative sentiment in the cryptocurrency market. Despite previous studies suggesting that sentiment may be useful in the BTC market, the impact of online sentiment sources has been marginal in recent years, according to Urquart (2018). Researchers have applied their empirical findings from previous studies that have found sentiment to be a significant predictor or associated factor from 2010 to 2017. (Garcia and Schweitzer, 2015). In light of cryptocurrency's temporal influence and widespread public recognition, it is critical to investigate the sentiment indicator utilising data from a more current period rather than large-scale or exclusively early-period data sets. Because of the limited availability of information sources and the uncertainties surrounding new technologies, preliminary indicators such as Google Trends or post counts on a website may directly impact the early stages of the cryptocurrencies market. In light of the above discussion, the expectation is that the sentiment index, which is constructed on a collection of narratives, will have a more significant impact on cryptocurrency prediction in the future.

To conclude, the application of ML methods in forecasting tasks has their outnumbered advantages over conventional statistical models. The proposed models in this thesis can improve the forecasting accuracy of time-series financial data in the cryptocurrency market. Another interesting finding is the examination of factors from both TA and FA fields. Momentum factors such as MA-style indicators have much better performance than other factors. The general results help investors make a better decision when dealing with indicator selection. Moreover, this thesis also brings evidence that the cryptocurrency market is moving towards efficiency.

6.2 Limitations Challenges

This thesis focuses on factor analysis and model examination. A large number of factors and numerous models are used to examine their predictive ability as well as profitability in the cryptocurrency market. The forecasting and examination framework is built upon combining statistical models and ML algorithms. Under this scenario, multiple tests are applied to reduce the influence of data-mining bias and high-dimension issues over the results. The overall outcomes suggest the significant forecasting ability of ML algorithms in the cryptocurrency market. Nonetheless, the challenges remaining are still worthy of discussion.

In this thesis, the samples are daily cryptocurrency prices from 2013 to 2019. Urquart (2016) suggested that the cryptocurrency market was in the weak efficiency before 2016 but was moving towards efficiency. The result of the inefficiency of BTC has been supported by follow-up studies which are Bariviera et al. (2017), Jiang et al. (2017), and Nadarajah and Chu (2017). The literature provides supportive evidence that TA factors' application in the cryptocurrency market can be profitable and may generate significant abnormal returns. However, the surge in price, especially BTC and ETH, at the end of 2017 might enormously impact the cryptocurrency market and distort the market structure. Recent papers indicate a structure-break may exist after 2017, accompanied by the dynamic efficiency in the cryptocurrency market (Song et al., 2019; Duan et al., 2021). One reason can be attributed to the regulatory-related announcements made by Korea, China, Europe, and the United States, among others. Therefore, the examination of the genuine forecasting ability of TA factors in the tested period (2013 to 2019) is crucial. Unsurprisingly, the overall results show the superior trading performance of TA factors may not be genuine but comes from data-snooping bias. The finding aligns with the above discussion that the cryptocurrency market is not inefficient.

However, this thesis does not put the intra-day data into consideration, leading to the failure to catch the high-frequency trading opportunities. Due to the no-stop property of the cryptocurrency market, automated trading strategies using intra-day information in hourly or even minutely frequency may generate significant trading opportunities. Unlike conventional financial markets, there is no regularized database for the cryptocurrency and related factors extracted from BCH. Although on-chain data provide open access, the reliance on data sources does not seem plausible. Recent studies also suggest trading data from cryptocurrency exchanges, including trading volumes and transaction history, may not be genuine but come from wash trading and other techniques (Alexander and Dakos, 2020; Lin et al., 2021; Pennec et al., 2021; Chen et al., 2022). Although the expectation of the profits of high-frequency trading can be high, the counterfeiting data source may indirectly influence the reliance on results.

On the other hand, the common FA factors extracted from BCH and macroeconomics at a high-frequency level are difficult to acquire. For example, online indices from Bitcointalk.org are no longer available after the tested period in the thesis. In addition, changes in BCH factors, such as blockchain size votes and BTC's unique address, are too small at the high-frequency level.

Despite the typical limitations of factor analysis, factor selection in the cryptocurrency market is also constrained. Since cryptocurrency trading has no stop, the number of TA factors can be unlimited based on different scales (e.g., time and magnitude). Classic and representative TA factors as we used in this research, it is hard to say if any small or even tiny adjustment of TA factor might significantly improve its forecasting ability. In addition, forecasting exercises or sample split periods may also influence the general performance of TA factors. The selected period may disturb the trend of technical forms, thus leading to a loss of forecasting ability given a specific period.

On the other hand, FA factors, especially factors extracted from blockchain information, may not be entirely trustworthy. For example, movements in whales' wallets or inter-movements in exchanges' wallets cannot be fully explainable and tractable. The reason can be ascribed to the fact that transactions in blockchains are anonymous and unreversed. The trajectory of on-chain data is transparent. However, the anonymity of transactions preserves the privacy of senders and their inter-wallet movements inside exchanges. Due to the lack of regulations, the manipulation of dealers provides access to wash trading and other kinds of market manipulation (Lin et al., 2021). Another concern is the feasibility and usability of factors because of the innovation and fast development of the cryptocurrency market. For example, Bitconnect (BCC), launched in 2016, was one of Coinmarketcap's best-performing programs in 2017, while it faded away just a few months later. As a result, factors involved in information from dead coins may lose their genuine forecasting ability in a particular period. Although Glassnode and other cryptocurrency databases may provide access to their unique factors extracted from BCH, it is rather expensive to acquire the membership.

By obtaining information from enormous amounts of historical data, ML models significantly improve decision-making performance. However, this technique does not fully work in financial data, especially cryptocurrency data. The failure is because models learn from in-sample (historical) data and may fail to catch the unseen condition in out-of-sample data. Another practical issue is computational speed. Complexity arises when many parameters and multiple hidden layers are applied in ML models, which costs plenty of time to get results. This thesis uses different techniques, such as PCA and RFE-RF (Chapter 5), to reduce the number of inputs, but it still needs a few days to complete a single algorithm with a high-performance personal computer. Moreover, the training of ML models requires a relatively long period of data, and test data (out-of-sample) also need a certain number of instances. However, it is challenging to fulfil such requirements in an innovative market when some cryptocurrencies only have a few months of life.

6.3 Future Work

This thesis emphasizes quantitative trading in the cryptocurrency market using factor analysis, investor sentiment and ML algorithms. As shown in Chapter 3, moving average rules outperform other TA factors, while most technical rules do not have genuine explanatory power in the cryptocurrency market. As for time-series forecasting tasks, only MA-style and Hashrate factors have predictive ability and profitability in the cryptocurrency market in Chapter 4. This study examines statistical and ML algorithms and proposes a hybrid leverage trading strategy by combining narrative sentiment and volatility in Chapter 5. In light of these findings, investors may understand the importance of factor selection and model selection in terms of investment decision-making in the cryptocurrency market. Additionally, proposed models and trading strategies can also be applied to other cryptocurrencies and financial markets in the future. Therefore, future work can be mainly summarized into three aspects as follows.

At first, it is crucial to explore further forecasting of cross-sectional returns on the cryptocurrency market. With the rapid expansion of the cryptocurrency market, the capitalization of altercoins (excluding the BTC market) is also increasing sharply, over 1.6 trillion USD on 13th Nov 2021 (data can be found from Coinmarketcap.com). Therefore, it is vital to put more effort into the whole cryptocurrency market rather than the solely BTC market to construct a healthy and regulated crypto-ecosystem. Furthermore, the maturity of blockchain technology, decentralized finance, meta-universe, and other fin-tech applications will further accelerate the prosperity of the cryptocurrency market. It is thus essential to identify what drives variations in cross-sectional returns on the cryptocurrency market. This thesis uses the LF method to control data-snooping bias regarding the examination methodology. Although the literature on the crypto market is fast increasing, examining the forecasting ability of factors is inadequate, especially for the cross-sectional returns. Recent papers have provided empirical evidence for classifying reliable data sources of cryptocurrencies (Lin et al., 2021). The current finding lays a solid foundation for a broader range and a higher frequency of dataset selection.

Secondly, a more comprehensive facto analysis of the time-series prediction of cryptocurrency is also needed. So far, the whole cryptocurrency market seems to follow the four-year halving cycle of BTC. However, it remains unclear whether the cryptocurrency market will still follow the same principle with the entry of institutional investors. Small investors or fans of BTC mainly support the cryptocurrency market before March 2020. At that time, large investors and media have negative attitudes toward the cryptocurrency market. However, the cryptocurrency market structure has changed after the engagement of institutional investors (e.g., MicroStrategy, Tesla and Galaxy Digital Holdings). In addition, the innovation of technology may also significantly influence the persistence of factors. With the vast amount of data available, the genuine drivers of cryptocurrency prices and returns are from multi-fold aspects. The above discussion indicates factor selection from on-chain data, including data extracted from blockchain information and exchange transactions, deserves more effort. In this thesis, results suggest that ML algorithms significantly improve forecasting performance. More sophisticated models will be used to strengthen the predictive ability and profitability in the cryptocurrency market.

Thirdly, manipulations of altercoins are also worthy of investigation. This study provides evidence that sentiment extracted from various narratives may improve the decision-making in cryptocurrency trading. On the other hand, celebrities or cryptocurrency whales may significantly influence the cryptocurrency market. Shahzad et al. (2022) also provide empirical evidence about the influential role of key persons through social media in cryptocurrency bubbles. However, the investigation into the implicit impacts of celebrities who are not well-known to the public lacks adequate effort. For example, the famous stock-to-flow model proposed by Plan B, an influencer in the cryptocurrency market, has been proven to be accurate since 2019. Moreover, the brand value of big exchanges also has significant influences on crypto projects. Momtaz (2021) suggests a size effect in the cryptocurrency market that large Initial Coin Offerings (ICOs) usually underperform in the long run while overpriced when coming to the market. Celebrities and their followers from multiple media platforms may thus significantly influence the cryptocurrency market.

Appendices

Appendix A (Chapter 4)

A.1 Technical Rules' Universe

This section provides a short description of the universe of trading rules applied and clarifies the calculation of the Sharpe ratio as one of our performance metrics. Additionally, we present the significant rules extracted from the LF method, when all the universe rules are considered candidate ones. Finally, the LF results obtained for the remaining crypto-coins are summarized in the end. For comparison, we basically follow the trading rules applicable to STW (Sullivan et al., 1999), including 7864 rules with five divisions.

- **a.** Moving Average Rule: A traditional approach to explore index price trends. Investors should hold the stock for a long time because the current price is still above the moving average price and will be short once the daily price drops below the moving average price.
- **b.** Support and Resistance Rule: Once the movement of the index price moves downward, it is more likely to stop at fixed level and rise to upwards some predetermined price level. In other words, the index price is unlikely to fall below its support level, rather than above the support level. In this way, once the price breaks through the support level, it is more likely to stop at a new support level. The resistance level is the opposite side of a support level.
- **c.** Channel Breakout Rule: The index price can gradually form a channel. Once the price drops below the channel, a sell-off signal will appear, and once the price breaks through the channel, a buy signal will appear.
- **d.** On-Balance Volume Rule (OBV): Instead of index price, we use the exponential volume to set the moving average trend. Compared to other technical indicators, OBV is more commonly used to assist the price changes. Once the index's closing price is higher (lower) than the previous trading day, the total trading volume for that day will be added (subtracted) to the OBV of the previous day.
- **e.** Filter Rule: Under a predetermined percentage of movement, investors may not pay attention to small changes in the index price. That is to say, once the price reverses a certain amount, investors should buy and hold the index and sell the index when the price rises by a certain percentage. Any other amount of exercise should be ignored.

A.2 Performance of Trading Algorithm

Since we have fully explained the Sortino ratio in our method, we provide the performance of technical rules and another measuring metric, Sharpe ratio in this section. Assuming we have L rules, we generate a trading signal $s_{k,t-1}$ for each prediction period, $L \le t \le T$ with each rule $k(1 \le k \le l)$. For a long position, $s_{k,t-1}$ is equal to 1, 0 for a neutral position, and -1 for a short position. In addition, we set the benchmark as the performance of trading rule with the buy-and-hold strategy that is fully invested in each coin.

Following Sullivan et al., (1999) and Bajgrowicz and Scaillet (2012), we use the Sharpe ratio as one of the metrics in our paper. Let y_t be the arithmetic return for each rule k during period t. Following Sullivan et al., (1999) we denote the excess return for each rule k as $f_{k,t}^{e} = 1_{\{s_{k,t=1} \neq 0\}}(s_{k,t-1} * y_t - r_{f,t})$, where $r_{f,t}$ is the risk-free rate, $1_{\{s_{k,t=1} \neq 0\}}$ denotes the trading signal. In this way, the mean excess return is $\overline{f}_{k}^{e} = (1/N)\sum_{t=L}^{T} f_{k,t+1}^{e}$, and the standard deviation can be denoted as $\sigma_k^e = \sqrt{(1/(N-1))\sum_{t=L}^{T}(f_{k,t+1}^{e} - \overline{f}_{k}^{e})^2}$, where $N = T - L + 1$ is the number of prediction periods. Then the Sharpe ratio should be $SR_k = \overline{f}_{k}^{e} / \sigma_k^e$.

A.3 Significant LF (whole universe)

The following table illustrates the number of statistically significant trading rules obtained from the LF method using the whole universe of STW's trading rules as candidate factors.

Table A. 1: Lucky factor rules across periods and cryptocurrencies series (all universe applied)

Panel A: Six Cryptocurrencies				
BTC	**Period 1** 2013/04/28-2014/06/28	**Period 2** 2014/06/28-2015/07/31	**Period 3** 2015/07/31-2016/10/31	**Period 4** 2016/10/31-2018/01/04
Channel Breakout	0	1808	0	0
Filter	0	106	0	0
Moving Average	0	330	0	0
On-Balance Volume	1	2	0	4
Support and Resistance	9	2	0	0
ETH	**Period 1** 2013/04/28-2014/06/28	**Period 2** 2014/06/28-2015/07/31	**Period 3** 2015/07/31-2016/10/31	**Period 4** 2016/10/31-2018/01/04
Channel Breakout	-	-	0	0
Filter	-	-	0	0
Moving Average	-	-	0	0
On-Balance Volume	-	-	0	0
Support and Resistance	-	-	0	0
XRP	**Period 1** 2013/04/28-2014/06/28	**Period 2** 2014/06/28-2015/07/31	**Period 3** 2015/07/31-2016/10/31	**Period 4** 2016/10/31-2018/01/04
Channel Breakout	0	0	0	0
Filter	0	0	0	0
Moving Average	0	0	0	0
On-Balance Volume	0	63	0	3
Support and Resistance	0	0	0	0
Panel B: Cryptocurrency Index				
CRIX	**Period 1** 2013/04/28-2014/06/28	**Period 2** 2014/06/28-2015/07/31	**Period 3** 2015/07/31-2016/10/31	**Period 4** 2016/10/31-2018/01/04
Channel Breakout	-	1936	0	0
Filter	-	331	0	0
Moving Average	-	1628	0	0
On-Balance Volume	-	-	-	-
Support and Resistance	-	1000	0	0

Note: This table presents the number of significantly technical rules obtained through the LF method (Harvey and Liu, 2017). In this case, the whole rules' universe is fed to the LF test. The total number of Channel Breakout (CB), Filter (F), Moving Average (MA), On-Balance Volume (OBV), and Support and Resistance (SR) is 2040,497,2058,2049 and 1220, respectively. The trading volume of CRIX is not available, therefore we cannot offer the results of OBVs. Additionally, for ETH and CRIX we do not have information for period 1, while for ETH we do not have data also for period 2.

Table A. 2: Lucky factor rules across periods and cryptocurrencies series (all universe applied)

DASH	**Period 1** 2013/04/28-2014/06/28	**Period 2** 2014/06/28-2015/07/31	**Period 3** 2015/07/31-2016/10/31	**Period 4** 2016/10/31-2018/01/04
Channel Breakout	-	1	11	2
Filter	-	0	0	0
Moving Average	-	0	0	0
On-Balance Volume	-	0	0	0
Support and Resistance	-	0	0	0
LTC	**Period 1** 2013/04/28-2014/06/28	**Period 2** 2014/06/28-2015/07/31	**Period 3** 2015/07/31-2016/10/31	**Period 4** 2016/10/31-2018/01/04
Channel Breakout	0	0	0	0
Filter	0	6	0	0
Moving Average	0	28	0	0
On-Balance Volume	5	4	0	5
Support and Resistance	0	0	0	0
XLM	**Period 1** 2013/04/28-2014/06/28	**Period 2** 2014/06/28-2015/07/31	**Period 3** 2015/07/31-2016/10/31	**Period 4** 2016/10/31-2018/01/04
Channel Breakout	-	0	0	0
Filter	-	0	0	0
Moving Average	-	0	0	0
On-Balance Volume	-	0	0	1
Support and Resistance	-	0	0	0

Note: This table presents the number of significantly technical rules obtained through the LF method (Harvey and Liu, 2017). In this case, the whole rules' universe is fed to the LF test. The total number of Channel Breakout (CB), Filter (F), Moving Average (MA), On-Balance Volume (OBV), and Support and Resistance (SR) is 2040,497,2058,2049 and 1220, respectively. Additionally, for DASH, and, XLM we do not have information for period.

For BTC, we can find that all types of trading rules are statistically significant during the second period, although only few of OBV rules show persistency in later periods. Moreover, all rules show a downward trend in the explanatory power on cryptocurrencies' expected return that nearly no rule is significant as time passes. On the other hand, there are always a certain number of OBV rules are significant in almost all four periods, which means volume of transactions can better explain the expected return of cryptocurrencies. Not only the OBV rules of BTC, but all the other cryptocurrencies' OBV rules show a longer lasting significance, compared to other technical indicators. Balcilar et al. (2017) also showed that trading volumes can be used to predict BTC's returns through the causality approach, especially when the market is working under normal conditions. Previous studies in stock markets show similar phenomenon, that is, volume can contribute to the stock returns (Chen, Firth and Rui, 2001). Brandvold et al. (2015) found that large cryptocurrency transactions dominated the price discovery process for BTC, and its control power declined while competitors increased. Therefore, as the collapse of Mt.Gox, which is one of the five largest cryptocurrency exchanges, the predictive power traditional technical trading rules can be influenced and disturbed with the turbulence of cryptocurrency market.

During Period 2, technical rules of all cryptocurrencies exhibit a better predictive power, especially, most of CB rules of BTC show significant results. Meanwhile, almost all types of technical indicators of two earliest coins, BTC and LTC have explanatory power and we find all types of technical indicator of CRIX also perform strong predictive power. On the other hand, there is barely any trading rules of Stellar have explanatory power and technical rules of Dash also has nearly no explanatory power that only eleven CB rules are significant. OBV rules of Ripple, however, have better performance than its behaviour in Period that 63 rules are significant.

During Period 3, except for OBV, most trading rules are no longer significant, which means less rules show explanatory power. Furthermore, CB rules of BTC and LTC plunge into bottom that none of them still show predictive power Period 3. With the development of blockchain technology and the adoption of the public, cryptocurrencies prices have begun to change dramatically, leading to failure or inefficiency in the use of traditional trading rules. The dominance of BTC and LTC is faced with great challenge with the occurrence of new idea of cryptocurrencies, like ETH. Therefore, not only for CB rule, but we can also see all kinds of technical indicators of these two coins show no significance in Period 3. During Period 4, the table shows that traditional trading rules are mostly ineffective for almost all cryptocurrencies. However, a small number of OBV rules show persistence in BTC, Eth, LTC, Ripple and Stellar. One more interesting finding is that from Period 3 to Period 4, all kinds of rules of CRIX show no explanatory power as technical indicators of all other coins lose predictive power. Although the universe of technical rules does not exhibit much predictive power, there are a few of them show genuine forecasting ability.

A.4 . Remaining LF results

In this section, we summarise our empirical results for the remaining altercoins, that is, DASH, ETH, LTC, XRP, XLM. Initially, the Sharpe ratio results are presented.

Table A. 3: Lucky Factors for DASH (Sharpe Ratio)

DASH	**Period 2 (Panel A: Baseline = No Factor)**				**Period 2 (Panel B: Baseline=3th Rank Rule)**			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)
1	0.134	-0.515	0.581	1	1.048	-0.897	0.845	1
2	0.134	-0.515	0.581	1	1.048	-0.897	0.845	1
3	-0.530	-0.508	0.034	1				
4	0.085	-0.522	0.557	1	0.503	-0.9	0.777	1
5	0.042	-0.522	0.522	1	0.998	-0.891	0.844	1
6	0.009	-0.525	0.493	1	0.965	-0.899	0.835	1
7	0.012	-0.521	0.495	0.632	0.947	-0.899	0.834	1
8	-0.045	-0.518	0.451	1	0.966	-0.898	0.836	1
9	-0.164	-0.527	0.348	1	0.929	-0.902	0.829	1
10	-0.156	-0.523	0.348	1	0.83	-0.895	0.824	1
11	-0.045	-0.518	0.451	1	0.797	-0.897	0.822	1
12	-0.192	-0.514	0.325	1	0.929	-0.902	0.829	1
13	-0.183	-0.525	0.332	1	0.772	-0.894	0.82	1
14	-0.098	-0.515	0.405	1	0.791	-0.892	0.821	1
15	-0.111	-0.512	0.391	1	0.868	-0.911	0.827	1
Multiple test: Min: -0.034 P-Value: 0.008					**Multiple test: Min:** -1 **P-Value:**0.824			
DASH	**Period 3 (Panel A: Baseline = No Factor)**				**Period 4 (Panel A: Baseline = No Factor)**			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)
1	2.399	-0.027	0.998	1	1.409	-0.081	0.968	1
2	2.398	-0.027	0.998	1	1.407	-0.08	0.968	1
3	1.074	-0.042	0.994	1	0.803	-0.075	0.954	1
4	2.273	-0.024	0.998	1	1.366	-0.088	0.967	1
5	2.155	-0.017	0.998	1	1.338	-0.08	0.967	1
6	1.993	-0.021	0.998	1	1.299	-0.086	0.967	1
7	2.019	-0.022	0.998	1	1.273	-0.077	0.966	1
8	1.838	-0.026	0.998	1	1.255	-0.077	0.966	1
9	1.973	-0.099	0.998	1	1.227	-0.003	0.966	1
10	1.910	-0.095	0.997	1	1.209	-0.001	0.967	1
11	1.725	-0.021	0.998	1	1.193	-0.074	0.966	1
12	1.917	-0.109	0.997	1	1.196	-0.015	0.967	1
13	1.798	-0.087	0.998	1	1.203	-0.005	0.966	1
14	1.697	-0.01	0.998	1	1.166	-0.074	0.965	1
15	1.581	-0.033	0.997	1	1.125	-0.053	0.965	1
Multiple test: Min: -0.92 **P-Value:**0.998					**Multiple test: Min:** -0.98 **P_Value:** 0.962			

Note: The difference in the equally-weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). The value of -0.53 (Panel 1, rule 3) means there is a reduction of 53% in the mean absolute scaling intercept, which has large contribution to the explanation of our model. SI_{ew}^{m} computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5th percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).

Table A. 4: Lucky Factors for ETH (Sharpe Ratio)

ETH	Period 3 (Panel A: Baseline = No Factor)				Period 4 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5^{th} perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5^{th} perc.	p-value	SPA (p-value)
1	0.278	-0.004	0.88	1	0.893	-0.137	0.986	1
2	0.278	-0.005	0.88	1	0.891	-0.136	0.985	1
3	0.272	-0.004	0.877	1	0.888	-0.135	0.987	1
4	0.274	-0.001	0.877	1	0.867	-0.133	0.985	0.632
5	0.277	0.000	0.882	1	0.864	-0.135	0.985	1
6	0.274	-0.003	0.878	1	0.836	-0.138	0.983	1
7	0.259	-0.004	0.867	1	0.827	-0.138	0.982	1
8	0.243	0.002	0.857	1	0.791	-0.136	0.983	1
9	0.258	-0.014	0.866	1	0.734	-0.157	0.979	1
10	0.257	-0.013	0.866	1	0.731	-0.155	0.980	1
11	0.257	-0.013	0.864	1	0.729	-0.151	0.980	1
12	0.235	0.000	0.853	1	0.760	-0.109	0.980	1
13	0.254	-0.005	0.861	1	0.728	-0.137	0.979	1
14	0.250	-0.012	0.859	1	0.727	-0.159	0.980	1
15	0.248	0.001	0.854	1	0.702	-0.128	0.979	1
Multiple test: Min: -0.994 **P-Value:** 0.881					**Multiple test: Min:** -0.314 **P-Value:**0.982			

Note: The difference in the equally-weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). The value of 0.278 (Panel 1, rule 1) means there is an increment of 27.8% in the mean absolute scaling intercept, which has no contribution to the explanation of our model. SI_{ew}^{m} computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5^{th} percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).

Table A. 5: Lucky Factors for LTC (Sharpe Ratio)

LTC	Period 1 (Panel A: Baseline = No Factor)				Period 2 Panel A: Baseline = No Factor			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)
1	0.839	-0.737	0.768	1	1.441	0.142	0.971	1
2	0.839	-0.732	0.768	1	1.443	0.118	0.97	1
3	0.845	-0.728	0.765	1	1.463	0.128	0.971	1
4	0.723	-0.734	0.744	1	1.394	0.188	0.973	1
5	0.648	-0.738	0.723	1	1.316	0.211	0.97	1
6	0.302	-0.724	0.635	1	1.311	0.197	0.966	1
7	-0.305	-0.774	0.350	1	1.172	0.109	0.959	1
8	-0.322	-0.773	0.340	1	1.186	0.122	0.960	1
9	-0.256	-0.775	0.391	1	1.147	0.145	0.957	1
10	-0.005	-0.716	0.520	1	0.996	0.139	0.967	1
11	-0.063	-0.787	0.495	1	1.097	0.175	0.956	1
12	0.233	-0.738	0.616	1	1.056	0.332	0.956	1
13	0.011	-0.778	0.533	1	1.059	0.313	0.957	1
14	-0.014	-0.774	0.511	1	1.063	0.295	0.957	1
15	-0.018	-0.775	0.508	1	1.057	0.303	0.957	1
Multiple test: Min: -0.998 **P-Value:** 0.49					Multiple test: Min: -0.998 P-Value:0.985			

LTC	Period 3 (Panel A: Baseline = No Factor)				Period 4 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)
1	1.031	0.087	0.998	1	0.530	0.331	0.968	1
2	1.014	0.090	0.998	1	0.533	0.341	0.968	1
3	0.996	0.106	0.994	1	0.518	0.329	0.954	1
4	0.899	0.067	0.998	1	0.519	0.322	0.967	1
5	0.838	0.035	0.998	1	0.515	0.326	0.967	1
6	0.924	0.069	0.998	1	0.508	0.290	0.967	1
7	0.822	0.091	0.998	1	0.451	0.284	0.966	1
8	0.835	0.089	0.998	1	0.452	0.283	0.966	1
9	0.846	0.048	0.998	1	0.441	0.281	0.966	1
10	0.827	0.086	0.997	1	0.472	0.319	0.967	1
11	0.740	0.087	0.998	1	0.437	0.269	0.966	1
12	0.691	0.064	0.997	1	0.405	0.268	0.967	1
13	0.684	0.06	0.998	1	0.406	0.270	0.966	1
14	0.679	0.039	0.998	1	0.408	0.275	0.965	1
15	0.682	0.035	0.997	1	0.408	0.275	0.965	1
Multiple test: Min: 0.073 **P-Value:** 0.985					**Multiple test: Min: -0.403 P-Value:**0.949			

Note: The difference in the equally-weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). The value of 0.839 (Panel 1, rule 1) means there is an increment of 83.9% in the mean absolute scaling intercept, which has no contribution to the explanation of our model. SI_{ew}^{m} computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5th percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).

Table A. 6: Lucky Factors for XRP (Sharpe Ratio)

XRP	Period 1 (Panel A: Baseline = No Factor)				Period 2 Panel A: Baseline = No Factor			
Rank	SI_{ew}^{m}	5^{th} perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5^{th} perc.	p-value	SPA (p-value)
1	0.709	-0.142	0.897	1	0.068	0.001	0.978	1
2	0.705	-0.138	0.896	1	0.071	0.002	0.979	1
3	0.699	-0.139	0.896	1	0.077	0.003	0.977	1
4	0.676	-0.132	0.897	1	0.075	0.005	0.974	1
5	0.565	-0.154	0.888	1	0.070	0.003	0.975	1
6	0.556	-0.11	0.878	1	0.062	0.003	0.973	1
7	0.509	-0.127	0.865	1	0.072	0.004	0.976	1
8	0.572	-0.032	0.866	1	0.075	0.003	0.972	1
9	0.580	-0.032	0.868	1	0.075	0.004	0.971	1
10	0.546	-0.034	0.867	1	0.077	0.004	0.974	1
11	0.485	-0.165	0.832	1	0.067	0.004	0.973	1
12	0.674	-0.073	0.871	1	0.064	0.001	0.969	1
13	0.607	-0.065	0.867	1	0.062	0.001	0.968	1
14	0.439	-0.08	0.841	1	0.068	0.003	0.971	1
15	0.501	-0.065	0.858	1	0.046	0.002	0.968	1
Multiple test: Min:0.353 **P-Value:** 0.891					**Multiple test: Min:** -0.998 **P-Value:**0.984			
XRP	**Period 3 (Panel A: Baseline = No Factor)**				**Period 4 (Panel A: Baseline = No Factor)**			
Rank	SI_{ew}^{m}	5^{th} perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5^{th} perc.	p-value	SPA (p-value)
1	1.383	-0.288	0.984	1	0.102	-0.019	0.997	1
2	1.373	-0.287	0.984	1	0.101	-0.018	0.997	1
3	1.386	-0.285	0.986	1	0.106	-0.020	0.997	1
4	1.263	-0.288	0.983	1	0.101	-0.020	0.997	1
5	1.140	-0.285	0.981	1	0.125	-0.026	0.999	1
6	1.047	-0.296	0.979	1	0.124	-0.029	0.998	1
7	1.263	-0.289	0.983	1	0.09	-0.017	0.997	1
8	1.146	-0.284	0.98	1	0.078	-0.021	0.994	1
9	1.146	-0.282	0.979	1	0.072	-0.019	0.991	1
10	1.152	-0.282	0.981	1	0.072	-0.020	0.992	1
11	1.413	-0.289	0.988	1	0.146	-0.020	0.999	1
12	1.101	-0.288	0.979	1	0.075	-0.021	0.992	1
13	1.055	-0.296	0.977	1	0.076	-0.019	0.991	1
14	1.151	-0.292	0.978	1	0.100	-0.025	0.997	1
15	0.847	-0.296	0.961	1	0.120	-0.027	0.998	1
Multiple test: Min: -0.140 **P-Value:** 0.972					**Multiple test: Min:** -0.682 **P-Value:**0.964			

Note: The difference in the equally-weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). The value of 0.709 (Panel 1, rule 1) means there is an increment of 70.9% in the mean absolute scaling intercept, which has no contribution to the explanation of our model. SI_{ew}^{m} computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5^{th} percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).

Table A. 7: Lucky Factors for XLM (Sharpe Ratio)

XLM	Period 2 (Panel A: Baseline = No Factor)				Period 3 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)
1	1.333	-0.915	0.887	1	0.410	0.001	0.941	1
2	1.362	-0.921	0.888	1	0.428	-0.008	0.941	1
3	1.411	-0.92	0.891	1	0.417	-0.007	0.938	1
4	1.237	-0.893	0.88	1	0.398	-0.009	0.934	0.632
5	0.925	-0.897	0.849	1	0.361	-0.006	0.926	1
6	0.795	-0.906	0.823	1	0.387	-0.001	0.930	1
7	0.563	-0.900	0.785	1	0.331	-0.014	0.920	1
8	-0.107	-0.853	0.529	1	0.318	-0.064	0.924	1
9	-0.075	-0.893	0.579	1	0.312	-0.011	0.916	1
10	-0.518	-0.851	0.224	1	0.308	-0.062	0.924	1
11	-0.200	-0.891	0.487	1	0.331	-0.003	0.924	1
12	0.294	-0.897	0.731	1	0.321	-0.022	0.922	1
13	-0.240	-0.900	0.449	1	0.334	0.005	0.926	1
14	-0.233	-0.900	0.452	1	0.326	0.003	0.927	1
15	-0.391	-0.885	0.329	1	0.298	-0.003	0.918	1
Multiple test: Min: -0.351 **P-Value:** 0.417					**Multiple test: Min:** -0.294 **P-Value:**0.947			

XLM	Period 4 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)
1	0.736	0.061	0.964	1
2	0.727	0.066	0.963	1
3	0.727	0.065	0.964	1
4	0.751	0.067	0.965	1
5	0.733	0.068	0.967	1
6	0.692	0.0600	0.962	1
7	0.724	0.063	0.965	1
8	0.690	0.023	0.964	1
9	0.699	0.066	0.961	1
10	0.715	0.041	0.963	1
11	0.622	0.055	0.961	1
12	0.619	0.059	0.957	1
13	0.609	0.057	0.959	1
14	0.607	0.057	0.958	1
15	0.000	0.056	0.962	1
Multiple test: Min: -0.211 **P-Value:** 0.974				

Note: The difference in the equally-weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). The value of -0.075 (Panel 1, rule 9) means there is a reduction of 7.5% in the mean absolute scaling intercept, which has no contribution to the explanation of our model. SI_{ew}^{m} computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5th percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).

An interesting finding is that there is a significant rule in the first period of DASH (Table A.2), which is Filter rule (0.005, 5). In other words, the Filter rule with the minimum periodic price change and the shortest holding days can explain the expected benefits of DASH in the early stage. To select the significant rules from the table, we start by checking the lowest statistic -0.53, which is much larger than other implemented statistic and the corresponding bootstrap's 5th percentile statistic. Importantly, the corresponding p-value is 0.034, further indicating that Filter rule (0.005, 5) was statistically significant from the standpoint of single factor testing. Moreover, the minimum statistic p value is 0.008, and the filtering rules (0.005, 5) from the multi-factor test perspective are statistically significant. Taking the Filter rule (0.005, 5) as a pre-selected factor, we continue to investigate further significant rules and results showing that no more rules are significant in single-factor and multi-factor tests. As shown in Panel A, we test whether the individual technical indicator can explain expected returns, and almost all rules are negligible throughout the whole period. Compared to our method, SPA test also shows the augmented model has no predictive power, consistent with the results of method. The results obtained through the Sortino ratio metric are shown below.

Table A. 8: Lucky Factors for DASH (Sortino Ratio)

DASH	Period 2 (Panel A: Baseline = No Factor)				Period 3 (Panel A: Baseline = No Factor)			
Rank	SI^{m}_{ew}	5th perc.	p-value	SPA (p-value)	SI^{m}_{ew}	5th perc.	p-value	SPA (p-value)
1	0.134	-0.532	0.605	1	-0.398	0.026	0.002	1
2	0.123	-0.531	0.599	1	-0.402	0.027	0.002	1
3	0.096	-0.53	0.582	1	-0.400	0.026	0.004	1
4	0.085	-0.529	0.578	1	-0.399	0.025	0.003	1
5	0.042	-0.533	0.556	1	-0.401	0.026	0.005	1
6	0.009	-0.535	0.533	1	-0.400	0.022	0.002	1
7	0.012	-0.533	0.539	1	-0.402	0.022	0.001	1
8	-0.045	-0.525	0.496	1	-0.404	0.038	0.001	1
9	-0.098	-0.529	0.451	1	-0.383	0.025	0.001	1
10	-0.111	-0.525	0.441	1	-0.460	0.037	0.001	1
11	-0.164	-0.53	0.378	1	-0.308	0.020	0.004	1
12	-0.156	-0.534	0.384	1	-0.315	0.019	0.003	1
13	-0.183	-0.538	0.352	1	-0.319	0.015	0.002	1
14	-0.192	-0.53	0.349	1	-0.257	0.017	0.008	1
15	-0.186	-0.527	0.367	1	-0.356	0.028	0.002	1
Multiple test: Min:0.353 **P-Value:** 0.891					**Multiple test: Min:** -0.387 **P-Value:**0.002			

DASH	Period 3 (Panel B: Baseline=10th Rank Rule)				Period 4 (Panel A: Baseline = No Factor)			
Rank	SI^{m}_{ew}	5th perc.	p-value	SPA (p-value)	SI^{m}_{ew}	5th perc.	p-value	SPA (p-value)
1	0.281	0.048	1	1	-0.177	-0.016	0.743	1
2	0.244	0.046	1	1	-0.176	-0.016	0.683	1
3	0.257	0.047	1	1	-0.168	-0.017	0.784	1
4	0.284	0.011	1	1	-0.17	-0.016	0.715	1
5	0.170	0.020	1	1	-0.177	-0.016	0.65	1
6	0.005	0.039	0.619	1	-0.167	-0.012	0.754	1
7	0.164	0.055	0.998	1	-0.162	-0.015	0.766	1
8	-0.026	0.008	0.116	1	-0.162	-0.015	0.608	1
9	-0.023	0.020	0.156	1	-0.159	-0.016	0.719	1
10					-0.144	-0.010	0.698	1
11	0.085	-0.004	0.99	1	-0.092	-0.005	0.982	1
12	0.257	-0.018	1	1	-0.099	-0.004	0.981	1
13	0.221	-0.015	1	1	-0.09	-0.001	0.986	1
14	0.195	-0.017	1	1	-0.1	-0.007	0.986	1
15	0.110	0.011	0.999	1	-0.139	-0.014	0.875	1
Multiple test: Min: -0.14 **P-Value:** 0.972					**Multiple test: Min:** -0.682 **P-Value:**0.964			

Note: The difference in the equally-weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). The value of -0.098 (Panel 1, rule 9) means there is a reduction of 9.8% in the mean absolute scaling intercept, which has tiny contribution to the explanation of our model. SI^{m}_{ew} computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5th percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).

Table A. 9: Lucky Factors for ETH (Sortino Ratio)

ETH	Period 3 (Panel A: Baseline = No Factor)				Period 4 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)
1	0.278	-0.009	0.88	1	0.893	-0.022	0.966	1
2	0.278	-0.010	0.88	1	0.891	-0.022	0.965	1
3	0.272	-0.011	0.877	1	0.888	-0.017	0.965	1
4	0.274	-0.010	0.877	1	0.867	-0.008	0.964	0.632
5	0.277	-0.011	0.882	1	0.864	-0.007	0.962	1
6	0.274	-0.015	0.878	1	0.836	0.001	0.959	1
7	0.259	-0.019	0.867	1	0.827	-0.032	0.958	1
8	0.243	-0.009	0.857	1	0.791	0.032	0.957	1
9	0.235	-0.008	0.866	1	0.760	-0.011	0.954	1
10	0.229	-0.008	0.866	1	0.724	0.043	0.959	1
11	0.258	-0.012	0.864	1	0.734	-0.050	0.957	1
12	0.257	-0.017	0.853	1	0.731	-0.051	0.956	1
13	0.254	-0.004	0.861	1	0.728	-0.027	0.955	1
14	0.250	-0.005	0.859	1	0.727	-0.043	0.954	1
15	0.248	-0.008	0.854	1	0.702	-0.025	0.956	1
Multiple test: Min: - 0.002 **P-Value:** 0.899					**Multiple test: Min:** -0.058 **P-Value:**0.962			

Note: The difference in the equally-weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). The value of 0.278 (Panel 1, rule 1) means there is an increment of 27.8% in the mean absolute scaling intercept, which has no contribution to the explanation of our model. SI_{ew}^{m} computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5th percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).

Table A. 10: Lucky Factors for LTC (Sortino Ratio)

LTC	Period 2 (Panel A: Baseline = No Factor)				Period 2 Panel A: Baseline = No Factor			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)
1	0.839	-0.737	0.768	1	1.463	-0.006	0.971	1
2	0.839	-0.732	0.768	1	1.441	-0.009	0.97	1
3	0.845	-0.728	0.765	1	1.443	-0.008	0.971	1
4	0.723	-0.734	0.744	1	1.394	-0.015	0.973	1
5	0.648	-0.738	0.723	1	1.316	-0.015	0.970	1
6	0.302	-0.724	0.635	1	1.253	-0.018	0.966	1
7	-0.305	-0.774	0.350	1	1.311	-0.016	0.959	1
8	-0.322	-0.773	0.340	1	1.075	-0.023	0.960	1
9	-0.256	-0.775	0.391	1	1.056	-0.016	0.957	1
10	-0.005	-0.716	0.520	1	1.059	-0.015	0.967	1
11	-0.063	-0.787	0.495	1	1.097	0.008	0.956	1
12	0.233	-0.738	0.616	1	0.996	0.025	0.956	1
13	0.011	-0.778	0.533	1	1.172	0.013	0.957	1
14	-0.014	-0.774	0.511	1	1.063	-0.012	0.957	1
15	-0.018	-0.775	0.508	1	1.057	-0.012	0.957	1
Multiple test: Min: -0.305 **P-Value**:0.515					**Multiple test: Min:** -0.008 **P-Value:** 0.98			
LTC	**Period 3 (Panel A: Baseline = No Factor)**				**Period 4 (Panel A: Baseline = No Factor)**			
Rank	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5th perc.	p-value	SPA (p-value)
1	0.996	0.107	0.998	1	0.686	0.124	0.968	1
2	1.031	0.110	0.998	1	0.690	0.111	0.968	1
3	1.014	0.098	0.994	1	0.688	0.115	0.954	1
4	0.899	0.123	0.998	1	0.680	0.121	0.967	1
5	0.838	0.143	0.998	1	0.668	0.104	0.967	1
6	0.726	0.024	0.998	1	0.649	0.104	0.967	1
7	0.924	0.141	0.998	1	0.654	0.115	0.966	1
8	0.577	-0.006	0.998	1	0.623	0.085	0.966	1
9	0.691	0.017	0.998	1	0.531	0.057	0.966	1
10	0.684	0.024	0.997	1	0.538	0.060	0.967	1
11	0.740	0.145	0.998	1	0.594	0.116	0.966	1
12	0.827	0.101	0.997	1	0.611	0.095	0.967	1
13	0.822	0.138	0.998	1	0.590	0.137	0.966	1
14	0.679	-0.028	0.998	1	0.526	0.072	0.965	1
15	0.682	-0.033	0.997	1	0.526	0.071	0.965	1
Multiple test: Min: -0.002 **P-Value**:0.998					**Multiple test: Min:** 0.047 **P-Value:**0.936			

Note: The difference in the equally-weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). The value of -0.256 (Panel 1, rule 9) means there is a reduction of 25.6% in the mean absolute scaling intercept, which has a certain amount of contribution to the explanation of our model. $\mathrm{SI}_{\mathrm{ew}}^{\mathrm{m}}$ computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5th percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).

Table A. 11: Lucky Factors for XRP (Sortino Ratio)

XRP	Period 2 (Panel A: Baseline = No Factor)				Period 2 Panel A: Baseline = No Factor			
Rank	SI_{ew}^{m}	5^{th} perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5^{th} perc.	p-value	SPA (p-value)
1	0.565	-0.180	0.895	1	2.475	0.018	0.968	1
2	0.556	-0.197	0.888	1	2.232	0.018	0.969	1
3	0.699	-0.152	0.902	1	3.405	0.014	0.969	1
4	0.709	-0.156	0.903	1	3.239	0.009	0.970	1
5	0.501	-0.240	0.857	1	2.010	0.018	0.966	1
6	0.676	-0.148	0.899	1	3.316	0.014	0.971	1
7	0.509	-0.163	0.875	1	2.378	0.006	0.970	1
8	0.486	-0.282	0.836	1	1.761	0.010	0.961	1
9	0.485	-0.177	0.826	1	3.514	0.028	0.970	1
10	0.572	-0.215	0.864	1	2.550	0.014	0.965	1
11	0.580	-0.210	0.870	1	2.541	0.011	0.965	1
12	0.546	-0.219	0.871	1	2.617	0.011	0.964	1
13	0.674	-0.198	0.877	1	2.590	0.015	0.965	1
14	0.607	-0.201	0.865	1	2.090	0.012	0.966	1
15	0.439	-0.228	0.839	1	2.175	0.018	0.966	1
Multiple test: Min: -0.014 **P-Value**: 0.892					**Multiple test: Min:** 0.002 **P-Value:**0.975			
XRP	Period 3 (Panel A: Baseline = No Factor)				Period 4 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5^{th} perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5^{th} perc.	p-value	SPA (p-value)
1	0.235	0.098	0.979	1	0.652	-0.068	0.948	1
2	0.220	0.104	0.971	1	0.635	-0.070	0.947	1
3	0.308	0.088	0.986	1	0.596	-0.068	0.948	1
4	0.322	0.078	0.986	1	0.595	-0.069	0.946	1
5	0.173	0.110	0.955	1	0.582	-0.068	0.942	1
6	0.264	0.089	0.983	1	0.589	-0.070	0.944	1
7	0.291	0.090	0.982	1	0.560	-0.071	0.938	1
8	0.140	0.114	0.936	1	0.569	-0.069	0.942	1
9	0.330	0.130	0.989	1	0.766	0.005	0.947	1
10	0.255	0.073	0.983	1	0.536	-0.071	0.939	1
11	0.257	0.069	0.982	1	0.528	-0.075	0.935	1
12	0.266	0.067	0.984	1	0.527	-0.075	0.934	1
13	0.246	0.091	0.978	1	0.514	-0.067	0.937	1
14	0.232	0.093	0.974	1	0.519	-0.069	0.935	1
15	0.266	0.100	0.980	1	0.534	-0.074	0.942	1
Multiple test: Min: 0.586 **P-Value:**0.96					**Multiple test: Min:** -0.007 **P-Value:** 0.962			

Note: The difference in the equally-weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). The value of 0.565 (Panel 1, rule 1) means there is an increment of 56.5% in the mean absolute scaling intercept, which has no contribution to the explanation of our model. SI_{ew}^{m} computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5^{th} percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).

Table A. 12: Lucky Factors for XLM (Sortino Ratio)

XLM	Period 2 (Panel A: Baseline = No Factor)				Period 3 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5^{th} perc.	p-value	SPA (p-value)	SI_{ew}^{m}	5^{th} perc.	p-value	SPA (p-value)
1	0.638	0.136	0.996	1	0.398	-0.063	0.931	1
2	0.574	0.169	0.995	1	0.361	-0.097	0.927	1
3	0.662	0.123	0.996	1	0.410	-0.040	0.934	1
4	0.659	0.138	0.996	1	0.428	-0.045	0.933	1
5	0.668	0.135	0.996	1	0.417	-0.051	0.93	1
6	0.556	0.132	0.995	1	0.387	-0.038	0.941	1
7	0.494	0.151	0.993	1	0.331	-0.088	0.921	1
8	0.371	0.157	0.980	1	0.312	-0.104	0.938	1
9	0.190	0.159	0.934	1	0.291	-0.105	0.930	1
10	0.365	0.180	0.982	1	0.318	-0.113	0.960	1
11	0.322	0.119	0.971	1	0.327	-0.104	0.956	1
12	0.344	0.086	0.981	1	0.331	-0.059	0.911	1
13	0.157	0.181	0.899	1	0.243	-0.114	0.923	1
14	0.333	0.089	0.978	1	0.334	-0.059	0.914	1
15	0.334	0.088	0.979	1	0.326	-0.056	0.914	1
Multiple test: Min: 0. 024 **P-Value:** 0.839					**Multiple test: Min:** 0.018 **P-Value:**0.954			

XLM	Period 4 (Panel A: Baseline = No Factor)			
Rank	SI_{ew}^{m}	5^{th} perc.	p-value	SPA (p-value)
1	0.755	0.017	0.996	1
2	0.737	0.032	0.996	1
3	0.741	0.024	0.997	1
4	0.731	0.029	0.997	1
5	0.732	0.029	0.997	1
6	0.696	0.025	0.993	1
7	0.729	0.028	0.995	1
8	0.703	0.029	0.995	1
9	0.681	0.039	0.993	1
10	0.695	-0.007	0.993	1
11	0.701	-0.003	0.994	1
12	0.626	0.006	0.991	1
13	0.639	0.008	0.993	1
14	0.613	-0.002	0.990	1
15	0.610	-0.003	0.989	1
Multiple test: Min: -0.001 **P-Value:**0.997				

Note: The difference in the equally-weighted mean absolute scaling intercept of the standard error as our measuring standard for the good-of-fitness of model, following Harvey and Liu (2021). The value of 0.638 (Panel 1, rule 1) means there is an increment of 63.8% in the mean absolute scaling intercept, which has great contribution to the explanation of our model. SI_{ew}^{m} computes the difference in the absolute scaling intercept of the standard error of the regression intercept under the original model. The next column refers to the 5^{th} percentile of bootstrapped statistics. The p-value is the result of the comparison between the realized minimum statistics and the bootstrapped distribution of minimum statistics. We also provide the SPA p-values (Hansen,2003). The SPA tests for rules genuine predictive power against benchmark (in this case a buy-and-hold strategy).

Through our tests based on the best 15 Sortino-ratio technical rules, none of them shows predictive power except F (0.03, 20) in second period of DASH. Apparently, most of our test statistic is positive, which means our technical indicator does not improve the performance of our basic model. Although some test statistic is negative, which means the augmented model is better that the basic model, the test statistic is too small that we cannot declare the predictive power of corresponding rules. Included the F (0.03, 20) in the baseline model, the reduction of the scaling intercept is 0.460 and the bootstrapped 5th_percentile statistic is 0.037. Moreover, the corresponding p-value is 0.001, so we declare it significant in the single-factor test. From the multiple-test perspective, the p-value is 0.002, suggesting F (0.03, 20) is a highly significant technical rule. Incorporating F (0.03, 20) into the selected rules, due to the significant rule emerges in the baseline model, no more important rules appear in the enhanced model. Consistent with our tested results, SPA tests also provide insignificant results, therefore we cannot reject the null hypothesis that any of tested rules has no predictive power.

Appendix B (Chapter 5)

B.1 Summary statistics of relevant factors and PMA ratios

Tables B.1 and Table B.2 present the descriptive statistics of the 57 factors and 5 PMA ratios utilized in this study.

Table B. 1: Summary statistics of cryptocurrency relevant factors (in levels)

Traditional Fundamental Factors	Min	Mean	Max	SD	ADF	S	K
3mBill	0	0.79	2.06	0.61	1.48*	0.60	-0.92
10yBill	0.24	0.92	1.51	0.31	-0.96	-0.16	-0.69
DJIA	1566	20497	26616	3023	-3.12***	0.29	-1.26
GLD	1050	1245	1370	75.61	-0.24	-0.75	-0.19
MAAA	3.18	3.77	4.18	0.23	-2.05**	-0.46	-0.72
MBaa	4.15	4.69	5.54	0.39	-2.04**	0.67	-0.66
MSCI	1468	1845	2248	195.5	-1.38	0.23	-1.26
NSQ	4266	5879	7932	997.3	-0.30	0.40	-1.13
OIL	26.19	51.01	77.41	10.43	0.57	0.32	-0.38
MER	-0.04	0.001	0.037	0.01	-0.92	-0.68	4
VIX	9.15	14.64	40.74	4.56	-4.82***	1.66	3.63
VXN	10.31	17.46	42.95	4.44	--4.50***	1.52	3.03
VXD	7.58	14.58	34.51	4.06	-4.23***	1.42	2.23
SP500	1829	2332	2872	278	-0.09	0.22	-1.20

Multiple Stock Indices Factors	Min	Mean	Max	SD	ADF	S	K
NI225	14952.	19691	24270	2351	-1.33	0.002	-1.17
IBVC	0.01	48.62	884	137	6.01***	3.36	11.62
BRA	37497	64765	89820	13855	-0.57	-0.05	-1.09
TSX	11843	14934	16567	1075	-1.47*	-0.68	-0.42
KOSPI	1829	2182	2598	207	-1.23	0.28	-1.44
ASX	4765	5633	6352	379	-1.73*	-0.21	-0.94
JCI	4120	8374	9612	1112	-3.33***	-2.66	7.05
SMI	7496	8640	9612	473	-2.66**	-0.31	-0.87
SSE	2486	3116	3993	252	-2.87**	0.04	0.15
RTS	628	1031	1324	149	-1.67*	-0.52	-0.57

Blockchain Information-based Factors	Min	Mean	Max	SD	ADF	S	K
BZ	35040	78210	99817	16571	-2.83**	-0.55	-0.72
BSV	30	117	192	33.95	-1.97*	-0.50	-0.12
HSH	2374	18717	11043	22904	0.58	1.42	1.07
MD	52699	17085	74549	22524	-0.54	1.37	0.48
TBT	6.67	9.64	18.76	1.12	-6.03***	1.62	8.59
TBM	14474	-0.46	17411	80287	--2.09*	-0.38	-0.84
DOD	36297	0.67	39330	857	-8.29***	13.21	260
UBA	20998	0.23	10728	2.84	-2.59**	1.16	2.83
DBT	86583	0.40	49064	59074	-2.87**	0.36	0.44
EPU	11.49	87.76	586	51.14	-3.13***	2.64	15.25

Notes: This table reports the descriptive statistics of all the cryptocurrency factors in levels. SD is the standard deviation; S is the skewness; K is the excess kurtosis, and ADF is the Augmented Dickey-Fuller statistic

Table B. 2: Summary statistics of cryptocurrency relevant factors (in levels)

	Min	Mean	Max	SD	ADF	S	K
Multiple Currency Factors							
AUD	0.68	0.75	0.81	0.03	2.37**	-0.01	-0.62
EURO	1.03	1.13	1.25	0.05	-1.82*	0.28	-0.59
YEN	0.79	0.89	1.00	0.04	-2.52**	0.11	0.11
CAD	0.68	0.76	0.82	0.02	-2.37**	-0.24	0.65
BRL	0.23	0.29	0.32	0.03	1.02	-0.39	-1.28
RMB	0.14	0.15	0.16	0.005	-1.46*	0.12	-1.22
CHF	0.97	1.01	1.08	0.02	-3.45***	0.32	-0.06
IDR	0.06	0.07	0.07	0.003	-1.51*	-1.11	0.47
KRW	0.00	0.001	0.001	0	-2.35**	0.06	-0.43
VEF	0	0.08	0.16	0.05	-0.92	-0.54	-0.81
GBP	1.20	1.35	1.57	0.09	2.21**	0.68	-0.50
RUB	0.01	0.01	0.02	0.001	-1.69*	-0.48	-0.13
TRY	0.14	0.28	0.36	0.06	-0.30	-0.61	-0.44
Bitcoin and Blockchain Trend-based Factors							
	Min	**Mean**	**Max**	**SD**	**ADF**	**S**	**K**
NTs	229	621.74	1905	291.59	2.03***	1.74	3.2
NPs	6060	16501	65556	12569	0.17	2.24	4.13
NUs	130	1032	7051	1036	0.54	2.45	7.16
PVs	91678	54.04	$7.9*10^6$	$1.3*10^6$	-1.27	1.21	0.54
Btc-W	12	41.91	100	14.96	-5.89***	0.89	1.65
Eth-W	1	4.81	36	3.91	-2.75**	2.63	10.65
Xrp-W	1	11.27	100	10.77	-3.66***	2.63	12.38
Btc-GT	5760	22248	34468	29959	-3.82***	5.09	35.39
Eth-GT	333	3453	30494	3610	-2.53**	2.54	8.73
Xrp-GT	113	1659	37555	3503	-4.35***	5.73	40.11

Notes: This table reports the descriptive statistics of all the cryptocurrency factors in levels. SD is the standard deviation; S is the skewness; K is the excess kurtosis, and ADF is the Augmented Dickey-Fuller statistic

Table B. 3: Summary statistics of PMA ratios for cryptocurrencies (in levels)

	BTC								ETH						
	Min	Mean	Max	SD	ADF	S	K		Min	Mean	Max	SD	ADF	S	K
PMA (1)	-0.25	0.01	0.36	0.06	-12.07***	-0.06	3.3	PMA (1)	-0.38	0.02	0.54	0.1	-8.62***	0.8	3.32
PMA (2)	-0.37	0.02	0.5	0.09	-7.84***	0.13	2.05	PMA (2)	-0.37	0.04	0.72	0.15	-7.68***	0.84	1.71
PMA (4)	-0.49	0.04	0.69	0.13	-4.95***	0.48	1.79	PMA (4)	-0.52	0.07	0.99	0.24	-4.25***	0.74	0.53
PMA (10)	-0.65	0.1	0.97	0.21	-3.1***	0.65	1.54	PMA (10)	-0.72	0.19	1.52	0.45	-2.58**	0.83	0.17
PMA (20)	-0.42	0.01	1.49	0.15	-2.14**	0.56	0.42	PMA (20)	-0.9	0.4	2.22	0.68	-3.59***	0.64	-0.41
	XRP								CRIX						
	Min	Mean	Max	SD	ADF	S	K		Min	Mean	Max	SD	ADF	S	K
PMA (1)	-0.42	0.01	1.31	0.12	-6.37***	3.27	22.65	PMA (1)	-0.21	0.01	0.17	0.04	-12.4***	-0.16	3.93
PMA (2)	-0.65	0.03	1.63	0.2	-5.73***	2.51	10.56	PMA (2)	-0.24	0.01	0.17	0.04	-12.33***	-0.42	4.52
PMA (4)	-0.67	0.06	1.95	0.31	-4.98***	2.39	7.12	PMA (4)	-0.25	0.02	0.17	0.04	-31.95***	-0.65	4.81
PMA (10)	-0.59	0.15	2.56	0.54	-3.41***	2.11	4.5	PMA (10)	-0.27	0.02	0.18	0.04	-10.54***	-0.88	5.1
PMA (20)	-0.72	0.29	3.34	0.76	-2.53**	1.85	2.94	PMA (20)	-0.26	0.03	0.19	0.04	-10.51***	-0.85	5.03

Notes: This table reports the descriptive statistics of all the PMA ratios for cryptocurrencies in levels. SD is the standard deviation; S is the skewness; K is the excess kurtosis, and ADF is the Augmented Dickey-Fuller statistic

We can see from Table B.1 - Table B.3 that conventional indices in economic or finance are quite different from cryptocurrencies that former factors are less volatile. In addition, there are relatively large gaps among the scale of each kind of factor, therefore we use log-returns of each factor to smooth series. PMA ratios of cryptocurrencies are, however, behaving like financial series, ranging from -0.9 to 3.34. One more interesting thing we can identify is that PMA series are all stationary.

B.2 Trading algorithm example with Sharpe Ratio

Assuming L technical rules, we generate a trading signal $s_{k,t-1}$ for each prediction period, $L \le t \le T$ with each rule $k(1 \le k \le l)$. For a long position, $s_{k,t-1}$ is equal to 1, 0 for a neutral position, and -1 for a short position. In addition, we set the benchmark as the performance of trading rule with the BH that is fully invested in each coin. Following Sullivan et al., (1999) and Bajgrowicz and Scaillet (2012), let y_t be the arithmetic return for each rule *k* during period *t*. We denote the excess return for each rule *k* as $f_{k,t}^{e} = 1_{\{s_{k,t=1} \neq 0\}}(s_{k,t-1} * y_t - r_{f,t})$, where $r_{f,t}$ is the risk-free rate and $1_{\{s_{k,t=1} \neq 0\}}$ denotes the trading signal. In this way, the mean excess return is $\overline{f}_k^{e} = (1/N)\sum_{t=L}^{T} f_{k,t+1}^{e}$ and the standard deviation can be denoted as $\sigma_k^e = \sqrt{(1/(N-1))\sum_{t=L}^{T}(f_{k,t+1}^{e} - \overline{f}_k^{e})^2}$, where $N = T - L + 1$ is the number of prediction periods. Finally, the Sharpe ratio is calculated as $SR_k = \overline{f}_k^{e} / \sigma_k^e$.

B.3 Wild Bootstrap Procedure

To generate pseudo sample, we need to implement the general multiple regressions organized by a constant and all used factors. We set the regression model as follows:

$$\hat{\varepsilon}_{t+1} = r_{t+1} - (\hat{\alpha} + \sum_{i=1}^{N} \hat{\beta}_{i,x} x_{i,t}) \qquad \textbf{(B. 1)}$$

where $\hat{\alpha}$, $\hat{\beta}_{i,x}$ are OLS estimates for the intercept and used regressors respectively. Meanwhile, we assume each variable follows an AR (1) model as follows:

$$x_{i,t+1} = \rho_{i,0} + \rho_{i,1} x_{i,t} + \upsilon_{i,t+1} \, for \ i = 1, 2, \ldots N \qquad \textbf{(B. 2)}$$

To overcome bias coefficients suggested by Stambaugh (1999) and Amihud and Hurvich (2004), we use the proxy for errors in the autoregressive model, which can be described as follow:

$$\hat{\upsilon}_{i,t+1} = x_{i,t+1} - (\hat{\rho}^{c}_{i,0} + \hat{\rho}^{c}_{i,1} x_{i,t}) \qquad \textbf{(B. 3)}$$

where $\hat{\rho}^{c}_{i,0}$ and $\hat{\rho}^{c}_{i,1}$ are reduced-bias estimates of AR model (19) in equation (A.13). With the above parameters and fitted residuals, we set up a pseudo sample for both regressors and expected values under the null hypothesis of no return predictability:

$$\begin{Bmatrix} r^{*}_{t+1} = \overline{r} + \hat{\varepsilon}_{t+1} w_{t+1} \\ x^{*}_{i,t+1} = \hat{\rho}^{c}_{i,0} + \rho^{c}_{i,1} x_{i,t} + \hat{\mu}^{c}_{i,t+1} w_{t+1} \end{Bmatrix} \qquad \textbf{(B. 4)}$$

where $\overline{r}$ is the sample mean of predicted cryptocurrency returns, w_{t+1} is a random draw from the standard normal sequence, and $x^{*}_{i,0}$ is the input of each factor (i = 1,...N). With the pseudo sample of cryptocurrency returns $[r^{*\,T-1}_{t+1\,t=0}]$ and N variables $[x^{*T-1}_{t\;t=0}(i = 1, \ldots, N)]$, we can measure the slop coefficients and corresponding heteroskedasticity-robust t-statistics for the bivariate predictive regressions. In this way, we contain the t-statistics for all the predictive regressions. After repeating the process 2000 times, we acquire the empirical distributions for each of the t-statistics. The empirical p-value is thus measured by the proportion of the bootstrapped t-statistics larger than the t-statistics of the original sample.

B.4 Robustness results for Sortino Ratio

This section summarizes the equivalent in-sample results presented in section 5.4 following the logic of Table 5.4 and Table 5.10. Table B.6 and B.7 present the in-sample results for PMAs and fundamental factors, while Table B.8 and Table B.9 the out-of-sample findings for the cases of using 50% and 90% of the total sample as out-of-sample.

Table B. 4: Technical rules profitability (top 15 performing rules under the Sortino ratio metric)

CRIX					
Technical Rule	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
MA(2,1,10)	1.837(0.010)	MA(2,1,0.001)	1.983(0.017)	MA(2,1,0.001)	1.312(0.016)
MA(2,1,0.001)	1.302(0.009)	PMA1	1.651(0.017)	MA(2,1,2)	1.054(0.011)
PMA1	1.232(0.009)	MA(2,1,10)	1.563(0.017	PMA1	1.051(0.015)
FR(0.01,1)	1.229(0.009)	FR(0.01,1)	1.520(0.016)	FR(0.01,1)	1.041(0.015)
MA(2,1,0.005)	1.218(0.009)	FR(0.03,2)	1.488(0.016)	FR(0.01,0.015)	1.007(0.011)
MA(5,2,1)	1.179(0.008)	FR(0.015,1)	1.479(0.016)	FR(0.06,1)	0.922(0.014)
FR(0.01,2)	1.167(0.008)	FR(0.015,6)	1.275(0.015)	FR(0.005,1)	0.900(0.014)
FR(0.005,1)	1.145(0.010)	MA(5,2,1)	1.271(0.015)	MA(5,2,0)	0.873(0.011)
FR(0.01,3)	1.131(0.008)	MA(2,1,0.01)	1.230(0.014)	FR(0.01,1)	0.865(0.014)
FR(0.01,0.015)	1.116(0.008)	FR(0.01,0.015)	1.151(0.015)	SR(5,3,2)	0.854(0.014)
FR(0.005,3)	1.093(0.008)	FR(0.015,2)	1.140(0.015)	FR(0.015,6)	0.851(0.014)
FR(0.015,2)	1.065(0.008)	FR(0.01,2)	1.012(0.014)	SR(10,2,3)	0.850(0.014)
FR(0.02,4)	1.055(0.008)	FR(0.07,1)	0.988(0.014)	SR(10,2,5)	0.843(0.010)
FR(0.01,3)	1.041(0.008)	SR(5,2,10)	0.969(0.011)	FR(0.08,1)	0.838(0.014)
FR(0.015,7)	1.038(0.007)	SR(5,3,10)	0.966(0.011)	SR(10,3,5)	0.835(0.010)
	0.079 (0.003)		0.286 (0.005)		0.174 (0.004)
XRP					
Technical Rule	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
MA(5,2,5)	1.048(0.019)	FR(0.045,0.01)	3.460(0.027)	MA(2,1,0.01)	5.498(0.027)
PMA1	0.702(0.014)	PMA1	1.602(0.021)	MA(2,1,0.02)	2.485(0.020)
MA(5,2,2)	0.621(0.012)	FR(0.01,0.015)	1.493(0.017)	PMA1	1.800(0.010)
PMA2	0.611(0.009)	FR(0.045,0.01)	0.999(0.013)	MA(2,1,0.01)	1.114(0.016)
PMA4	0.610(0.008)	FR(0.14,10)	0.767(0.013)	MA(2,1,0.02)	1.093(0.008)
MA(5,2,0)	0.592(0.007)	FR(5,2,5)	0.747(0.012)	MA(5,2,1)	1.049(0.008)
MA(5,2,1)	0.584(0.007)	PMA20	0.623(0.012)	MA(2,1,0.005)	1.047(0.013)
FR(0.04,0.015)	0.582(0.007)	MA(40,25,0.05)	0.603(0.008)	MA(2,1,0.03)	1.006(0.005)
FR(0.045,5)	0.556(0.007)	FR(0.045,50)	0.587(0.012)	MA(5,2,5)	1.003(0.014)
FR(0.025,5)	0.537(0.007)	MA(5,2,1)	0.581(0.012)	MA(2,1,0.001)	0.987(0.014)
FR(0.045,25)	0.529(0.006)	FR(0.14,5)	0.580(0.011)	MA(2,1,5)	0.956(0.014)
FR(0.045,10)	0.527(0.006)	MA(40,25,0.04)	0.573(0.008)	FR(0.005,1)	0.932(0.014)
FR(0.14,1)	0.524(0.006)	FR(0.01,3)	0.559(0.011)	MA(5,1,0.04)	0.871(0.007)
FR(0.04,3)	0.518(0.006)	FR(0.12,0.005)	0.554(0.011)	MA(5,2,10)	0.870(0.013)
FR(0.01,5)	0.504(0.006)	FR(0.045,0.005)	0.550(0.011)	MA(2,1,0.04)	0.822(0.004)
	0.210 (0.005)		0.387 (0.009)		0.318(0.007)

Note: This table presents the Sortino ratios and mean returns (in parentheses) of the top 15 technical rules for XRP and CRIX. PMA denotes the log-price to MAs ratio (e.g. PMA1 is the PMA ratio generated by one-week gap). MA are Moving Average rules (e.g., MA (5,1,5) represents MA rule with 5-day slow MA, 1-day fast MA and 5-day position held). FR represents the Filter rule (e.g., FR (0.005,1) denotes a 0.005% change of price with 1 day of constant holding period). CB denotes the Channel-Break rule (e.g. CB(5,0.0075,5,0.001) denotes the 5 days of channel , 0.075 difference between high and low channel, 5 days of constant holding period and 0.001 percentage band). SR denotes the Support and Resistance rule (e.g., SR (5,3,2) is 5 days to generate extrema, 3 days for time delay of transaction and 2 day of constant holding period). As benchmark a BH strategy is used. 50%, 75% and 90% IS denotes that we use as in-sample the 50%, 75% and 90% of the total dataset in period 1, period 2 and period 3 respectively. The equivalent Sharpe Ratio results are shown in Table 5.4 of the main text.

Table B. 5: Technical rules profitability (top 15 performing rules under the Sortino ratio metric)

BTC						
Rank	**Technical Rule**	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
1	CB(5,0.075,5,0.001)	2.698(0.011)	CB(5,0.075,5,0)	5.658(0.016)	PMA1	6.905(0.015)
2	CB(5,0.075,5,0)	2.640(0.006)	MA(5,1,5)	5.544(0.014)	CB(5,0.075,5,0)	6.765(0.017)
3	PMA1	2.429(0.006)	PMA1	5.160(0.010)	MA(5,1,5)	6.339(0.011)
4	CB(5,0.075,5,0)	2.419(0.006)	CB(5,0.075,5,0.001)	4.716(0.010)	CB(5,0.05,5,0.001)	5.806(0.011)
5	CB(5,0.075,5,0.01)	2.365(0.006)	CB(5,0.075,5,0.005)	4.369(0.010)	MA(5,2,0.01)	5.402(0.011)
6	MA(5,1,5)	2.181(0.007)	MA(5,2,2)	4.262(0.011)	MA(5,1,2)	5.204(0.013)
7	MA(5,2,1)	2.168(0.006)	MA(5,2,1)	4.166(0.009)	CB(5,0.075,5,0.01)	5.087(0.010)
8	CB(5,0.075,5,0)	2.053(0.005)	MA(5,2,0)	3.853(0.013)	MA(5,2,2)	4.752(0.012)
9	CB(5,0.075,5,0.015)	2.003(0.005)	SR(250,2,5)	3.807(0.008)	CB(5,0.075,5,0)	4.731(0.009)
10	CB(5,0.075,5,0.005)	1.997(0.005)	MA(5,1,0.001)	3.491(0.013)	CB(5,0.075,5,0.001)	4.325(0.009)
11	CB(5,0.03,5, 0.01)	1.958(0.006)	SR(10,2,0.005)	3.412(0.008)	CB(5,0.075,5,0.015)	4.040(0.010)
12	MA(5,2,10)	1.823(0.006)	MA(5,1,0.005)	3.282(0.012)	MA(5,2,0)	4.003(0.013)
13	CB(5,0.075,5,0.02)	1.788(0.005)	CB(5,0.075,5,0.015)	3.240(0.008)	CB(5,0.075,5,0.02)	3.857(0.013)
14	MA(5,2,0)	1.722(0.007)	CB(5,0.05,5,0.01)	3.071(0.008)	MA(5,1,0.05)	3.833(0.013)
15	MA(5,1,0.05)	1.630(0.007)	CB(5,0.075,5,0.02)	2.944(0.009)	MA(5,1,0.001)	3.623(0.013)
	Benchmark	0.050 (0.003)		0.234 (0.005)		0.160(0.004)
ETH						
Rank	**Technical Rule**	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
1	PMA1	1.266(0.028)	MA(2,1,0.005)	1.693(0.029)	MA(2,1,0.005)	2.416(0.028)
2	PMA2	0.923(0.022)	FR (0.005,1)	1.533(0.023)	MA(2,1,0.001)	2.097(0.021)
3	FR(0.015,5)	0.913(0.016)	PMA1	1.475(0.017)	PMA1	1.983(0.016)
4	FR(0.01,3)	0.888(0.011)	FR(0.01,1)	1.366(0.013)	PMA2	1.836(0.014)
5	FR(0.01,0.015)	0.885(0.010)	MA(2,1,0.01)	1.350(0.011)	PMA4	1.777(0.015)
6	PMA4	0.850(0.005)	PMA2	1.348(0.012)	FR(0.005,1)	1.774(0.015)
7	MA(5,2,5)	0.836(0.005)	MA(5,2,1)	1.279(0.010)	FR(0.01,0.015)	1.760(0.013)
8	PMA20	0.700(0.005)	FR(0.01,2)	1.277(0.012)	MA(2,1,5)	1.738(0.015)
9	FR (0.01,1)	0.685(0.005)	FR(0.06,1)	1.252(0.011)	FR(0.01,2)	1.731(0.014)
10	FR (0.05,1)	0.612(0.005)	FR(0.01,0.015)	1.198(0.011)	FR(0.01,3)	1.644(0.014)
11	FR (0.015, 2)	0.584(0.005)	MA(2,1,5)	1.186(0.011)	MA(5,2,10)	1.594(0.011)
12	MA(25,5,5)	0.546(0.005)	FR(0.015,1)	1.165(0.011)	FR(0.015,6)	1.524(0.014)
13	FR (0.12,0.01)	0.536(0.005)	MA(2,1,0.015)	1.134(0.008)	FR(0.005,2)	1.495(0.014)
14	MA(30,25,5)	0.531(0.015)	MA(5,2,10)	1.125(0.011)	FR(0.06,1)	1.481(0.014)
15	FR (0.16,1)	0.509(0.004)	FR(0.015,2)	1.097(0.011)	FR(0.015,2)	1.448(0.013)
	Benchmark	0.241 (0.01)		0.387 (0.01)		0.268 (0.008)

Note: This table presents the Sortino ratios and mean returns (in parentheses) of the top 15 technical rules for the BTC, ETH. PMA denotes the log-price to MAs ratio (e.g. PMA1 is the PMA ratio generated by one-week gap). MA are Moving Average rules (e.g., MA (5,1,5) represents MA rule with 5-day slow MA, 1-day fast MA and 5-day position held). FR represents the Filter rule (e.g., FR (0.005,1) denotes a 0.005% change of price with 1 day of constant holding period). CB denotes the Channel-Break rule (e.g. CB(5,0.0075,5,0.001) denotes the 5 days of channel , 0.075 difference between high and low channel, 5 days of constant holding period and 0.001 percentage band). SR denotes the Support and Resistance rule (e.g., SR (5,3,2) is 5 days to generate extrema, 3 days for time delay of transaction and 2 day of constant holding period). As benchmark a BH strategy is used. 50%, 75% and 90% IS denotes that we use as in-sample the 50%, 75% and 90% of the total dataset in period 1, period 2 and period 3 respectively. The equivalent Sharpe Ratio results are shown in Table 5.4 of the main text.

Table B. 6: In-sample Predictive Regression Estimation Results (Sortino Ratio – F1, F2, F3)

Rank	Technical Rule	Period 1 (50%IS) 08/08/2015-05/04/2017	Technical Rule	Period 2 (75% IS) 08/08/2015-06/02/2018	Technical Rule	Period 3 (90% IS) 08/08/2015-03/08/2018
BTC						
1	CB(5,0.075,5,0.001)	0.158(0.105)	CB(5,0.075,5,0)	0.146(0.215)	**PMA1**	**0.052*(1.743)**
2	CB(5,0.075,5,0)	0.026(0.785)	MA(5,1,5)	0.052(0.432)	CB(5,0.075,5,0)	0.045(0.418)
3	**PMA1**	**0.067*(1.73)**	**PMA1**	**0.038*(1.532)**	MA(5,1,5)	0.138(0.179)
4	CB(5,0.075,5,0)	0.068(1.716)	CB(5,0.075,5,0.001)	0.037(1.517)	CB(5,0.05,5,0.001)	0.052(1.741)
5	CB(5,0.075,5,0.01)	0.070(1.73)	CB(5,0.075,5,0.005)	0.045(1.609)	MA(5,2,0.01)	0.071(1.201)
6	MA(5,1,5)	0.047(0.667)	MA(5,2,2)	0.063(0.441)	MA(5,1,2)	0.062(0.369)
7	MA(5,2,1)	0.031(1.114)	MA(5,2,1)	0.051(1.312)	**CB(5,0.075,5,0.01)**	**0.064*(1.836)**
8	CB(5,0.075,5,0)	0.042(0.653)	MA(5,2,0)	0.051(0.504)	MA(5,2,2)	0.059(0.369)
9	CB(5,0.075,5,0.015)	0.004(1.046)	SR(250,2,5)	0.004(1.077)	CB(5,0.075,5,0)	0.003(1.065)
10	CB(5,0.075,5,0.005)	0.001(1.018)	MA(5,1,0.001)	0.003(1.048)	CB(5,0.075,5,0.001)	0.067(1.046)
11	CB(5,0.03,5, 0.01)	0.003(0.852)	SR(10,2,0.005)	0.102(0.913)	**CB(5,0.075,5,0.015)**	**0.065*(1.843)**
12	MA(5,2,10)	0.238(1.211)	MA(5,1,0.005)	0.056(0.414)	MA(5,2,0)	0.056(0.334)
13	CB(5,0.075,5,0.02)	0.105(0.309)	CB(5,0.075,5,0.015)	0.069(0.347)	CB(5,0.075,5,0.02)	0.061(1.108)
14	MA(5,2,0)	0.090(1.306)	CB(5,0.05,5,0.01)	0.08(0.505)	MA(5,1,0.05)	0.055(0.584)
15	MA(5,1,0.05)	0.114(0.239)	CB(5,0.075,5,0.02)	0.06(0.391)	MA(5,1,0.001)	0.059(0.313)
ETH						
Rank	**Technical Rule**	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
1	**PMA1**	**0.059*(1.482)**	MA(2,1,0.005)	0.363(0.621)	MA(2,1,0.005)	0.315(0.156)
2	PMA2	0.432(0.496)	FR (0.005,1)	0.391(0.547)	MA(2,1,0.001)	0.335(0.437)
3	FR(0.015,5)	0.360(0.538)	**PMA1**	**0.068*(1.742)**	**PMA1**	**0.071*(1.801)**
4	FR(0.01,3)	0.046(0.645)	**FR(0.01,1)**	**0.093*(1.846)**	**PMA2**	**0.097*(1.897)**
5	FR(0.01,0.015)	0.103(0.907)	MA(2,1,0.01)	0.092(1.87)	PMA4	0.096(1.915)
6	PMA4	0.023(0.793)	PMA2	0.083(1.84)	FR(0.005,1)	0.084(1.88)
7	MA(5,2,5)	0.061(1.231)	MA(5,2,1)	0.058(1.074)	FR(0.01,0.015)	0.073(1.023)
8	PMA20	0.038(0.654)	FR(0.01,2)	0.084(1.846)	MA(2,1,5)	0.087(1.891)
9	FR (0.01,1)	0.028(0.747)	FR(0.06,1)	0.043(1.529)	FR(0.01,2)	0.054(1.68)
10	FR (0.05,1)	0.087(0.297)	FR(0.01,0.015)	0.039(0.874)	FR(0.01,3)	0.021(0.907)
11	FR (0.015, 2)	0.088(0.762)	MA(2,1,5)	0.046(1.474)	MA(5,2,10)	0.041(1.214)
12	MA(25,5,5)	0.108(0.191)	FR(0.015,1)	0.054(1.639)	FR(0.015,6)	0.062(1.743)
13	FR (0.12,0.01)	0.015(0.863)	MA(2,1,0.015)	0.052(1.623)	FR(0.005,2)	0.059(1.724)
14	MA(30,25,5)	0.044(0.607)	MA(5,2,10)	0.032(1.081)	FR(0.06,1)	0.037(1.513)
15	FR (0.16,1)	0.031(0.72)	FR(0.015,2)	0.044(1.539)	FR(0.015,2)	0.05(1.648)

Note: We report the estimation of the slope coefficient and the heteroskedasticity-consistent t-statistic (in in the parenthesis) for the bivariate predictive regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$, where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 (main text) respectively. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, based on two-sided wild bootstrapped p-values. 50% IS corresponds to period 1 as outlined in Table 5.4 (main text). The equivalent Sharpe Ratio results are shown in Panels A of Tables 5.6-5.9 of the main text.

Table B. 7: In-sample Predictive Regression Estimation Results (Sortino Ratio – F1, F2, F3)

Technical Rule	Period 1 (50%IS) 08/08/2015-05/04/2017	Technical Rule	Period 2 (75% IS) 08/08/2015-06/02/2018	Technical Rule	Period 3 (90% IS) 08/08/2015-03/08/2018
CRIX					
MA(2,1,10)	0.139*(1.738)	**MA(2,1,0.001)**	**0.087*(1.598)**	**MA(2,1,0.001)**	**0.106*(1.771)**
MA(2,1,0.001)	0.07(0.76)	PMA1	**0.073*(1.731)**	MA(2,1,2)	0.12(0.393)
PMA1	**0.121*(1.746)**	MA(2,1,10)	0.108(0.507)	**PMA1**	**0.047*(1.615)**
FR(0.01,1)	0.118(1.731)	FR(0.01,1)	0.001(1.016)	FR(0.01,1)	0.012(0.835)
MA(2,1,0.005)	0.075(1.575)	FR(0.03,2)	0.042(0.927)	FR(0.01,0.015)	0.128(1.021)
MA(5,2,1)	0.13(1.102)	**FR(0.015,1)**	**0.078*(1.76)**	**FR(0.06,1)**	**0.053*(1.668)**
FR(0.01,2)	0.126(1.747)	FR(0.015,6)	0.005(0.946)	FR(0.005,1)	0.019(0.742)
FR(0.005,1)	0.075(1.576)	MA(5,2,1)	0.031(1.)	MA(5,2,0)	0.002(0.159)
FR(0.01,3)	0.128(1.759)	MA(2,1,0.01)	0.005(0.944)	FR(0.01,1)	0.006(0.917)
FR(0.01,0.015)	0.021(0.954)	FR(0.01,0.015)	0.017(0.107)	SR(5,3,2)	0.117(0.352)
FR(0.005,3)	0.013(1.059)	FR(0.015,2)	0.146(0.259)	FR(0.015,6)	0.138(0.168)
FR(0.015,2)	0.013(1.06)	FR(0.01,2)	0.14(0.275)	SR(10,2,3)	0.027(0.647)
FR(0.02,4)	0.028(1.307)	FR(0.07,1)	0.002(1.031)	SR(10,2,5)	0.013(0.817)
FR(0.01,3)	0.03(1.211)	SR(5,2,10)	0.029(1.346)	FR(0.08,1)	0.045(1.596)
FR(0.015,7)	0.076(1.548)	SR(5,3,10)	0.001(1.018)	SR(10,3,5)	0.007(0.901)
XRP					
Technical Rule	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
MA(5,2,5)	0.920(0.374)	FR(0.045,0.01)	0.789(0.741)	MA(2,1,0.01)	0.751(0.214)
PMA1	**0.103*(1.575)**	**PMA1**	**0.138*(0.358)**	MA(2,1,0.02)	0.736(0.312)
MA(5,2,2)	0.916(0.684)	FR(0.01,0.015)	0.789(0.347)	**PMA1**	**0.125*(1.984)**
PMA2	0.922(0.914)	FR(0.045,0.01)	0.882(0.216)	MA(2,1,0.01)	0.799(0.261)
PMA4	0.033(0.628)	**FR(0.14,10)**	**0.08*(1.764)**	**MA(2,1,0.02)**	**0.08*(1.821)**
MA(5,2,0)	**0.097*(1.521)**	FR(5,2,5)	0.016(1.413)	MA(5,2,1)	0.021(1.364)
MA(5,2,1)	0.041(1.417)	PMA20	0.109(0.28)	MA(2,1,0.005)	0.092(0.369)
FR(0.04,0.015)	0.127(1.384)	**MA(40,25,0.05)**	**0.147*(1.771)**	**MA(2,1,0.03)**	**0.095*(1.672)**
FR(0.045,5)	0.164(0.182)	FR(0.045,50)	0.126(0.164)	MA(5,2,5)	0.032(1.203)
FR(0.025,5)	0.156(0.223)	MA(5,2,1)	0.133(1.072)	MA(2,1,0.001)	0.105(0.265)
FR(0.045,25)	0.159(0.202)	FR(0.14,5)	0.121(0.183)	MA(2,1,5)	0.106(0.253)
FR(0.045,10)	0.158(0.207)	MA(40,25,0.04)	0.101(0.309)	FR(0.005,1)	0.087(0.382)
FR(0.14,1)	0.097(0.654)	FR(0.01,3)	0.063(1.59)	MA(5,1,0.04)	0.069(1.687)
FR(0.04,3)	0.211(0.926)	FR(0.12,0.005)	0.113(0.233)	MA(5,2,10)	0.041(1.312)
FR(0.01,5)	0.239(1.571)	FR(0.045,0.005)	0.17(1.818)	MA(2,1,0.04)	0.094(1.623)

Note: We report the estimation of the slope coefficient and the heteroskedasticity-consistent t-statistic (in in the parenthesis) for the bivariate predictive regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$, where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 (main text) respectively. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, based on two-sided wild bootstrapped p-values. 50% IS corresponds to period 1 as outlined in Table 5.3 (main text). The equivalent Sharpe Ratio results are shown in Panels A of Tables 5.6-5.9 of the main text.

Table B. 8: Out-of-sample Predictive Regression Estimation Results (Sortino Ratio – F1, F2, F3)

Rank	Technical Rule	Period 1 (50%IS) 08/08/2015-05/04/2017	Technical Rule	Period 2 (75% IS) 08/08/2015-06/02/2018	Technical Rule	Period 3 (90% IS) 08/08/2015-03/08/2018
BTC						
1	CB(5,0.075,5,0.001)	-0.009(0.241)	CB(5,0.075,5,0)	-0.098(0.48)	PMA1	**0.096*(1.742)**
2	CB(5,0.075,5,0)	-0.009(0.357)	MA(5,1,5)	-0.105(0.543)	CB(5,0.075,5,0)	-0.523(0.462)
3	**PMA1**	**0.01*(1.412)**	**PMA1**	**0.08*(1.474)**	MA(5,1,5)	-0.541(0.466)
4	CB(5,0.075,5,0)	-0.001(0.210)	CB(5,0.075,5,0.001)	-0.08(0.473)	CB(5,0.05,5,0.001)	-0.196(0.742)
5	CB(5,0.075,5,0.01)	0.001(0.209)	CB(5,0.075,5,0.005)	-0.079(0.471)	MA(5,2,0.01)	-0.174(0.914)
6	MA(5,1,5)	-0.010(0.338)	MA(5,2,2)	-0.103(0.571)	MA(5,1,2)	-0.528(0.461)
7	MA(5,2,1)	-0.012(0.279)	MA(5,2,1)	-0.095(0.471)	CB(5,0.075,5,0.01)	-0.198(0.757)
8	CB(5,0.075,5,0)	-0.009(0.325)	MA(5,2,0)	-0.099(0.553)	MA(5,2,2)	-0.522(0.459)
9	CB(5,0.075,5,0.015)	-0.001(0.175)	SR(250,2,5)	-0.068(0.474)	CB(5,0.075,5,0)	-0.151(0.629)
10	CB(5,0.075,5,0.005)	-0.001(0.171)	MA(5,1,0.001)	-0.069(0.471)	CB(5,0.075,5,0.001)	-0.514(0.102)
11	CB(5,0.03,5, 0.01)	-0.021(0.137)	SR(10,2,0.005)	-0.082(0.745)	CB(5,0.075,5,0.015)	-0.197(0.757)
12	MA(5,2,10)	-0.011(0.347)	MA(5,1,0.005)	-0.621(0.27)	MA(5,2,0)	-0.523(0.459)
13	CB(5,0.075,5,0.02)	-0.011(0.37)	CB(5,0.075,5,0.015)	-0.068(0.467)	CB(5,0.075,5,0.02)	-0.138(0.857)
14	MA(5,2,0)	-0.015(0.267)	CB(5,0.05,5,0.01)	-0.084(0.539)	MA(5,1,0.05)	-0.262(0.839)
15	MA(5,1,0.05)	-0.008(0.348)	CB(5,0.075,5,0.02)	-0.623(0.269)	MA(5,1,0.001)	-0.524(0.459)
ETH						
Rank	**Technical Rule**	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
1	**PMA1**	**0.424*(1.661)**	MA(2,1,0.005)	-0.034(0.375)	MA(2,1,0.005)	-0.005(0.388)
2	PMA2	-0.011(0.583)	FR (0.005,1)	0.112(0.234)	MA(2,1,0.001)	0.487(0.311)
3	FR(0.015,5)	-0.467(0.137)	**PMA1**	**0.221*(1.997)**	**PMA1**	**0.09*(1.831)**
4	FR(0.01,3)	-1.154(0.157)	FR(0.01,1)	-1.618(0.421)	PMA2	-0.092(0.907)
5	FR(0.01,0.015)	-0.874(0.153)	MA(2,1,0.01)	-1.612(0.242)	PMA4	-0.088(1.076)
6	PMA4	-0.425(0.161)	PMA2	-1.061(0.325)	FR(0.005,1)	-0.093(1.034)
7	MA(5,2,5)	-0.857(0.364)	MA(5,2,1)	-1.217(1.349)	FR(0.01,0.015)	-0.032(0.708)
8	PMA20	-0.852(0.159)	FR(0.01,2)	-1.685(0.277)	MA(2,1,5)	-0.086(1.077)
9	FR (0.01,1)	-0.437(0.160)	FR(0.06,1)	-1.594(0.652)	FR(0.01,2)	-0.099(1.058)
10	FR (0.05,1)	-0.421(0.161)	FR(0.01,0.015)	-0.479(1.279)	FR(0.01,3)	-0.087(1.231)
11	FR (0.015, 2)	-0.433(1.052)	MA(2,1,5)	-2.119(0.222)	MA(5,2,10)	-0.126(0.979)
12	MA(25,5,5)	-0.417(0.162)	FR(0.015,1)	-2.386(0.711)	FR(0.015,6)	-0.167(0.636)
13	FR (0.12,0.01)	-0.438(0.161)	MA(2,1,0.015)	-1.594(0.984)	FR(0.005,2)	-0.101(1.059)
14	MA(30,25,5)	-0.432(0.159)	MA(5,2,10)	-0.065(1.012)	FR(0.06,1)	-0.147(0.79)
15	FR (0.16,1)	-0.436(0.160)	FR(0.015,2)	-2.387(0.813)	FR(0.015,2)	-0.091(1.01)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each one of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 (main text) respectively. We report the R^2_{os} (%) and the MSFE-adj statistics from testing the null hypothesis that the historical average forecast MSFE is less than or equal to the actual forecast MSFE. The historical average (HA) forecast is given by $\hat{r}^{HA}_{t+1} = (1/t)\sum_{s=1}^{t} r_s$. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. 50% IS corresponds to period 1, as outlined in Table 5.3 (main text), keeping 50% of the total dataset out-of-sample. The equivalent Sharpe Ratio results are shown in Panels A of Tables 5.13-5.16 of the main text.

Table B. 9: Out-of-sample Predictive Regression Estimation Results (Sortino Ratio – F1, F2, F3)

CRIX					
Technical Rule	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
MA(2,1,10)	0.002(0.37)	MA(2,1,0.001)	-0.113(0.426)	MA(2,1,0.001)	-0.089(0.451)
MA(2,1,0.001)	-0.017(0.346)	PMA1	**0.133*(1.496)**	MA(2,1,2)	-0.256(0.67)
PMA1	**0.002*(1.427)**	MA(2,1,10)	-0.102(0.494)	**PMA1**	**0.061*(1.729)**
FR(0.01,1)	0.002(0.248)	FR(0.01,1)	-0.132(0.493)	FR(0.01,1)	-0.325(0.663)
MA(2,1,0.005)	0.005(0.124)	FR(0.03,2)	-0.028(0.361)	FR(0.01,0.015)	-0.313(0.741)
MA(5,2,1)	0.001(0.137)	FR(0.015,1)	-0.136(0.499)	FR(0.06,1)	-0.174(0.705)
FR(0.01,2)	0.001(0.254)	FR(0.015,6)	-0.124(0.517)	FR(0.005,1)	-0.333(0.658)
FR(0.005,1)	0.005(0.128)	MA(5,2,1)	-0.127(0.538)	MA(5,2,0)	-0.138(0.816)
FR(0.01,3)	0.001(0.258)	MA(2,1,0.01)	-0.126(0.521)	FR(0.01,1)	-0.33(0.656)
FR(0.01,0.015)	-0.097(0.102)	FR(0.01,0.015)	-0.309(0.412)	SR(5,3,2)	-0.271(0.673)
FR(0.005,3)	0.001(0.287)	FR(0.015,2)	-0.296(0.353)	FR(0.015,6)	-0.341(0.79)
FR(0.015,2)	-0.001(0.263)	FR(0.01,2)	-0.298(0.357)	SR(10,2,3)	-0.182(0.861)
FR(0.02,4)	-0.007(1.024)	FR(0.07,1)	-0.121(0.746)	SR(10,2,5)	-0.126(0.771)
FR(0.01,3)	-0.006(0.273)	SR(5,2,10)	-0.126(0.527)	FR(0.08,1)	-0.198(0.748)
FR(0.015,7)	0.005(0.179)	SR(5,3,10)	-0.123(0.486)	SR(10,3,5)	-0.176(0.707)
XRP					
Technical Rule	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
MA(5,2,5)	0.224(0.313)	FR(0.045,0.01)	-0.089(0.524)	MA(2,1,0.01)	-0.248(0.473)
PMA1	0.198(0.288)	**PMA1**	**0.138**(2.358)**	MA(2,1,0.02)	-0.346(0.501)
MA(5,2,2)	**0.036(1.28)**	FR(0.01,0.015)	-0.256(0.874)	**PMA1**	**0.037*(1.469)**
PMA2	0.355(0.475)	FR(0.045,0.01)	-0.134(0.387)	MA(2,1,0.01)	-0.498(0.39)
PMA4	-0.144(0.169)	FR(0.14,10)	-0.152(0.363)	MA(2,1,0.02)	-0.197(0.617)
MA(5,2,0)	-0.346(0.226)	FR(5,2,5)	-0.318(0.714)	MA(5,2,1)	-0.204(0.609)
MA(5,2,1)	-0.216(0.735)	PMA20	-0.389(0.261)	MA(2,1,0.005)	-0.321(0.473)
FR(0.04,0.015)	-0.162(0.387)	MA(40,25,0.05)	-0.090(0.687)	MA(2,1,0.03)	-0.202(0.605)
FR(0.045,5)	-0.038(0.342)	FR(0.045,50)	-0.388(0.261)	MA(5,2,5)	-0.241(0.443)
FR(0.025,5)	-0.026(0.442)	MA(5,2,1)	-0.417(0.145)	MA(2,1,0.001)	-0.234(0.626)
FR(0.045,25)	-0.026(0.42)	FR(0.14,5)	-0.392(0.261)	MA(2,1,5)	-0.238(0.632)
FR(0.045,10)	-0.043(0.354)	MA(40,25,0.04)	-0.389(0.259)	FR(0.005,1)	-0.188(0.732)
FR(0.14,1)	-0.024(0.319)	FR(0.01,3)	-0.129(0.406)	MA(5,1,0.04)	-0.212(0.643)
FR(0.04,3)	-0.091(0.483)	FR(0.12,0.005)	-0.388(0.263)	MA(5,2,10)	-0.183(0.497)
FR(0.01,5)	-0.011(0.322)	FR(0.045,0.005)	-0.089(0.632)	MA(2,1,0.04)	-0.093(0.672)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each one of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 (main text) respectively. We report the R^2_{os} (%) and the MSFE-adj statistics from testing the null hypothesis that the historical average forecast MSFE is less than or equal to the actual forecast MSFE. The historical average (HA) forecast is given by $\hat{r}^{HA}_{t+1} = (1/t)\sum_{s=1}^{t} r_s$. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. 50% IS corresponds to period 1, as outlined in Table 5.3-5.4 (main text), keeping 50% of the total dataset out-of-sample. The equivalent Sharpe Ratio results are shown in Panels A of Tables 5.13-5.16 of the main text.

Table B. 10: Out-of-sample profitability performance Results (Sortino Ratio – F1, F2, F3)

Rank	Technical Rule	Period 1 (50%IS) 08/08/2015-05/04/2017	Technical Rule	Period 2 (75% IS) 08/08/2015-06/02/2018	Technical Rule	Period 3 (90% IS) 08/08/2015-03/08/2018
BTC						
1	CB(5,0.075,5,0.001)	0.504(0.013)	CB(5,0.075,5,0)	0.204(0.005)	PMA1	0.159(0.002)
2	CB(5,0.075,5,0)	0.843(0.033)	MA(5,1,5)	0.304(0.006)	CB(5,0.075,5,0)	0.298(0.004)
3	**PMA1**	**1.078(0.013)**	**PMA1**	**0.137(0.004)**	MA(5,1,5)	0.127(0.002)
4	CB(5,0.075,5,0)	1.076(0.013)	CB(5,0.075,5,0.001)	0.132(0.004)	CB(5,0.05,5,0.001)	0.128(0.002)
5	CB(5,0.075,5,0.01)	1.505(0.013)	CB(5,0.075,5,0.005)	0.123(0.004)	MA(5,2,0.01)	0.1(0.001)
6	MA(5,1,5)	0.638(0.017)	MA(5,2,2)	0.217(0.002)	MA(5,1,2)	0.079(0.006)
7	MA(5,2,1)	1.398(0.013)	MA(5,2,1)	0.095(0.001)	CB(5,0.075,5,0.01)	0.122(0.004)
8	CB(5,0.075,5,0)	0.648(0.016)	MA(5,2,0)	0.213(0.002)	MA(5,2,2)	0.084(0.006)
9	CB(5,0.075,5,0.015)	1.098(0.014)	SR(250,2,5)	0.154(0.003)	CB(5,0.075,5,0)	0.08(0.004)
10	CB(5,0.075,5,0.005)	1.099(0.014)	MA(5,1,0.001)	0.154(0.003)	CB(5,0.075,5,0.001)	0.08(0.004)
11	CB(5,0.03,5, 0.01)	1.265(0.013)	SR(10,2,0.005)	0.082(0.001)	CB(5,0.075,5,0.015)	0.123(0.004)
12	MA(5,2,10)	0.754(0.018)	MA(5,1,0.005)	0.222(0.002)	MA(5,2,0)	0.117(0.004)
13	CB(5,0.075,5,0.02)	0.716(0.016)	CB(5,0.075,5,0.015)	0.236(0.003)	CB(5,0.075,5,0.02)	0.081(0.004)
14	MA(5,2,0)	0.552(0.015)	CB(5,0.05,5,0.01)	0.165(0.003)	MA(5,1,0.05)	0.158(0.005)
15	MA(5,1,0.05)	0.747(0.017)	CB(5,0.075,5,0.02)	0.217(0.002)	MA(5,1,0.001)	0.115(0.004)
ETH						
Rank	**Technical Rule**	**Period 1 (50%IS) 08/08/2015-05/04/2017**	**Technical Rule**	**Period 2 (75% IS) 08/08/2015-06/02/2018**	**Technical Rule**	**Period 3 (90% IS) 08/08/2015-03/08/2018**
1	**PMA1**	**0.957(0.021)**	MA(2,1,0.005)	0.621(0.004)	MA(2,1,0.005)	0.211(0.005)
2	PMA2	0.917(0.025)	FR (0.005,1)	0.583(0.004)	MA(2,1,0.001)	0.152(0.004)
3	FR(0.015,5)	1.262(0.021)	**PMA1**	**0.466(0.004)**	PMA1	0.149(0.004)
4	FR(0.01,3)	1.019(0.022)	FR(0.01,1)	0.471(0.004)	PMA2	0.134(0.004)
5	FR(0.01,0.015)	1.068(0.022)	MA(2,1,0.01)	0.494(0.004)	PMA4	0.149(0.004)
6	PMA4	1.017(0.021)	PMA2	0.474(0.004)	FR(0.005,1)	0.152(0.004)
7	MA(5,2,5)	1.151(0.021)	MA(5,2,1)	0.435(0.004)	FR(0.01,0.015)	0.182(0.005)
8	PMA20	1.173(0.022)	FR(0.01,2)	0.497(0.004)	MA(2,1,5)	0.145(0.004)
9	FR (0.01,1)	1.247(0.021)	FR(0.06,1)	0.47(0.004)	FR(0.01,2)	0.092(0.004)
10	FR (0.05,1)	1.248(0.021)	FR(0.01,0.015)	0.448(0.004)	FR(0.01,3)	0.207(0.005)
11	FR (0.015, 2)	0.817(0.021)	MA(2,1,5)	0.428(0.004)	MA(5,2,10)	0.186(0.005)
12	MA(25,5,5)	1.118(0.02)	FR(0.015,1)	0.31(0.004)	FR(0.015,6)	0.196(0.005)
13	FR (0.12,0.01)	0.989(0.021)	MA(2,1,0.015)	0.493(0.004)	FR(0.005,2)	0.097(0.004)
14	MA(30,25,5)	1.035(0.02)	MA(5,2,10)	0.366(0.004)	FR(0.06,1)	0.148(0.004)
15	FR (0.16,1)	1.235(0.021)	FR(0.015,2)	0.467(0.004)	FR(0.015,2)	0.168(0.005)

Note: This table reports the Sortino ratio and mean returns (in parentheses) and the benchmark is the buy-and-hold strategy. Panel A and Panels B-F are the results for each one of the top fifteen technical rules selected in the previous step and the selected factors listed in the Table 3 (main text), respectively. 50% IS corresponds to period 1, as outlined in Table 4 (main text), keeping 50% of the total dataset out-of-sample. The equivalent Sharpe Ratio results are shown in Panels A of Tables 5.17-5.20 of the main text.

Table B. 11: Out-of-sample profitability performance Results (Sortino Ratio – F1, F2, F3)

Technical Rule	Period 1 (50%IS) 08/08/2015-05/04/2017	Technical Rule	Period 2 (75% IS) 08/08/2015-06/02/2018	Technical Rule	Period 3 (90% IS) 08/08/2015-03/08/2018
CRIX					
MA(2,1,10)	1.204(0.016)	MA(2,1,0.001)	0.151(0.002)	MA(2,1,0.001)	0.001(0.005)
MA(2,1,0.001)	1.09(0.016)	**PMA1**	**0.12(0.002)**	MA(2,1,2)	0.003(0.005)
PMA1	**0.905(0.017)**	MA(2,1,10)	0.118(0.002)	**PMA1**	**0.029(0.006)**
FR(0.01,1)	0.839(0.016)	FR(0.01,1)	0.138(0.002)	FR(0.01,1)	0.019(0.005)
MA(2,1,0.005)	0.635(0.016)	FR(0.03,2)	0.142(0.002)	FR(0.01,0.015)	0.187(0.003)
MA(5,2,1)	0.85(0.017)	FR(0.015,1)	0.124(0.002)	FR(0.06,1)	0.02(0.005)
FR(0.01,2)	0.827(0.016)	FR(0.015,6)	0.103(0.002)	FR(0.005,1)	0.119(0.004)
FR(0.005,1)	0.763(0.015)	MA(5,2,1)	0.149(0.002)	MA(5,2,0)	0.188(0.003)
FR(0.01,3)	0.808(0.016)	MA(2,1,0.01)	0.124(0.002)	FR(0.01,1)	0.12(0.004)
FR(0.01,0.015)	0.807(0.017)	FR(0.01,0.015)	0.133(0.002)	SR(5,3,2)	0.03(0.006)
FR(0.005,3)	0.058(0.026)	FR(0.015,2)	0.148(0.003)	FR(0.015,6)	0.046(0.004)
FR(0.015,2)	0.963(0.016)	FR(0.01,2)	0.162(0.003)	SR(10,2,3)	0.043(0.004)
FR(0.02,4)	0.81(0.016)	FR(0.07,1)	0.14(0.002)	SR(10,2,5)	0.189(0.003)
FR(0.01,3)	0.724(0.017)	SR(5,2,10)	0.129(0.002)	FR(0.08,1)	0.017(0.005)
FR(0.015,7)	0.789(0.016)	SR(5,3,10)	0.14(0.002)	SR(10,3,5)	0.19(0.003)
XRP					
Technical Rule	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
MA(5,2,5)	0.49(0.028)	FR(0.045,0.01)	0.145(0.003)	MA(2,1,0.01)	0.129(0.009)
PMA1	**0.542(0.03)**	**PMA1**	**0.159(0.003)**	MA(2,1,0.02)	0.115(0.007)
MA(5,2,2)	0.595(0.029)	FR(0.01,0.015)	0.14(0.003)	**PMA1**	**0.239(0.009)**
PMA2	0.541(0.03)	FR(0.045,0.01)	0.157(0.003)	MA(2,1,0.01)	0.045(0.005)
PMA4	0.605(0.03)	FR(0.14,10)	0.21(0.004)	MA(2,1,0.02)	0.167(0.008)
MA(5,2,0)	0.565(0.03)	FR(5,2,5)	0.133(0.003)	MA(5,2,1)	0.19(0.008)
MA(5,2,1)	0.46(0.031)	PMA20	0.154(0.003)	MA(2,1,0.005)	0.203(0.008)
FR(0.04,0.015)	0.522(0.03)	MA(40,25,0.05)	0.18(0.003)	MA(2,1,0.03)	0.04(0.006)
FR(0.045,5)	0.499(0.029)	FR(0.045,50)	0.15(0.003)	MA(5,2,5)	0.091(0.007)
FR(0.025,5)	0.498(0.031)	MA(5,2,1)	0.15(0.003)	MA(2,1,0.001)	0.17(0.008)
FR(0.045,25)	0.559(0.03)	FR(0.14,5)	0.147(0.003)	MA(2,1,5)	0.193(0.008)
FR(0.045,10)	0.532(0.029)	MA(40,25,0.04)	0.146(0.003)	FR(0.005,1)	0.204(0.009)
FR(0.14,1)	0.506(0.029)	FR(0.01,3)	0.129(0.003)	MA(5,1,0.04)	0.05(0.007)
FR(0.04,3)	0.522(0.029)	FR(0.12,0.005)	0.148(0.003)	MA(5,2,10)	0.085(0.007)
FR(0.01,5)	0.727(0.03)	FR(0.045,0.005)	0.15(0.003)	MA(2,1,0.04)	0.018(0.005)

Note: This table reports the Sortino ratio and mean returns (in parentheses) and the benchmark is the buy-and-hold strategy. Panel A and Panels B-F are the results for each one of the top fifteen technical rules selected in the previous step and the selected factors listed in the Table 3 (main text), respectively. 50% IS corresponds to period 1, as outlined in Table 4 (main text), keeping 50% of the total dataset out-of-sample. The equivalent Sharpe Ratio results are shown in Panels A of Tables 5.17-5.20 of the main text.

From Table B.3 to Table.6, we can find PMA ratios are all statistically significant, so we can declare their predictive power in in-sample periods. What interests us is the coefficient of PMA(1) is larger than that of PMA(20). Similar situations can be found on PMA(2) and PMA(4) as well. That is, short horizons of PMA ratios seem to have larger influence on cryptocurrency market than long horizon predictors. Meanwhile, most FA factors do not show predictive power in our in-sample periods while factors from Blockchain information, such as MD, HSH and DOD are statistically significant. Moreover, advanced sentiment factors from BitcoinTalk, like NTs, NPs, NUs, PVs are statistically significant and primary sentiment factors, such as BTC-W and BTC-GT as well. However, large out-of-sample results of either 50% or 90% periods suggest the predictive power of FA in in-sample period is not genuine.

B.5 Robustness results for altercoins (BYTE-CASINO-DASH-DOGE)

Table B. 12: Summary statistics of cryptocurrency prices and returns.

Prices	BYTE	CAS	DASH	DOGE	Returns	BYTE	CAS	DASH	DOGE
mean	0.001	0.024	176.714	0.002	**mean**	0.011	0.032	0.004	0.005
SD	0.002	0.067	249.413	0.002	**D**	0.19	0.295	0.062	0.073
min	0	0	2.06	0	**min**	-0.598	-0.999	-0.216	-0.389
max	0.03	0.533	1550.85	0.017	**max**	3.942	4.573	0.549	0.679
S	3.429	4.536	2.165	1.99	**S**	12.815	5.936	1.56	2.323
K	22.843	21.839	5.323	5.595	**K**	239.46	66.201	9.916	18.594
JB	0***	0***	0***	0***	**JB**	0***	0***	0***	0***
ADF	0.03**	0.011**	0.109	0.027**	**ADF**	0***	0***	0***	0***

Notes: This table reports the sample statistics of BYTE, CASINO, DASH, and DOGE. SD is the standard deviation; S is the skewness; K is the excess kurtosis; JB stands for Jarque-Bera statistic; and ADF is the Augmented Dickey-Fuller statistic. Significance level: * 10%, ** 5%, *** 1%. JB is the Jarque-Bera test. The number of observations is 1218 for all series.

From the table above, high volatility and low mean returns also exist in altercoins with small capitalization. In addition, both prices and returns series display non-normal distribution. After transformation, none of return series has unit root.

Table B. 13: Technical rules profitability (top 15 performing rules under the Sharpe ratio metric)

BYTE	Rule	**Period 1** 08/08/2015-31/10/2016	Rule	**Period 2** 01/11/2016-07/12/2017	Rule	**Period 3** 08/12/2017-08/12/2018
1	cb(10, 0.01, 10, 5)	0.290(0.012)	PMA1	0.384(0.064)	PMA1	0.364(0.067)
2	cb(10, 0.01, 25, 10)	0.276(0.011)	ma(5, 1, 0)	0.383(0.064)	ma(2, 1, 0.04)	0.363(0.067)
3	ma(2,1,0.005)	0.269(0.046)	ma(5, 1, 0.005)	0.376(0.063)	ma(5, 1, 0)	0.362(0.067)
4	ma(5, 1, 0.005)	0.263(0.045)	ma(5, 1, 0.015)	0.365(0.061)	ma(5, 1, 0.005)	0.356(0.066)
5	cb(10, 0.01, 25, 20)	0.261(0.010)	ma(5, 1, 0.03)	0.356(0.060)	ma(5, 1, 0.015)	0.345(0.064)
6	ma(5, 1, 0.015)	0.255(0.044)	ma(5, 1, 0.05)	0.329(0.055)	ma(5, 1, 0.03)	0.334(0.062)
7	ma(5, 1, 0.03)	0.248(0.042)	ma(5, 2, 0.001)	0.297(0.050)	ma(5, 1, 0.05)	0.307(0.058)
8	cb(10, 0.01, 25, 50)	0.239(0.009)	cb(10, 0.01, 10,5)	0.289(0.014)	ma(5, 2, 0.001)	0.271(0.051)
9	cb(10, 0.01, 25, 150)	0.232(0.009)	cb(10, 0.01,10,15)	0.288(0.014)	ma(5, 2, 0.02)	0.265(0.051)
10	ma(5, 1, 0.05)	0.228(0.039)	cb(100.01,10,100)	0.281(0.013)	ma(10, 1, 0.03)	0.264(0.050)
11	cb(5, 0.15, 10, 5)	0.225(0.007)	cb(10,0.01 10200)	0.278(0.013)	ma(10, 1, 0.05)	0.263(0.050)
12	cb(5, 0.15, 25, 10)	0.209(0.006)	ma(5, 2, 0.02)	0.276(0.047)	ma(10, 2, 0.001)	0.262(0.050)
13	ma(5, 2, 0.001)	0.207(0.036)	ma(10, 1, 0.05)	0.274(0.047)	ma(10, 2, 0.01)	0.261(0.049)
14	ma(10, 1, 0.03)	0.206(0.036)	ma(10, 2, 0.001)	0.273(0.047)	ma(10, 2, 0.02)	0.260(0.049)
15	ma(10, 1, 0.05)	0.204(0.035)	ma(10, 2, 0.01)	0.272(0.046)	ma(10, 2, 0.04)	0.250(0.047)
CAS	**Rule**	**Period 1** 08/08/2015-31/10/2016	**Rule**	**Period 2** 01/11/2016-07/12/2017	**Rule**	**Period 3** 08/12/2017-08/12/2018
1	ma(2,1,0.005)	0.528(0.020)	PMA1	0.634(0.031)	PMA1	0.698(0.033)
2	ma(5, 1, 0)	0.527(0.020)	ma(5, 1, 0)	0.633(0.031)	ma(5, 1, 0)	0.697(0.033)
3	ma(5, 1, 0.005)	0.500(0.019)	ma(5, 1, 0.005)	0.611(0.030)	ma(5, 1, 0.005)	0.672(0.032)
4	ma(5, 1, 0.015)	0.445(0.017)	ma(5, 1, 0.015)	0.564(0.029)	ma(5, 1, 0.015)	0.620(0.030)
5	ma(5, 1, 0.03)	0.393(0.016)	ma(5, 1, 0.03)	0.507(0.026)	ma(5, 1, 0.03)	0.556(0.028)
6	ma(5, 1, 0.05)	0.372(0.011)	ma(5, 1, 0.05)	0.451(0.023)	ma(5, 1, 0.05)	0.490(0.025)
7	ma(5, 2, 0.001)	0.367(0.008)	ma(5, 2, 0.001)	0.399(0.017)	ma(5, 2, 0.001)	0.445(0.023)
8	ma(5, 2, 0.01)	0.366(0.008)	ma(5, 2, 0.01)	0.389(0.021)	ma(5, 2, 0.01)	0.444(0.023)
9	ma(10, 2, 0.02)	0.356(0.015)	ma(10, 2, 0.001)	0.386(0.021)	ma(10, 2, 0.001)	0.441(0.023)
10	ma(10, 2, 0.04)	0.355(0.008)	ma(5, 2, 0.02)	0.381(0.021)	ma(10, 2, 0.02)	0.435(0.023)
11	ma(5, 2, 0.02)	0.353(0.015)	ma(10, 1, 0.05)	0.377(0.020)	ma(5, 2, 0.02)	0.434(0.018)
12	ma(10, 2, 0.001)	0.347(0.014)	ma(10, 2, 0.04)	0.373(0.012)	ma(10, 5, 0)	0.426(0.022)
13	ma(10, 1, 0.05)	0.338(0.007)	ma(10, 5, 0)	0.369(0.020)	ma(10, 5, 0.005)	0.413(0.021)
14	ma(10, 5, 0)	0.337(0.007)	ma(10, 5, 0.005)	0.365(0.011)	s(10, 0.005, 10)	0.398(0.013)
15	ma(10, 5, 0.005)	0.334(0.014)	s(10, 0.005, 10)	0.357(0.019)	ma(15, 5, 0.01)	0.387(0.012)

Note: This table presents the Sharp ratios and mean returns (in parentheses) of the top 15 technical rules for the BYTE, CAS, DASH, and DOGE. PMA denotes the log-price to MAs ratio (e.g. PMA1 is the PMA ratio generated by one-week gap). MA are Moving Average rules (e.g., MA (5,1,5) represents MA rule with 5-day slow MA, 1-day fast MA and 5-day position held). FR represents the Filter rule (e.g., FR (0.005,1) denotes a 0.005% change of price with 1 day of constant holding period). CB denotes the Channel-Break rule (e.g. CB(5,0.0075,5,0.001) denotes the 5 days of channel , 0.075 difference between high and low channel, 5 days of constant holding period and 0.001 percentage band). SR denotes the Support and Resistance rule (e.g., SR (5,3,2) is 5 days to generate extrema, 3 days for time delay of transaction and 2 day of constant holding period). 50%, 75% and 90% IS denotes that we use as in-sample the 50%, 75% and 90% of the total dataset in period 1, period 2 and period 3 respectively.

Table B. 14: Technical rules profitability (top 15 performing rules under the Sharpe ratio metric)

DASH	Rule	**Period 1** 08/08/2015-31/10/2016	**Rule**	**Period 2** 01/11/2016-07/12/2017	**Rule**	**Period 3** 08/12/2017-08/12/2018
1	ma(2,1,0.005)	0.457(0.013)	PMA1	0.545(0.032)	PMA1	0.609(0.034)
2	ma(2, 1, 0.04)	0.402(0.012)	ma(2, 1, 0.04)	0.521(0.031)	ma(2, 1, 0.04)	0.584(0.033)
3	ma(5, 1, 0)	0.328(0.005)	ma(5, 1, 0)	0.478(0.029)	ma(5, 1, 0)	0.537(0.031)
4	ma(5, 1, 0.005)	0.327(0.006)	ma(5, 1, 0.005)	0.437(0.027)	ma(5, 1, 0.005)	0.489(0.029)
5	ma(5, 1, 0.015)	0.324(0.010)	ma(5, 1, 0.015)	0.410(0.025)	ma(5, 1, 0.015)	0.452(0.027)
6	PMA2	0.309(0.004)	ma(5, 1, 0.03)	0.358(0.022)	ma(5, 1, 0.03)	0.389(0.024)
7	cb(10, 0.01, 10, 5)	0.296(0.006)	PMA2	0.346(0.022)	ma(10, 1, 0.03)	0.388(0.024)
8	cb(10, 0.01, 10, 15)	0.294(0.005)	ma(5, 2, 0.02)	0.344(0.022)	ma(5, 2, 0.02)	0.387(0.024)
9	ma(5, 2, 0.02)	0.284(0.009)	ma(10, 1, 0.03)	0.340(0.022)	ma(10, 1, 0.05)	0.384(0.023)
10	cb(10, 0.01, 10, 25)	0.282(0.009)	ma(10, 2, 0.001)	0.339(0.021)	ma(10, 2, 0.001)	0.383(0.023)
11	ma(10, 1, 0.03)	0.278(0.004)	ma(10, 2, 0.01)	0.335(0.021)	PMA2	0.379(0.023)
12	ma(10, 1, 0.05)	0.273(0.004)	cb(10, 0.01,10,5)	0.328(0.021)	ma(10, 2, 0.01)	0.373(0.023)
13	cb(5, 0.15, 10, 5)	0.266(0.005)	ma(10, 2, 0.02)	0.325(0.020)	ma(10, 2, 0.02)	0.366(0.022)
14	cb(5, 0.15, 10, 15)	0.265(0.008)	cb(10,0.01,10,25)	0.320(0.017)	cb(10, 0.01,10,5)	0.359(0.018)
15	ma(10, 2, 0.001)	0.257(0.004)	ma(5, 1, 0.05)	0.317(0.019)	cb(10,0.01,10,25)	0.351(0.020)
DOGE	**Rule**	**Period 1** 08/08/2015-31/10/2016	**Rule**	**Period 2** 01/11/2016-07/12/2017	**Rule**	**Period 3** 08/12/2017-08/12/2018
1	ma(2,1,0.005)	0.487(0.077)	PMA1	0.459(0.122)	PMA1	0.472(0.116)
2	ma(5, 1, 0)	0.485(0.077)	ma(5, 1, 0)	0.458(0.122)	ma(5, 1, 0)	0.470(0.116)
3	cb(5, 0.15, 10, 5)	0.481(0.076)	ma(5, 1, 0.005)	0.454(0.121)	ma(5, 1, 0.005)	0.465(0.115)
4	cb(10, 0.01, 10, 5)	0.473(0.075)	ma(5, 1, 0.015)	0.449(0.120)	ma(5, 1, 0.015)	0.458(0.113)
5	ma(5, 1, 0.005)	0.464(0.074)	ma(5, 1, 0.03)	0.443(0.118)	ma(5, 1, 0.03)	0.451(0.112)
6	cb(5, 0.075, 10, 5)	0.434(0.070)	ma(5, 1, 0.05)	0.424(0.114)	ma(10, 1, 0.03)	0.432(0.108)
7	cb(10, 0.01, 10, 25)	0.413(0.067)	ma(5, 2, 0.02)	0.406(0.110)	ma(10, 1, 0.05)	0.411(0.103)
8	cb(5, 0.15, 10, 25)	0.381(0.062)	ma(10, 1, 0.03)	0.387(0.105)	ma(5, 2, 0.02)	0.390(0.098)
9	ma(5, 2, 0.02)	0.332(0.055)	ma(10, 1, 0.05)	0.317(0.088)	ma(10, 2, 0.001)	0.326(0.084)
10	ma(10, 1, 0.03)	0.331(0.054)	ma(10, 2, 0.001)	0.316(0.088)	ma(5, 1, 0.05)	0.325(0.084)
11	cb(5, 0.03, 10, 200)	0.330(0.055)	ma(10, 2, 0.02)	0.315(0.088)	ma(10, 2, 0.02)	0.324(0.084)
12	cb(5, 0.075, 10, 25)	0.329(0.055)	ma(10, 2, 0.01)	0.314(0.087)	ma(10, 2, 0.01)	0.313(0.080)
13	cb(10, 0.01, 10, 100)	0.327(0.055)	ma(10, 2, 0.04)	0.304(0.084)	ma(10, 2, 0.04)	0.306(0.078)
14	ma(5, 1, 0.015)	0.322(0.053)	PMA2	0.298(0.082)	PMA2	0.264(0.061)
15	cb(5, 0.15, 10, 100)	0.318(0.052)	ma(10, 5, 0)	0.265(0.066)	ma(10, 5, 0)	0.249(0.066)

Note: This table presents the Sharp ratios and mean returns (in parentheses) of the top 15 technical rules for the BYTE, CAS, DASH, and DOGE. PMA denotes the log-price to MAs ratio (e.g. PMA1 is the PMA ratio generated by one-week gap). MA are Moving Average rules (e.g., MA (5,1,5) represents MA rule with 5-day slow MA, 1-day fast MA and 5-day position held). FR represents the Filter rule (e.g., FR (0.005,1) denotes a 0.005% change of price with 1 day of constant holding period). CB denotes the Channel-Break rule (e.g. CB(5,0.0075,5,0.001) denotes the 5 days of channel , 0.075 difference between high and low channel, 5 days of constant holding period and 0.001 percentage band). SR denotes the Support and Resistance rule (e.g., SR (5,3,2) is 5 days to generate extrema, 3 days for time delay of transaction and 2 day of constant holding period). 50%, 75% and 90% IS denotes that we use as in-sample the 50%, 75% and 90% of the total dataset in period 1, period 2 and period 3 respectively.

Table B. 15: In-sample Predictive Regression Estimation Results (Sharpe Ratio – F1, F2, F3)

Rank	Technical Rule	Period 1 (50%IS) 08/08/2015-05/04/2017	Technical Rule	Period 2 (75% IS) 08/08/2015-06/02/2018	Technical Rule	Period 3 (90% IS) 08/08/2015-03/08/2018
BYTE						
1	cb(10,0.01,10,5)	0.007(0.493)	PMA1	0.005(0.676)	PMA1	0.004(0.76)
2	cb(10,0.01,25,10)	-0.004(1.182)	ma(5, 1, 0)	-0.006(1.242)	ma(2, 1, 0.04)	-0.008(1.366)
3	ma(2,1,0.005)	-0.045(1.778)	ma(5,1,0.005)	-0.047(1.874)	ma(5, 1, 0)	-0.063(1.945)
4	ma(5, 1, 0.005)	-0.01(1.625)	ma(5,1,0.015)	-0.021(1.781)	ma(5, 1, 0.005)	-0.018(1.957)
5	cb(10,0.01,25,20)	0.142(0)	ma(5, 1, 0.03)	0.12(0.002)	ma(5, 1, 0.015)	0.057(0.287)
6	ma(5, 1, 0.015)	0.021(0.793)	ma(5, 1, 0.05)	0.006(0.933)	ma(5, 1, 0.03)	-0.011(1.135)
7	ma(5, 1, 0.03)	-0.023(1.973)	ma(5,2,0.001)	-0.028(1.992)	ma(5, 1, 0.05)	-0.026(2)
8	cb(10,0.01,25,50)	0.004(0.831)	cb(10,0.01,10,5)	-0.003(1.17)	ma(5,2,0.001)	-0.006(1.311)
9	cb(10,0.01,25,150)	0.108(0.132)	cb(10,0.01,10,15)	0.074(0.277)	ma(5, 2, 0.02)	0.05(0.438)
10	ma(5, 1, 0.05)	-0.139(1.989)	cb(10,0.01,10,100)	-0.036(1.889)	ma(10,1,0.03)	-0.047(1.89)
11	cb(5, 0.15, 10, 5)	0.056(0.36)	cb(10,0.01,10,200)	0.01(0.631)	ma(10,1,0.05)	0.005(0.795)
12	cb(5, 0.15, 25, 10)	0.064(0.244)	ma(5,2,0.02)	0.027(0.635)	ma(10,2,0.001)	0.002(0.973)
13	ma(5, 2, 0.001)	0(0.981)	ma(10, 1,0.05)	-0.005(1.316)	ma(10, 2, 0.01)	-0.02(1.803)
14	ma(10, 1, 0.03)	0.002(0.948)	ma(10, 2, 0.001)	0(1.009)	ma(10, 2, 0.02)	0.016(0.708)
15	ma(10, 1, 0.05)	0.036(0.647)	ma(10, 2, 0.01)	-0.006(1.103)	ma(10, 2, 0.04)	-0.06(1.748)
CAS						
Rank	**Technical Rule**	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
1	ma(2,1,0.005)	0.022(0.472)	PMA1	0.05(0.113)	PMA1	0.044(0.12)
2	ma(5, 1, 0)	0.004(0.846)	ma(5, 1, 0)	-0.001(1.04)	ma(5, 1, 0)	-0.004(1.205)
3	ma(5, 1, 0.005)	0.001(0.976)	ma(5, 1, 0.005)	0.012(0.794)	ma(5, 1, 0.005)	0.005(0.881)
4	ma(5, 1, 0.015)	0.024(0.343)	ma(5, 1, 0.015)	0.026(0.449)	ma(5, 1, 0.015)	0.024(0.379)
5	ma(5, 1, 0.03)	-0.021(1.723)	ma(5, 1, 0.03)	-0.037(1.681)	ma(5, 1, 0.03)	-0.03(1.612)
6	ma(5, 1, 0.05)	0.04(0.228)	ma(5, 1, 0.05)	0.078(0.317)	ma(5, 1, 0.05)	0.053(0.403)
7	ma(5, 2, 0.001)	0.017(0.598)	ma(5, 2, 0.001)	0.04(0.277)	ma(5, 2, 0.001)	0.032(0.246)
8	ma(5, 2, 0.01)	0.012(0.618)	ma(5, 2, 0.01)	0.021(0.483)	ma(5, 2, 0.01)	0.022(0.439)
9	ma(10, 2, 0.02)	-0.031(1.568)	ma(10, 2, 0.001)	0.152(0.388)	ma(10,2,0.001)	0.135(0.357)
10	ma(10, 2, 0.04)	-0.051(1.929)	ma(5, 2, 0.02)	0.046(0.526)	ma(10, 2, 0.02)	0.039(0.518)
11	ma(5, 2, 0.02)	0.094(0.126)	ma(10, 1, 0.05)	0.064(0.125)	ma(5, 2, 0.02)	0.06(0.121)
12	ma(10, 2, 0.001)	0.049(0.366)	ma(10, 2, 0.04)	0.062(0.181)	ma(10, 5, 0)	0.061(0.163)
13	ma(10, 1, 0.05)	0.012(0.726)	ma(10, 5, 0)	0.088(0.181)	ma(10,5,0.005)	0.077(0.186)
14	ma(10, 5, 0)	0.001(0.962)	ma(10, 5, 0.005)	-0.04(1.676)	s(10, 0.005,10)	-0.028(1.657)
15	ma(10, 5, 0.005)	0.199(0.149)	s(10, 0.005, 10)	0.153(0.209)	ma(15, 5, 0.01)	0.128(0.209)

Note: We report the estimation of the slope coefficient and the heteroskedasticity-consistent t-statistic (in in the parenthesis) for the bivariate predictive regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$, where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, based on two-sided wild bootstrapped p-values. 50% IS corresponds to period 1 as outlined in Table 5.6 (main text).

Table B. 16: In-sample Predictive Regression Estimation Results (Sharpe Ratio – F1, F2, F3)

Technical Rule	Period 1 (50%IS) 08/08/2015-05/04/2017	Technical Rule	Period 2 (75% IS) 08/08/2015-06/02/2018	Technical Rule	Period 3 (90% IS) 08/08/2015-03/08/2018
DASH					
ma(2,1,0.005)	0.008(0.847)	PMA1	-0.006(1.114)	PMA1	-0.007(1.153)
ma(2, 1, 0.04)	-0.04(1.812)	ma(2,1,0.04)	-0.046(1.684)	ma(2,1,0.04)	-0.045(1.755)
ma(5, 1, 0)	-0.018(1.303)	ma(5, 1, 0)	-0.078(1.933)	ma(5, 1, 0)	-0.069(1.93)
ma(5, 1, 0.005)	0.004(0.927)	ma(5,1,0.005)	-0.023(1.401)	ma(5,1,0.005)	-0.033(1.616)
ma(5, 1, 0.015)	-0.032(1.696)	ma(5,1,0.015)	-0.018(1.49)	ma(5,1,0.015)	-0.034(1.827)
PMA2	-0.004(1.096)	ma(5, 1, 0.03)	-0.011(1.208)	ma(5, 1, 0.03)	-0.002(1.035)
cb(10, 0.01, 10, 5)	0.011(0.753)	PMA2	0.006(0.857)	ma(10,1,0.03)	0.002(0.944)
cb(10, 0.01,10,15)	0.008(0.793)	ma(5,2,0.02)	-0.017(1.331)	ma(5,2,0.02)	-0.035(1.686)
ma(5, 2, 0.02)	-0.012(1.191)	ma(10,1,0.03)	-0.027(1.539)	ma(10,1,0.05)	-0.009(1.214)
cb(10, 0.01,10,25)	-0.035(1.742)	ma(10,2,0.001)	-0.056(1.934)	ma(10,2,0.001)	-0.079(1.992)
ma(10, 1, 0.03)	-0.032(1.669)	ma(10, 2, 0.01)	-0.013(1.322)	PMA2	0.001(0.979)
ma(10, 1, 0.05)	-0.038(1.695)	cb(10, 0.01, 10,5)	-0.074(1.906)	ma(10, 2, 0.01)	-0.055(1.838)
cb(5, 0.15, 10, 5)	0.005(0.916)	ma(10, 2, 0.02)	-0.037(1.563)	ma(10, 2, 0.02)	-0.042(1.71)
cb(5, 0.15, 10, 15)	-0.072(1.982)	cb(10,0.01,10,25)	-0.055(1.957)	cb(10,0.01,10,5)	-0.046(1.936)
ma(10, 2, 0.001)	0.012(0.776)	ma(5, 1, 0.05)	-0.038(1.617)	cb(10,0.01,10,25)	-0.052(1.828)
DOGE					
Technical Rule	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
ma(2,1,0.005)	-0.08(1.907)	PMA1	0.017(0.712)	PMA1	0.017(0.698)
ma(5, 1, 0)	-0.058(1.942)	ma(5, 1, 0)	-0.006(1.086)	ma(5, 1, 0)	0.003(0.953)
cb(5, 0.15, 10, 5)	0.019(0.438)	ma(5, 1, 0.005)	-0.037(1.739)	ma(5, 1, 0.005)	-0.035(1.723)
cb(10, 0.01, 10, 5)	-0.007(1.278)	ma(5, 1, 0.015)	-0.078(1.981)	ma(5, 1, 0.015)	-0.078(1.984)
ma(5, 1, 0.005)	-0.059(1.892)	ma(5, 1, 0.03)	-0.014(1.169)	ma(5, 1, 0.03)	-0.009(1.13)
cb(5, 0.075, 10, 5)	0(0.993)	ma(5, 1, 0.05)	-0.036(1.715)	ma(10, 1, 0.03)	-0.042(1.803)
cb(10, 0.01,10,25)	0.015(0.527)	ma(5, 2, 0.02)	-0.037(1.737)	ma(10, 1, 0.05)	-0.043(1.815)
cb(5, 0.15, 10, 25)	-0.053(1.934)	ma(10, 1, 0.03)	-0.057(1.799)	ma(5, 2, 0.02)	-0.046(1.727)
ma(5, 2, 0.02)	-0.043(1.964)	ma(10, 1, 0.05)	-0.005(1.115)	ma(10, 2, 0.001)	-0.005(1.112)
ma(10, 1, 0.03)	0(1.006)	ma(10, 2, 0.001)	0.021(0.604)	ma(5, 1, 0.05)	0.037(0.361)
cb(5, 0.03,10,200)	-0.009(1.191)	ma(10, 2, 0.02)	-0.094(1.955)	ma(10, 2, 0.02)	-0.133(1.997)
cb(5, 0.075,10,25)	-0.05(1.852)	ma(10, 2, 0.01)	-0.077(1.93)	ma(10, 2, 0.01)	-0.084(1.977)
cb(10,0.01,10,100)	-0.057(1.799)	ma(10, 2, 0.04)	0.082(0.239)	ma(10, 2, 0.04)	0.097(0.13)
ma(5, 1, 0.015)	-0.024(1.415)	PMA2	-0.021(1.273)	PMA2	-0.015(1.219)
cb(5, 0.15, 10,100)	-0.015(1.318)	ma(10, 5, 0)	-0.004(1.077)	ma(10, 5, 0)	-0.009(1.178)

Note: We report the estimation of the slope coefficient and the heteroskedasticity-consistent t-statistic (in in the parenthesis) for the bivariate predictive regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$, where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, based on two-sided wild bootstrapped p-values. 50% IS corresponds to period 1 as outlined in Table 5.6 (main text).

Table B. 17: Out-of-sample Predictive Regression Estimation Results (Sharpe Ratio – F1, F2, F3)

BYTE						
Rank	**Technical Rule**	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
1	cb(10, 0.01, 10, 5)	-0.025(1.406)	PMA1	-0.125(1.146)	PMA1	-0.242(1.895)
2	cb(10, 0.01, 25, 10)	-0.017(1.419)	ma(5, 1, 0)	-0.137(1.331)	ma(2, 1, 0.04)	-0.077(1.586)
3	ma(2,1,0.005)	-0.043(1.505)	ma(5, 1, 0.005)	-0.085(1.358)	ma(5, 1, 0)	-0.171(2.424)
4	ma(5, 1, 0.005)	-0.029(1.027)	ma(5, 1, 0.015)	-0.108(1.381)	ma(5, 1, 0.005)	-0.269(1.415)
5	cb(10, 0.01, 25, 20)	-0.014(0.885)	ma(5, 1, 0.03)	-0.188(1.422)	ma(5, 1, 0.015)	-0.144(2.543)
6	ma(5, 1, 0.015)	-0.012(0.976)	ma(5, 1, 0.05)	-0.234(1.502)	ma(5, 1, 0.03)	-0.16(2.508)
7	ma(5, 1, 0.03)	-0.039(1.314)	ma(5, 2, 0.001)	-9.978(0.604)	ma(5, 1, 0.05)	-0.404(1.324)
8	cb(10, 0.01, 25, 50)	-0.049(1.368)	cb(10, 0.01, 10, 5)	-0.119(1.663)	ma(5, 2, 0.001)	-0.096(2.52)
9	cb(10, 0.01, 25, 150)	-0.021(1.814)	cb(10, 0.01, 10, 15)	-0.34(0.856)	ma(5, 2, 0.02)	-0.853(1.128)
10	ma(5, 1, 0.05)	-0.024(1.386)	cb(10, 0.01, 10, 100)	-0.149(1.74)	ma(10, 1, 0.03)	-0.102(1.482)
11	cb(5, 0.15, 10, 5)	-0.017(1.004)	cb(10, 0.01, 10, 200)	-0.165(1.812)	ma(10, 1, 0.05)	-0.376(1.475)
12	cb(5, 0.15, 25, 10)	-0.009(1.428)	ma(5, 2, 0.02)	-0.473(1.038)	ma(10, 2, 0.001)	-0.585(1.221)
13	ma(5, 2, 0.001)	-0.019(1.501)	ma(10, 1, 0.05)	-0.227(1.504)	ma(10, 2, 0.01)	-0.179(2.588)
14	ma(10, 1, 0.03)	-0.043(1.38)	ma(10, 2, 0.001)	-0.107(1.477)	ma(10, 2, 0.02)	-0.194(2.223)
15	ma(10, 1, 0.05)	-0.011(1.716)	ma(10, 2, 0.01)	-0.249(1.292)	ma(10, 2, 0.04)	-0.193(2.201)
CAS						
Rank	**Technical Rule**	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
1	ma(2,1,0.005)	-0.106(1.596)	PMA1	-0.064(1.978)	PMA1	-0.221(1.55)
2	ma(5, 1, 0)	-0.233(0.913)	ma(5, 1, 0)	-0.161(0.777)	ma(5, 1, 0)	-0.216(2.161)
3	ma(5, 1, 0.005)	-0.337(0.873)	ma(5, 1, 0.005)	-0.059(1.782)	ma(5, 1, 0.005)	-0.135(1.598)
4	ma(5, 1, 0.015)	-0.106(0.815)	ma(5, 1, 0.015)	-0.08(1.4)	ma(5, 1, 0.015)	-0.175(2.188)
5	ma(5, 1, 0.03)	-0.257(0.692)	ma(5, 1, 0.03)	-0.097(1.101)	ma(5, 1, 0.03)	-0.127(3.148)
6	ma(5, 1, 0.05)	-0.146(1.252)	ma(5, 1, 0.05)	-0.11(1.193)	ma(5, 1, 0.05)	-0.13(3.393)
7	ma(5, 2, 0.001)	-0.179(0.998)	ma(5, 2, 0.001)	-9.527(0.599)	ma(5, 2, 0.001)	-0.309(1.105)
8	ma(5, 2, 0.01)	-0.412(0.63)	ma(5, 2, 0.01)	-0.065(1.839)	ma(5, 2, 0.01)	-0.219(1.993)
9	ma(10, 2, 0.02)	-0.134(0.94)	ma(10, 2, 0.001)	-0.446(0.678)	ma(10, 2, 0.001)	-1.085(1.135)
10	ma(10, 2, 0.04)	-0.077(1.133)	ma(5, 2, 0.02)	-0.075(1.374)	ma(10, 2, 0.02)	-0.098(2.159)
11	ma(5, 2, 0.02)	-0.056(1.16)	ma(10, 1, 0.05)	-0.096(1.403)	ma(5, 2, 0.02)	-0.487(1.289)
12	ma(10, 2, 0.001)	-0.292(0.55)	ma(10, 2, 0.04)	-0.222(0.741)	ma(10, 5, 0)	-0.753(1.064)
13	ma(10, 1, 0.05)	-0.112(1.213)	ma(10, 5, 0)	-0.085(1.464)	ma(10, 5, 0.005)	-0.189(2.104)
14	ma(10, 5, 0)	-0.165(0.901)	ma(10, 5, 0.005)	-0.064(1.647)	s(10, 0.005, 10)	-0.186(1.852)
15	ma(10, 5, 0.005)	-0.097(1.049)	s(10, 0.005, 10)	-0.111(1.305)	ma(15, 5, 0.01)	-0.197(2.653)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. We report the R_{os}^2 (%) and the MSFE-adj statistics from testing the null hypothesis that the historical average forecast MSFE is less than or equal to the actual forecast MSFE. The historical average (HA) forecast is given by $\hat{r}_{t+1}^{HA} = (1/t)\sum_{s=1}^{t} r_s$. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. 50% IS corresponds to period 1, as outlined in Table 5.13 (main text), keeping 50% of the total dataset out-of-sample.

Table B. 18: Out-of-sample Predictive Regression Estimation Results (Sharpe Ratio – F1, F2, F3)

DASH					
Technical Rule	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
ma(2,1,0.005)	-0.142(0.626)	PMA1	-0.059(1.696)	PMA1	-0.127(2.654)
ma(2, 1, 0.04)	-0.042(1.332)	ma(2, 1, 0.04)	-0.11(0.83)	ma(2, 1, 0.04)	-0.098(2.003)
ma(5, 1, 0)	-0.055(1.167)	ma(5, 1, 0)	-0.039(1.51)	ma(5, 1, 0)	-0.071(1.54)
ma(5, 1, 0.005)	-0.06(0.645)	ma(5, 1, 0.005)	-0.064(1.796)	ma(5, 1, 0.005)	-0.073(2.169)
ma(5, 1, 0.015)	-0.037(1.096)	ma(5, 1, 0.015)	-0.074(1.088)	ma(5, 1, 0.015)	-0.07(1.991)
PMA2	-0.033(1.16)	ma(5, 1, 0.03)	-0.102(1.25)	ma(5, 1, 0.03)	-0.06(1.956)
cb(10, 0.01, 10, 5)	-0.067(1.134)	PMA2	-4.204(0.601)	ma(10, 1, 0.03)	-0.301(1.374)
cb(10, 0.01,10,15)	-0.075(1.068)	ma(5, 2, 0.02)	-0.059(1.552)	ma(5, 2, 0.02)	-0.077(2.182)
ma(5, 2, 0.02)	-0.035(1.258)	ma(10, 1, 0.03)	-0.288(0.762)	ma(10, 1, 0.05)	-0.316(1.121)
cb(10, 0.01,10,25)	-0.033(0.948)	ma(10, 2, 0.001)	-0.033(2.011)	ma(10, 2, 0.001)	-0.026(1.234)
ma(10, 1, 0.03)	-0.045(1.072)	ma(10, 2, 0.01)	-0.118(0.934)	PMA2	-0.168(1.471)
ma(10, 1, 0.05)	-0.017(1.126)	cb(10, 0.01, 10, 5)	-0.15(1.138)	ma(10, 2, 0.01)	-0.251(1.153)
cb(5, 0.15, 10, 5)	-0.041(1.223)	ma(10, 2, 0.02)	-0.093(1.196)	ma(10, 2, 0.02)	-0.08(1.554)
cb(5, 0.15, 10, 15)	-0.047(1.024)	cb(10, 0.01, 10, 25)	-0.053(1.642)	cb(10, 0.01, 10, 5)	-0.082(1.797)
ma(10, 2, 0.001)	-0.062(0.838)	ma(5, 1, 0.05)	-0.094(1.38)	cb(10, 0.01,10,25)	-0.104(2.621)
DOGE					
Technical Rule	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
ma(2,1,0.005)	-0.044(1.37)	PMA1	-0.069(2.035)	PMA1	-0.152(2.519)
ma(5, 1, 0)	-0.062(1.254)	ma(5, 1, 0)	-0.031(1.163)	ma(5, 1, 0)	-0.124(1.951)
cb(5, 0.15, 10, 5)	-0.051(1.233)	ma(5, 1, 0.005)	-0.031(1.465)	ma(5, 1, 0.005)	-0.115(2.746)
cb(10, 0.01, 10, 5)	-0.033(1.347)	ma(5, 1, 0.015)	-0.054(1.387)	ma(5, 1, 0.015)	-0.187(1.882)
ma(5, 1, 0.005)	-0.132(0.581)	ma(5, 1, 0.03)	-0.037(1.328)	ma(5, 1, 0.03)	-0.18(1.892)
cb(5, 0.075, 10, 5)	-0.107(0.634)	ma(5, 1, 0.05)	-0.076(1.123)	ma(10, 1, 0.03)	-0.131(2.748)
cb(10, 0.01,10,25)	-0.058(1.308)	ma(5, 2, 0.02)	-1.019(0.622)	ma(10, 1, 0.05)	-0.543(1.535)
cb(5, 0.15, 10, 25)	-0.154(0.654)	ma(10, 1, 0.03)	-0.055(1.788)	ma(5, 2, 0.02)	-0.176(2.334)
ma(5, 2, 0.02)	-0.054(1.343)	ma(10, 1, 0.05)	-0.065(1.276)	ma(10, 2, 0.001)	-0.329(2.003)
ma(10, 1, 0.03)	-0.021(0.981)	ma(10, 2, 0.001)	-0.048(1.75)	ma(5, 1, 0.05)	-0.134(2.287)
cb(5, 0.03,10,200)	-0.007(0.766)	ma(10, 2, 0.02)	-0.078(0.909)	ma(10, 2, 0.02)	-0.113(2.105)
cb(5, 0.075,10,25)	-0.037(0.993)	ma(10, 2, 0.01)	-0.145(0.846)	ma(10, 2, 0.01)	-0.175(1.848)
cb(10,0.01,10,100)	-0.018(0.975)	ma(10, 2, 0.04)	-0.062(1.152)	ma(10, 2, 0.04)	-0.131(1.657)
ma(5, 1, 0.015)	-0.052(1.134)	PMA2	-0.057(1.841)	PMA2	-0.129(2.82)
cb(5, 0.15, 10,100)	-0.041(1.101)	ma(10, 5, 0)	-0.069(2.065)	ma(10, 5, 0)	-0.214(2.635)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. We report the R_{os}^2 (%) and the MSFE-adj statistics from testing the null hypothesis that the historical average forecast MSFE is less than or equal to the actual forecast MSFE. The historical average (HA) forecast is given by $\hat{r}_{t+1}^{HA} = (1/t)\sum_{s=1}^{t} r_s$. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. 50% IS corresponds to period 1, as outlined in Table 5.13 (main text), keeping 50% of the total dataset out-of-sample.

Table B. 19: Out-of-sample profitability performance Results (Sharpe Ratio – F1, F2, F3)

BYTE						
Rank	**Technical Rule**	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
1	cb(10, 0.01, 10, 5)	1.255(0.02)	PMA1	0.723(0.009)	PMA1	0.162(0.004)
2	cb(10, 0.01, 25, 10)	1.639(0.019)	ma(5, 1, 0)	0.386(0.009)	ma(2, 1, 0.04)	0.457(0.002)
3	ma(2,1,0.005)	0.477(0.02)	ma(5, 1, 0.005)	0.687(0.008)	ma(5, 1, 0)	0.331(0.002)
4	ma(5, 1, 0.005)	1.426(0.019)	ma(5, 1, 0.015)	0.808(0.01)	ma(5, 1, 0.005)	0.413(0.003)
5	cb(10, 0.01, 25, 20)	1.128(0.02)	ma(5, 1, 0.03)	0.761(0.008)	ma(5, 1, 0.015)	0.161(0.004)
6	ma(5, 1, 0.015)	1.524(0.018)	ma(5, 1, 0.05)	0.487(0.009)	ma(5, 1, 0.03)	0.316(0.003)
7	ma(5, 1, 0.03)	0.521(0.021)	ma(5, 2, 0.001)	0.261(0.01)	ma(5, 1, 0.05)	0.467(0.002)
8	cb(10, 0.01, 25, 50)	0.682(0.023)	cb(10, 0.01, 10, 5)	0.353(0.009)	ma(5, 2, 0.001)	0.119(0.003)
9	cb(10, 0.01, 25, 150)	1.562(0.019)	cb(10, 0.01, 10, 15)	0.263(0.009)	ma(5, 2, 0.02)	0.367(0.003)
10	ma(5, 1, 0.05)	0.927(0.02)	cb(10, 0.01, 10, 100)	0.323(0.009)	ma(10, 1, 0.03)	0.088(0.006)
11	cb(5, 0.15, 10, 5)	0.963(0.02)	cb(10, 0.01, 10, 200)	0.545(0.01)	ma(10, 1, 0.05)	0.25(0.003)
12	cb(5, 0.15, 25, 10)	0.969(0.02)	ma(5, 2, 0.02)	0.566(0.008)	ma(10, 2, 0.001)	0.29(0.003)
13	ma(5, 2, 0.001)	0.97(0.021)	ma(10, 1, 0.05)	0.566(0.008)	ma(10, 2, 0.01)	0.218(0.002)
14	ma(10, 1, 0.03)	1.036(0.019)	ma(10, 2, 0.001)	0.326(0.01)	ma(10, 2, 0.02)	0.281(0.002)
15	ma(10, 1, 0.05)	0.909(0.021)	ma(10, 2, 0.01)	0.515(0.009)	ma(10, 2, 0.04)	0.222(0.003)
CAS						
Rank	**Technical Rule**	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
1	ma(2,1,0.005)	0.852(0.038)	PMA1	0.178(0.009)	PMA1	0.166(0.004)
2	ma(5, 1, 0)	0.46(0.038)	ma(5, 1, 0)	0.129(0.006)	ma(5, 1, 0)	0.248(0.003)
3	ma(5, 1, 0.005)	0.185(0.044)	ma(5, 1, 0.005)	0.13(0.007)	ma(5, 1, 0.005)	0.252(0.007)
4	ma(5, 1, 0.015)	0.912(0.036)	ma(5, 1, 0.015)	0.107(0.009)	ma(5, 1, 0.015)	0.099(0.006)
5	ma(5, 1, 0.03)	0.827(0.035)	ma(5, 1, 0.03)	0.084(0.014)	ma(5, 1, 0.03)	0.072(0.009)
6	ma(5, 1, 0.05)	0.606(0.04)	ma(5, 1, 0.05)	0.245(0.01)	ma(5, 1, 0.05)	0.097(0.007)
7	ma(5, 2, 0.001)	0.906(0.037)	ma(5, 2, 0.001)	0.069(0.01)	ma(5, 2, 0.001)	0.216(0.003)
8	ma(5, 2, 0.01)	0.907(0.035)	ma(5, 2, 0.01)	0.096(0.007)	ma(5, 2, 0.01)	0.212(0.005)
9	ma(10, 2, 0.02)	0.928(0.034)	ma(10, 2, 0.001)	0.282(0.009)	ma(10, 2, 0.001)	0.098(0.005)
10	ma(10, 2, 0.04)	0.793(0.037)	ma(5, 2, 0.02)	0.182(0.007)	ma(10, 2, 0.02)	0.07(0.007)
11	ma(5, 2, 0.02)	0.627(0.039)	ma(10, 1, 0.05)	0.092(0.007)	ma(5, 2, 0.02)	0.114(0.005)
12	ma(10, 2, 0.001)	0.602(0.043)	ma(10, 2, 0.04)	0.411(0.01)	ma(10, 5, 0)	0.157(0.004)
13	ma(10, 1, 0.05)	0.771(0.035)	ma(10, 5, 0)	0.231(0.006)	ma(10, 5, 0.005)	0.117(0.005)
14	ma(10, 5, 0)	0.641(0.036)	ma(10, 5, 0.005)	0.166(0.005)	s(10, 0.005, 10)	0.08(0.006)
15	ma(10, 5, 0.005)	0.545(0.037)	s(10, 0.005, 10)	0.18(0.011)	ma(15, 5, 0.01)	0.117(0.006)

Note: This table reports the Sortino ratio and mean returns (in parentheses) and the benchmark is the buy-and-hold strategy. 50% IS corresponds to period 1, as outlined in Table 5.17 (main text), keeping 50% of the total dataset out-of-sample.

Table B. 20: Out-of-sample profitability performance Results (Sharpe Ratio – F1, F2, F3)

Technical Rule	Period 1 (50%IS) 08/08/2015-05/04/2017	Technical Rule	Period 2 (75% IS) 08/08/2015-06/02/2018	Technical Rule	Period 3 (90% IS) 08/08/2015-03/08/2018
DASH					
ma(2,1,0.005)	0.181(0.009)	PMA1	0.029(0.005)	PMA1	0.163(0.001)
ma(2, 1, 0.04)	0.132(0.01)	ma(2, 1, 0.04)	0.079(0.005)	ma(2, 1, 0.04)	0.15(0.001)
ma(5, 1, 0)	0.017(0.011)	ma(5, 1, 0)	0.037(0.005)	ma(5, 1, 0)	0.155(0.001)
ma(5, 1, 0.005)	0.031(0.012)	ma(5, 1, 0.005)	0.022(0.005)	ma(5, 1, 0.005)	0.157(0.001)
ma(5, 1, 0.015)	0.107(0.01)	ma(5, 1, 0.015)	0.023(0.005)	ma(5, 1, 0.015)	0.138(0.001)
PMA2	0.142(0.01)	ma(5, 1, 0.03)	0.024(0.006)	ma(5, 1, 0.03)	0.142(0.001)
cb(10, 0.01, 10, 5)	0.211(0.009)	PMA2	0.019(0.005)	ma(10, 1, 0.03)	3.272(0.008)
cb(10, 0.01,10,15)	0.114(0.01)	ma(5, 2, 0.02)	0(0.006)	ma(5, 2, 0.02)	0.114(0.001)
ma(5, 2, 0.02)	0.078(0.01)	ma(10, 1, 0.03)	0.124(0.005)	ma(10, 1, 0.05)	0.031(0.002)
cb(10, 0.01,10,25)	0.138(0.014)	ma(10, 2, 0.001)	0.01(0.006)	ma(10, 2, 0.001)	0.065(0.002)
ma(10, 1, 0.03)	0.207(0.009)	ma(10, 2, 0.01)	0.194(0.004)	PMA2	0.087(0.002)
ma(10, 1, 0.05)	0.104(0.01)	cb(10, 0.01, 10, 5)	0.013(0.005)	ma(10, 2, 0.01)	0.134(0.001)
cb(5, 0.15, 10, 5)	0.087(0.01)	ma(10, 2, 0.02)	0.076(0.005)	ma(10, 2, 0.02)	0.037(0.002)
cb(5, 0.15, 10, 15)	0.166(0.009)	cb(10, 0.01, 10, 25)	0.088(0.005)	cb(10, 0.01, 10, 5)	0.139(0.001)
ma(10, 2, 0.001)	0.058(0.01)	ma(5, 1, 0.05)	0.003(0.005)	cb(10, 0.01,10,25)	0.137(0.001)
DOGE					
Technical Rule	**Period 1 (50%IS)** 08/08/2015-05/04/2017	**Technical Rule**	**Period 2 (75% IS)** 08/08/2015-06/02/2018	**Technical Rule**	**Period 3 (90% IS)** 08/08/2015-03/08/2018
ma(2,1,0.005)	0.792(0.016)	PMA1	0.034(0.004)	PMA1	0.112(0.004)
ma(5, 1, 0)	0.59(0.017)	ma(5, 1, 0)	0.038(0.004)	ma(5, 1, 0)	0.113(0.004)
cb(5, 0.15, 10, 5)	0.874(0.018)	ma(5, 1, 0.005)	0.012(0.005)	ma(5, 1, 0.005)	0.109(0.004)
cb(10, 0.01, 10, 5)	0.845(0.017)	ma(5, 1, 0.015)	0.257(0.004)	ma(5, 1, 0.015)	0.177(0.003)
ma(5, 1, 0.005)	0.631(0.017)	ma(5, 1, 0.03)	0.25(0.004)	ma(5, 1, 0.03)	0.147(0.003)
cb(5, 0.075, 10, 5)	0.601(0.017)	ma(5, 1, 0.05)	0.058(0.004)	ma(10, 1, 0.03)	0.508(0.004)
cb(10, 0.01,10,25)	0.988(0.016)	ma(5, 2, 0.02)	0.154(0.003)	ma(10, 1, 0.05)	0.192(0.003)
cb(5, 0.15, 10, 25)	0.987(0.016)	ma(10, 1, 0.03)	0.246(0.003)	ma(5, 2, 0.02)	0.234(0.003)
ma(5, 2, 0.02)	0.859(0.017)	ma(10, 1, 0.05)	0.361(0.003)	ma(10, 2, 0.001)	0.146(0.003)
ma(10, 1, 0.03)	0.773(0.016)	ma(10, 2, 0.001)	0.013(0.005)	ma(5, 1, 0.05)	0.21(0.004)
cb(5, 0.03,10,200)	0.758(0.017)	ma(10, 2, 0.02)	0.011(0.005)	ma(10, 2, 0.02)	0.236(0.003)
cb(5, 0.075,10,25)	0.159(0.02)	ma(10, 2, 0.01)	0.009(0.005)	ma(10, 2, 0.01)	0.087(0.004)
cb(10,0.01,10,100)	0.577(0.018)	ma(10, 2, 0.04)	0.242(0.004)	ma(10, 2, 0.04)	0.14(0.003)
ma(5, 1, 0.015)	1.032(0.016)	PMA2	0.31(0.003)	PMA2	0.262(0.003)
cb(5, 0.15, 10,100)	0.748(0.017)	ma(10, 5, 0)	0.073(0.004)	ma(10, 5, 0)	0.257(0.003)

Note: This table reports the Sortino ratio and mean returns (in parentheses) and the benchmark is the buy-and-hold strategy. 50% IS corresponds to period 1, as outlined in Table 5.17 (main text), keeping 50% of the total dataset out-of-sample.

Table B. 21: In-sample Predictive Regression Estimation Results (Sharpe Ratio – 50%)

Panel A: Traditional Fundamental Factors					Panel B: Multiple Currency Factors				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
3mBill	0.08(0.077)	-0.11(1.906)	0.029(0.466)	-0.003(1.073)	AUD	0.065(0.118)	-0.119(1.908)	0.027(0.56)	0.104(0.133)
10yBill	-0.05(1.665)	0.108(0.077)	-0.074(1.931)	-0.031(1.663)	EUR	-0.055(1.722)	0.049(0.333)	0.032(0.544)	0.066(0.216)
DJIA	0.058(0.196)	-0.098(1.886)	0.005(0.915)	-0.012(1.313)	YEN	0.031(0.518)	-0.084(1.922)	0.056(0.158)	0.036(0.237)
GLD	0.028(0.585)	-0.074(1.884)	0.057(0.188)	0.034(0.329)	CAD	0.018(0.685)	-0.008(1.161)	0.036(0.489)	0.042(0.566)
MAAA	-0.021(1.274)	0.058(0.16)	-0.054(1.791)	-0.031(1.541)	BRL	0.052(0.225)	-0.103(1.906)	0.016(0.704)	-0.005(1.121)
MBaa	-0.053(1.703)	0.086(0.072)	-0.046(1.732)	-0.003(1.08)	RMB	-0.077(1.877)	0.096(0.11)	-0.028(1.485)	0.031(0.455)
MSCI	0.032(0.416)	-0.086(1.87)	-0.027(1.438)	-0.021(1.503)	CHF	-0.069(1.822)	0.037(0.406)	0.04(0.471)	0.042(0.335)
NSQ	0.041(0.337)	-0.087(1.882)	-0.017(1.274)	-0.023(1.489)	IDR	0.077(0.063)	-0.167(1.859)	0.078(0.065)	0.062(0.145)
OIL	0.018(0.717)	-0.013(1.335)	0.011(0.807)	-0.032(1.645)	KRW	0.01(0.814)	-0.063(1.832)	-0.023(1.435)	0.051(0.159)
MER	0.008(0.856)	0(1.002)	0.041(0.422)	-0.066(1.803)	VEF	-0.065(1.866)	0.102(0.08)	-0.039(1.595)	-0.027(1.478)
VIX	-0.068(1.863)	0.104(0.141)	-0.04(1.576)	-0.02(1.441)	GBP	-0.069(1.863)	0.094(0.095)	-0.029(1.529)	0.005(0.883)
VXN	-0.06(1.803)	0.101(0.136)	-0.036(1.556)	-0.003(1.077)	RUB	0.029(0.493)	-0.021(1.546)	-0.012(1.209)	-0.021(1.494)
VXD	-0.067(1.852)	0.098(0.139)	-0.047(1.654)	-0.019(1.4)	TRY	-0.039(1.552)	0.035(0.308)	0.003(0.953)	0.045(0.386)
SP500	0.054(0.218)	-0.105(1.895)	-0.003(1.05)	-0.019(1.457)	-				
Panel C: Blockchain Technology-based Factors					Panel D: Multiple Stock Indices				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
BZ	0.052(0.229)	-0.099(1.803)	0.088(0.041)	-0.009(1.184)	NI225	0.001(0.984)	-0.007(1.165)	-0.085(1.88)	-0.052(1.808)
BSV	0.046(0.266)	-0.134(1.955)	0.066(0.122)	0.027(0.53)	IBVC	0.053(0.317)	-0.052(1.791)	0.006(0.892)	-0.004(1.104)
HSH	-0.024(1.418)	0.091(0.104)	-0.056(1.807)	-0.008(1.174)	BRA	0.052(0.234)	-0.073(1.854)	-0.003(1.061)	0.01(0.749)
MD	0.046(0.342)	-0.045(1.778)	0.011(0.821)	-0.03(1.563)	TSX	0.046(0.319)	-0.072(1.862)	-0.009(1.146)	-0.033(1.656)
TBT	-0.006(1.096)	-0.009(1.142)	-0.004(1.067)	-0.028(1.421)	KOSPI	0.031(0.44)	-0.062(1.875)	-0.011(1.203)	-0.005(1.129)
TBM	0.075(0.087)	-0.113(1.915)	0.051(0.193)	0.005(0.859)	ASX	0.041(0.346)	-0.093(1.907)	-0.026(1.375)	-0.035(1.649)
DOD	0.07(0.026)	-0.07(1.977)	0.074(0.192)	-0.025(1.663)	JCI	0.086(0.012)	-0.147(1.851)	0.053(0.126)	0.04(0.172)
UBA	0.074(0.103)	-0.097(1.85)	0.044(0.258)	0.016(0.644)	SMI	-0.03(1.553)	0.001(0.974)	-0.099(1.947)	-0.039(1.714)
DBT	0.067(0.142)	-0.093(1.857)	0.045(0.255)	0.041(0.216)	SSE	-0.015(1.306)	0.002(0.964)	-0.094(1.956)	-0.038(1.665)
EPU	0.106(0.085)	-0.011(1.223)	0.042(0.358)	-0.026(1.412)	RTS	0.064(0.186)	-0.074(1.858)	0.03(0.51)	-0.012(1.276)

Note: We report the estimation of the slope coefficient and the heteroskedasticity-consistent t-statistic (in in the parenthesis) for the bivariate predictive regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$, where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 (main text) respectively. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, based on two-sided wild bootstrapped p-values. 50% IS corresponds to period 1 as outlined in Table 4 (main text). The equivalent Sharpe Ratio results are shown in Panels A of Tables 5.6-5.9 of the main text.

Table B. 22: In-sample Predictive Regression Estimation Results (Sharpe Ratio – 75%)

Panel A: Traditional Fundamental Factors					Panel B: Multiple Currency Factors				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
3mBill	0.076(0.311)	-0.042(1.649)	0.07(0.169)	0.027(0.569)	AUD	0.076(0.241)	-0.071(1.788)	0.033(0.421)	0.088(0.073)
10yBill	-0.081(1.726)	0.073(0.133)	-0.112(1.98)	-0.049(1.78)	EUR	0.071(0.407)	0.01(0.769)	0.071(0.146)	0.067(0.2)
DJIA	0.091(0.32)	-0.047(1.716)	0.068(0.212)	0.036(0.493)	YEN	0.017(0.371)	-0.064(1.891)	0.03(0.292)	0.035(0.19)
GLD	0.055(0.277)	-0.059(1.842)	0.055(0.134)	0.045(0.216)	CAD	0.062(0.314)	-0.022(1.49)	0.067(0.138)	0.048(0.321)
MAAA	-0.046(1.711)	0.046(0.203)	-0.083(1.98)	-0.035(1.707)	BRL	0.037(0.174)	-0.075(1.834)	0.025(0.473)	0.003(0.937)
MBaa	-0.053(1.791)	0.059(0.188)	-0.073(1.943)	-0.012(1.305)	RMB	0.018(0.692)	0.051(0.279)	-0.007(1.165)	0.052(0.232)
MSCI	0.082(0.343)	-0.039(1.646)	0.051(0.343)	0.031(0.561)	CHF	0.011(0.768)	0.032(0.366)	-0.006(1.127)	0.041(0.356)
NSQ	0.079(0.333)	-0.039(1.64)	0.056(0.293)	0.027(0.609)	IDR	0.036(0.046)	-0.127(1.829)	0.027(0.395)	0.053(0.132)
OIL	0.067(0.344)	-0.036(1.864)	0.092(0.093)	0.018(0.688)	KRW	0.083(0.345)	-0.053(1.821)	0.041(0.41)	0.076(0.118)
MER	0.011(0.555)	0.007(0.848)	-0.004(1.088)	-0.023(1.387)	VEF	-0.04(1.888)	0.077(0.131)	-0.045(1.813)	-0.025(1.581)
VIX	0.019(0.695)	0.068(0.214)	-0.082(1.959)	0.03(0.368)	GBP	-0.016(1.6)	0.063(0.199)	-0.031(1.691)	0.018(0.619)
VXN	0.007(0.867)	0.066(0.219)	-0.054(1.876)	0.027(0.412)	RUB	0.047(0.317)	-0.017(1.431)	0.013(0.755)	0(1.01)
VXD	0.019(0.704)	0.062(0.247)	-0.073(1.943)	0.024(0.467)	TRY	-0.053(1.689)	0.027(0.422)	-0.054(1.756)	0.011(0.819)
SP500	0.085(0.319)	-0.05(1.728)	0.059(0.262)	0.031(0.556)	-				
Panel C: Blockchain Technology-based Factors					**Panel D: Multiple Stock Indices**				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
BZ	0.041(0.234)	-0.059(1.651)	0.065(0.074)	0.005(0.895)	NI225	0.08(0.374)	-0.016(1.37)	0.032(0.57)	0.02(0.712)
BSV	0.084(0.226)	-0.11(1.976)	0.103(0.027)	0.065(0.154)	IBVC	0.124(0.37)	-0.031(1.852)	0.047(0.466)	0.064(0.411)
HSH	0.018(0.492)	0.016(0.702)	-0.131(1.997)	0.029(0.437)	BRA	0.076(0.292)	-0.051(1.782)	0.047(0.326)	0.034(0.47)
MD	0.126(0.355)	-0.028(1.764)	0.024(0.689)	0.073(0.382)	TSX	0.062(0.289)	-0.054(1.799)	0.043(0.356)	0.003(0.935)
TBT	-0.045(1.746)	-0.002(1.039)	-0.033(1.575)	-0.038(1.649)	KOSPI	0.062(0.366)	-0.019(1.375)	0.062(0.215)	0.022(0.626)
TBM	0.065(0.228)	-0.066(1.791)	0.075(0.083)	0.021(0.593)	ASX	0.058(0.317)	-0.058(1.797)	0.045(0.375)	0.005(0.912)
DOD	0.033(0.379)	-0.048(1.967)	0.062(0.047)	-0.018(1.643)	JCI	0.059(0.121)	-0.107(1.81)	0.064(0.05)	0.044(0.137)
UBA	0.074(0.291)	-0.068(1.88)	0.119(0.068)	0.031(0.37)	SMI	0.047(0.456)	-0.009(1.205)	0.01(0.851)	0.009(0.854)
DBT	0.047(0.225)	-0.084(1.925)	0.096(0.076)	0.037(0.185)	SSE	0.037(0.428)	-0.011(1.302)	-0.033(1.598)	-0.003(1.051)
EPU	0.012(0.683)	-0.017(1.391)	0.015(0.663)	-0.011(1.238)	RTS	0.081(0.247)	-0.062(1.857)	0.044(0.307)	0.021(0.645)

Note: We report the estimation of the slope coefficient and the heteroskedasticity-consistent t-statistic (in in the parenthesis) for the bivariate predictive regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$, where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 (main text) respectively. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, based on two-sided wild bootstrapped p-values. 50% IS corresponds to period 1 as outlined in Table 4 (main text). The equivalent Sharpe Ratio results are shown in Panels A of Tables 5.6-5.9 of the main text.

Table B. 23: In-sample Predictive Regression Estimation Results (Sharpe Ratio – 90%)

Panel A: Traditional Fundamental Factors					Panel B: Multiple Currency Factors				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
3mBill	0.083(0.06)	0.046(0.4)	0.066(0.11)	0.069(0.151)	AUD	0.085(0.109)	-0.058(1.854)	0.04(0.261)	0.108(0.005)
10yBill	-0.085(1.929)	-0.028(1.387)	-0.09(1.978)	-0.068(1.892)	EUR	0.104(0.084)	0.018(0.468)	0.081(0.04)	0.126(0.01)
DJIA	0.095(0.106)	0.025(0.6)	0.069(0.107)	0.073(0.103)	YEN	0.04(0.059)	-0.041(1.843)	0.038(0.147)	0.065(0.014)
GLD	0.072(0.081)	-0.031(1.657)	0.061(0.063)	0.074(0.028)	CAD	0.066(0.192)	-0.024(1.672)	0.075(0.055)	0.067(0.064)
MAAA	-0.031(1.566)	0.049(0.105)	-0.063(1.941)	-0.019(1.511)	BRL	0.045(0.088)	-0.093(1.959)	0.024(0.465)	0.035(0.214)
MBaa	-0.051(1.836)	0.05(0.124)	-0.066(1.949)	-0.022(1.666)	RMB	0.058(0.147)	0.041(0.255)	0.02(0.541)	0.098(0.021)
MSCI	0.088(0.119)	0.028(0.547)	0.056(0.187)	0.067(0.138)	CHF	0.051(0.147)	-0.008(1.233)	0.014(0.689)	0.109(0.008)
NSQ	0.082(0.097)	0.046(0.392)	0.054(0.191)	0.061(0.18)	IDR	0.004(0.868)	-0.122(1.957)	-0.001(1.026)	0.004(0.908)
OIL	0.084(0.062)	0.05(0.338)	0.077(0.074)	0.069(0.158)	KRW	0.107(0.082)	-0.004(1.074)	0.06(0.152)	0.12(0.009)
MER	0.01(0.637)	0.017(0.499)	-0.01(1.218)	0.015(0.697)	VEF	-0.071(1.941)	-0.04(1.526)	-0.054(1.829)	-0.087(1.917)
VIX	0.025(0.531)	0.035(0.377)	-0.07(1.951)	0.034(0.204)	GBP	0.001(0.961)	0.026(0.456)	-0.021(1.554)	0.037(0.192)
VXN	0.019(0.554)	0.044(0.215)	-0.047(1.857)	0.036(0.181)	RUB	0.073(0.071)	-0.02(1.654)	0.02(0.559)	0.057(0.097)
VXD	0.037(0.359)	0.035(0.329)	-0.057(1.905)	0.052(0.057)	TRY	-0.058(1.903)	-0.056(1.702)	-0.051(1.795)	-0.021(1.355)
SP500	0.089(0.105)	0.028(0.578)	0.06(0.151)	0.065(0.14)	-				
Panel C: Blockchain Technology-based Factors					Panel D: Multiple Stock Indices				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
BZ	-0.007(1.137)	-0.072(1.806)	0.033(0.346)	-0.038(1.703)	NI225	0.082(0.181)	0.04(0.352)	0.042(0.35)	0.049(0.265)
BSV	0.092(0.065)	-0.017(1.268)	0.094(0.011)	0.077(0.033)	IBVC	-0.001(1.048)	0.106(0.125)	0.005(0.894)	-0.016(1.293)
HSH	0.022(0.453)	0.081(0.104)	-0.036(1.605)	-0.006(1.105)	BRA	0.101(0.044)	-0.003(1.078)	0.063(0.112)	0.099(0.035)
MD	0.078(0.059)	0.076(0.2)	0.039(0.332)	0.086(0.124)	TSX	0.059(0.166)	0.015(0.745)	0.041(0.299)	0.015(0.657)
TBT	-0.04(1.76)	-0.025(1.54)	-0.022(1.428)	-0.013(1.288)	KOSPI	0.08(0.115)	0.017(0.635)	0.067(0.108)	0.064(0.118)
TBM	0.078(0.043)	0.011(0.832)	0.074(0.048)	0.057(0.153)	ASX	0.058(0.133)	0.018(0.697)	0.048(0.258)	0.027(0.486)
DOD	0.009(0.773)	-0.052(1.984)	0.061(0.032)	-0.03(1.905)	JCI	0.062(0.045)	-0.064(1.73)	0.063(0.024)	0.05(0.03)
UBA	0.055(0.364)	-0.076(1.964)	0.103(0.072)	0.015(0.583)	SMI	0.052(0.318)	-0.003(1.089)	0.018(0.688)	0.026(0.465)
DBT	0.019(0.612)	-0.097(1.977)	0.07(0.148)	-0.004(1.116)	SSE	0.032(0.427)	-0.038(1.823)	-0.025(1.522)	0.014(0.69)
EPU	-0.031(1.686)	-0.011(1.317)	0.021(0.606)	-0.024(1.501)	RTS	0.104(0.045)	-0.015(1.332)	0.053(0.144)	0.082(0.054)

Note: We report the estimation of the slope coefficient and the heteroskedasticity-consistent t-statistic (in in the parenthesis) for the bivariate predictive regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$, where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 (main text) respectively. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, based on two-sided wild bootstrapped p-values. 50% IS corresponds to period 1 as outlined in Table 5.3-5.44 (main text). The equivalent Sharpe Ratio results are shown in Panels A of Tables 5.6-5.9 of the main text.

Table B. 24: In-sample Predictive Regression Estimation Results (Sharpe Ratio – 50%, 75% and 90%)

F1					F2			
	BYTE	CAS	DASH	DOGE	BYTE	CAS	DASH	DOGE
NTs	0.065(0.363)	-0.046(1.812)	0.111(0.061)	0.038(0.35)	-0.021(1.346)	-0.065(1.825)	0.018(0.687)	0.013(0.728)
NPs	0.079(0.354)	-0.033(1.741)	0.118(0.043)	0.042(0.396)	0.015(0.735)	-0.102(1.927)	0.094(0.105)	0.022(0.607)
NUs	0.051(0.423)	-0.038(1.808)	0.107(0.088)	0.022(0.564)	-0.022(1.337)	-0.023(1.538)	-0.056(1.967)	-0.031(1.813)
PVs	0.032(0.484)	0.021(0.65)	0.091(0.075)	-0.002(1.042)	-0.036(1.646)	0.048(0.442)	-0.046(1.751)	-0.057(1.91)
Btc-W	0.051(0.455)	-0.045(1.961)	0.155(0.053)	0.028(0.382)	0.015(0.723)	-0.063(1.894)	0.014(0.759)	0.015(0.734)
Eth-W	0.072(0.35)	-0.012(1.271)	0.093(0.131)	0.032(0.364)	0.056(0.152)	-0.06(1.751)	0.023(0.647)	-0.009(1.204)
Xrp-W	0.066(0.417)	-0.034(1.842)	0.108(0.192)	0.047(0.207)	0.043(0.263)	-0.068(1.936)	0.017(0.658)	0.012(0.759)
Btc-GT	0.029(0.469)	-0.055(1.91)	0.033(0.48)	-0.035(1.573)	-0.029(1.459)	-0.06(1.863)	0.048(0.342)	-0.018(1.26)
Eth-GT	0.015(0.367)	0.02(0.688)	-0.018(1.515)	-0.023(1.671)	0.067(0.126)	-0.079(1.835)	0.032(0.524)	-0.01(1.237)
Xrp-GT	-0.01(1.285)	0.013(0.734)	0.013(0.777)	-0.087(1.91)	-0.029(1.303)	0.002(0.976)	0.025(0.459)	0.019(0.544)

F3				
	BYTE	CAS	DASH	DOGE
NTs	0.083(0.135)	-0.012(1.327)	0.108(0.024)	0.075(0.039)
NPs	0.078(0.081)	0.061(0.285)	0.085(0.044)	0.069(0.145)
NUs	0.061(0.247)	-0.022(1.698)	0.102(0.054)	0.046(0.122)
PVs	0.044(0.247)	0.022(0.502)	0.088(0.043)	0.026(0.341)
Btc-W	0.043(0.472)	-0.043(1.991)	0.131(0.06)	0.015(0.532)
Eth-W	0.055(0.364)	-0.025(1.686)	0.06(0.248)	0.004(0.894)
Xrp-W	0.063(0.372)	-0.03(1.919)	0.097(0.176)	0.037(0.184)
Btc-GT	-0.028(1.524)	0.012(0.734)	-0.007(1.124)	-0.103(1.98)
Eth-GT	-0.007(1.291)	0.029(0.417)	-0.027(1.719)	-0.052(1.98)
Xrp-GT	-0.004(1.125)	0.004(0.894)	0.026(0.511)	-0.051(1.826)

Note: We report the estimation of the slope coefficient and the heteroskedasticity-consistent t-statistic (in in the parenthesis) for the bivariate predictive regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$, where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 (main text) respectively. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, based on two-sided wild bootstrapped p-values. 50% IS corresponds to period 1 as outlined in Table 5.3-5.4 (main text). The equivalent Sharpe Ratio results are shown in Panels A of Tables 5.6-5.9 of the main text.

Table B. 25: Out-of-sample Predictive Regression Estimation Results (Sharpe Ratio – 50%)

Panel A: Traditional Fundamental Factors					Panel B: Multiple Currency Factors				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
3mBill	-0.023(1.373)	-0.152(1.252)	-0.035(1.174)	-0.052(1.356)	AUD	-0.023(1.314)	-0.219(0.713)	-0.055(1.188)	-0.016(0.861)
10yBill	-0.013(1.33)	-0.088(1.596)	-0.057(1.218)	-0.03(1.254)	EUR	-0.021(1.526)	-0.2(0.769)	-0.079(0.849)	-0.054(1.349)
DJIA	0.01(1.066)	0.157(1.279)	0.027(1.12)	0.019(1.013)	YEN	-0.015(1.343)	-0.392(0.539)	-0.054(0.687)	-0.086(0.757)
GLD	-0.026(1.598)	-0.098(1.723)	-0.067(0.989)	0.061(1.411)	CAD	-0.018(1.481)	-0.113(1.052)	-0.026(1.061)	-0.063(1.166)
MAAA	-0.021(0.549)	-0.085(1.065)	-0.061(0.662)	-0.065(0.646)	BRL	-0.017(1.12)	-0.457(0.732)	-0.065(0.623)	-0.058(0.728)
MBaa	-0.009(1.246)	-0.058(1.289)	-0.045(1.168)	-0.037(1.205)	RMB	-0.017(1.12)	-0.457(0.732)	-0.065(0.623)	-0.058(0.728)
MSCI	0.012(1.418)	0.044(1.322)	-0.038(1.266)	-0.033(1.027)	CHF	-0.048(0.928)	-0.186(0.879)	-0.042(1.142)	-0.086(0.674)
NSQ	0.027(1.431)	0.086(1.328)	0.075(0.593)	0.031(1.071)	IDR	-0.041(1.278)	-0.074(1.343)	-0.029(1.013)	-0.031(1.142)
OIL	-0.027(1.384)	-0.112(1.409)	-0.048(0.958)	-0.037(1.269)	KRW	-1.464(0.425)	-1.228(0.424)	-0.954(0.431)	-0.025(0.424)
MER	0.012(1.321)	0.093(0.884)	0.053(0.701)	0.027(1.057)	VEF	-0.003(0.894)	-0.11(1.323)	-0.095(0.517)	-0.029(1.191)
VIX	-0.021(1.407)	-0.138(0.833)	-0.064(0.689)	-0.062(0.981)	GBP	-0.008(1.077)	-0.21(0.7)	-0.147(0.626)	-0.041(1.007)
VXN	-0.011(1.546)	-0.167(1.05)	-0.045(0.652)	-0.026(0.983)	RUB	-0.1(0.466)	-129(0.423)	-0.558(0.517)	-12.105(0.425)
VXD	-0.036(1.479)	-0.152(1.097)	-0.066(1.392)	-0.064(1.47)	TRY	-0.023(1.613)	-0.066(1.212)	-0.043(1.177)	-0.03(1.335)
SP500	0.018(1.095)	0.112(1.086)	-0.038(0.703)	0.022(1.034)	-				
Panel C: Blockchain Technology-based Factors					Panel D: Multiple Stock Indices				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
BZ	-0.014(0.355)	-0.023(0.274)	-0.009(0.326)	-0.036(0.24)	NI225	0.035(1.284)	0.116(0.936)	0.077(0.941)	-.051(1.175)
BSV	-0.102(0.253)	-0.019(0.31)	-0.021(0.272)	-0.011(0.328)	IBVC	-0.076(1.367)	-0.152(1.893)	-0.128(0.937)	-0.072(1.654)
HSH	0.069(0.187)	1.378(0.159)	0.003(0.298)	0.011(0.365)	BRA	-0.008(0.981)	-0.078(1.259)	-0.045(0.928)	-0.019(0.982)
MD	-0.007(0.28)	-0.017(0.296)	-0.047(0.2)	-0.011(0.297)	TSX	-0.009(1.282)	-0.117(0.995)	-0.036(1.058)	-0.02(0.951)
TBT	-0.035(0.206)	-0.015(0.379)	-0.009(0.265)	-0.008(0.293)	KOSPI	-0.016(1.21)	-0.102(1.429)	-0.249(0.439)	-0.037(1.129)
TBM	-0.017(1.394)	-0.077(1.098)	-0.087(0.566)	-0.026(0.878)	ASX	-0.013(0.986)	-0.096(1.438)	-0.089(0.551)	-0.041(0.747)
DOD	-0.012(1.207)	-0.095(1.441)	-0.051(1.222)	-0.038(1.24)	JCI	-0.018(0.817)	-0.04(1.078)	-0.015(0.846)	-0.053(0.978)
UBA	-0.021(1.21)	-0.121(0.855)	-0.051(0.842)	-0.033(1.194)	SMI	-0.007(1.095)	-0.149(1.622)	-0.067(0.962)	-0.03(1.182)
DBT	-0.078(1.508)	-0.133(2.096)	-0.106(1.454)	-0.093(1.872)	SSE	-0.014(0.343)	-0.014(0.358)	-0.012(0.348)	-0.007(0.254)
EPU	-0.009(0.323)	-0.068(0.204)	-0.01(0.306)	-0.011(0.307)	RTS	-0.008(0.302)	-0.011(0.312)	-0.068(0.199)	-0.009(0.279)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each one of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 (main text) respectively. We report the R^2_{os} (%) and the MSFE-adj statistics from testing the null hypothesis that the historical average forecast MSFE is less than or equal to the actual forecast MSFE. The historical average (HA) forecast is given by $\hat{r}^{HA}_{t+1} = (1/t)\sum_{s=1}^{t} r_s$. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. 50% IS corresponds to period 1, as outlined in Table 5.3-5.4 (main text), keeping 50% of the total dataset out-of-sample. The equivalent Sharpe Ratio results are shown in Panels A of Tables 7.1-7.3 of the main text.

Table B. 26: Out-of-sample Predictive Regression Estimation Results (Sharpe Ratio –75%)

Panel A: Traditional Fundamental Factors					Panel B: Multiple Currency Factors				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
3mBill	0.268(1.334)	-0.126(1.408)	-0.102(1.486)	-0.08(2.127)	AUD	-0.152(1.801)	-0.076(1.535)	-0.077(1.457)	-0.058(1.254)
10yBill	-0.234(1.268)	-0.104(1.252)	-0.088(1.314)	-0.062(2)	EUR	-0.13(1.891)	-0.065(1.92)	-0.054(1.475)	-0.041(1.386)
DJIA	0.242(1.28)	0.107(1.277)	0.091(1.346)	0.065(2.034)	YEN	-0.407(0.827)	-0.257(0.726)	-0.127(1.111)	-0.097(1.382)
GLD	-0.274(1.28)	-0.12(1.459)	-0.098(1.494)	-0.08(2.063)	CAD	-0.408(0.919)	-0.222(0.706)	-0.088(1.109)	-0.063(1.456)
MAAA	-0.127(1.575)	-0.112(0.979)	-0.186(0.976)	-0.056(1.632)	BRL	-0.089(1.836)	-0.054(1.428)	-0.052(1.276)	-0.034(1.893)
MBaa	-0.052(1.697)	-0.068(0.964)	-0.065(1.037)	-0.033(1.828)	RMB	-0.089(1.836)	-0.054(1.428)	-0.052(1.276)	-0.034(1.893)
MSCI	0.062(1.798)	0.1(0.896)	0.085(0.995)	0.039(1.663)	CHF	-0.17(1.037)	-0.243(0.697)	-0.181(0.902)	-0.053(1.823)
NSQ	0.084(1.316)	0.074(2.179)	0.044(1.586)	0.036(1.597)	IDR	-0.161(1.694)	-0.076(1.192)	-0.083(1.293)	-0.042(1.993)
OIL	-0.123(1.298)	-0.078(1.859)	-0.064(1.804)	--0.071(1.817)	KRW	-0.191(1.372)	-0.074(1.963)	-0.062(1.182)	-0.05(1.539)
MER	0.188(0.815)	0.12(0.936)	0.065(1.764)	0.092(1.453)	VEF	-0.149(1.58)	-0.133(0.926)	-0.118(1.095)	-0.056(1.444)
VIX	-0.197(1.616)	-0.08(1.65)	-0.143(0.899)	-0.045(1.719)	GBP	-0.32(1.143)	-0.149(0.89)	-0.114(1.266)	-0.106(1.394)
VXN	-0.242(0.922)	-0.088(1.564)	-0.088(1.584)	-0.242(0.747)	RUB	-4.035(0.623)	-3.624(0.604)	-1.654(0.642)	-0.478(0.692)
VXD	-0.117(1.519)	-0.083(1.87)	-0.079(1.874)	-0.071(1.444)	TRY	-0.314(0.877)	-0.275(0.694)	-0.097(0.955)	-0.09(1.508)
SP500	0.099(1.442)	0.069(1.31)	0.054(1.926)	0.049(1.762)	-				
Panel C: Blockchain Technology-based Factors					Panel D: Multiple Stock Indices				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
BZ	-0.142(0.461)	-0.026(0.645)	-0.06(0.653)	-0.045(0.539)	NI225	0.907(0.65)	0.685(0.623)	0.278(0.69)	0.14(0.887)
BSV	-0.504(0.263)	-0.023(0.426)	-0.058(0.59)	-0.058(0.703)	IBVC	-0.202(1.542)	-0.095(1.855)	-0.098(1.413)	-0.327(0.762)
HSH	0.029(0.535)	0.023(0.586)	0.064(0.574)	0.04(0.56)	BRA	-0.324(0.829)	-0.206(0.752)	-0.058(1.433)	-0.107(1.165)
MD	-0.019(0.881)	-0.05(0.495)	-0.117(0.291)	-0.044(0.555)	TSX	-0.124(1.278)	-0.089(1.482)	-0.064(1.903)	-0.046(1.842)
TBT	-0.053(0.369)	-0.149(0.259)	-0.071(0.479)	-0.101(0.291)	KOSPI	0.106(1.356)	0.084(1.57)	0.08(1.513)	0.087(1.207)
TBM	-0.119(1.366)	-0.085(1.688)	-0.093(1.243)	-0.073(1.707)	ASX	-0.096(1.363)	-0.058(1.373)	-0.081(1.108)	-0.109(1.064)
DOD	-0.139(1.619)	-0.075(2.046)	-0.085(1.635)	-0.083(2.003)	JCI	-0.06(1.184)	-0.033(1.413)	-0.029(1.526)	-0.032(1.899)
UBA	-0.202(1.273)	-0.092(1.141)	-0.051(1.834)	-0.057(1.748)	SMI	-0.192(1.136)	-0.69(0.633)	-0.458(0.641)	-0.04(1.737)
DBT	-0.35(1.43)	-0.285(0.825)	-0.217(1.209)	-0.093(1.924)	SSE	-0.026(0.789)	-0.374(0.229)	-0.092(0.302)	-0.066(0.514)
EPU	-0.022(0.659)	-0.028(0.601)	-0.069(0.477)	-0.066(0.51)	RTS	-0.016(0.863)	-0.597(0.239)	-0.13(0.342)	-0.085(0.63)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each one of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 (main text) respectively. We report the R^2_{os} (%) and the MSFE-adj statistics from testing the null hypothesis that the historical average forecast MSFE is less than or equal to the actual forecast MSFE. The historical average (HA) forecast is given by $\hat{r}^{HA}_{t+1} = (1/t)\sum_{s=1}^{t} r_s$. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. 50% IS corresponds to period 1, as outlined in Table 5.13 (main text), keeping 50% of the total dataset out-of-sample. The equivalent Sharpe Ratio results are shown in Panels A of Tables 5.13-5.17 of the main text.

Table B. 27: Out-of-sample Predictive Regression Estimation Results (Sharpe Ratio –90%)

Panel A: Traditional Fundamental Factors					Panel B: Multiple Currency Factors				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
3mBill	-0.21(2.286)	-0.215(2.751)	-0.113(2.679)	-0.236(2.771)	AUD	-0.071(1.707)	-0.209(2.654)	-0.126(2.129)	-0.208(2.62)
10yBill	-0.18(2.138)	-0.185(2.586)	-0.099(2.584)	-0.198(2.525)	EUR	-0.163(2.16)	-0.117(2.659)	-0.067(2.646)	-0.135(2.573)
DJIA	0.187(2.17)	0.191(2.619)	0.101(2.602)	0.206(2.582)	YEN	-0.115(2.002)	-0.286(1.276)	-0.063(2.161)	-0.16(2.599)
GLD	-0.211(2.259)	-0.223(2.588)	-0.116(2.701)	-0.242(2.697)	CAD	-0.229(2.224)	-0.15(3.268)	-0.105(2.44)	-0.145(3.086)
MAAA	-0.424(2.738)	-0.443(1.522)	-0.758(1.03)	-0.18(2.895)	BRL	-0.228(2.654)	-0.125(2.05)	-0.139(1.637)	-0.079(2.304)
MBaa	-0.072(2.378)	-0.067(1.91)	-0.054(1.814)	-0.155(1.943)	RMB	-0.228(2.654)	-0.125(2.05)	-0.139(1.637)	-0.079(2.304)
MSCI	-0.092(2.545)	0.059(2.015)	0.03(1.545)	0.147(1.906)	CHF	-0.06(2.087)	-0.058(1.886)	-0.042(1.597)	-0.117(2.666)
NSQ	-0.225(2.357)	0.138(1.917)	0.118(2.213)	0.121(2.203)	IDR	-0.166(1.3)	-0.324(1.582)	-0.043(1.498)	-0.109(2.368)
OIL	-0.224(1.714)	-0.187(1.92)	-0.007(1.601)	-0.237(1.767)	KRW	-0.444(1.067)	-0.654(1.092)	-0.111(1.012)	-0.066(2.282)
MER	0.005(0.957)	0.257(0.959)	3.547(0.971)	2.229(1.037)	VEF	-0.192(1.642)	-0.191(1.559)	-0.041(2.099)	-0.162(2.011)
VIX	-0.078(2.059)	-0.169(2.287)	-0.007(1.567)	-0.134(3.02)	GBP	-0.409(1.422)	-1.135(1.14)	-0.083(1.904)	-0.42(1.365)
VXN	-0.099(1.957)	-0.206(2.424)	-0.13(2.753)	-0.163(2.202)	RUB	-0.681(0.945)	-1.457(0.942)	-1.432(0.952)	-9.027(0.955)
VXD	-0.056(1.199)	-0.156(2.186)	-0.025(1.593)	-0.117(2.38)	TRY	-0.064(2.659)	-0.153(1.514)	-0.034(1.35)	-0.126(2.248)
SP500	0.167(2.314)	0.118(1.98)	0.115(2.144)	0.2(1.777)	-				
Panel C: Blockchain Technology-based Factors					Panel D: Multiple Stock Indices				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
BZ	-0.512(0.779)	-0.025(1.224)	-0.068(0.655)	-0.042(0.536)	NI225	0.037(2.058)	0.167(1.999)	-0.047(1.581)	-0.173(2.049)
BSV	-0.109(0.354)	-0.08(0.474)	-0.054(0.624)	-0.062(0.604)	IBVC	-0.092(1.582)	-0.078(2.192)	-0.066(2.453)	-0.131(2.432)
HSH	-0.526(0.37)	-0.002(0.629)	-0.054(0.64)	-0.031(0.518)	BRA	0.078(2.808)	0.139(1.676)	-0.022(1.191)	-0.122(2.252)
MD	-0.75(0.572)	-0.04(0.962)	-0.052(0.615)	-0.088(0.768)	TSX	0.081(2.02)	0.087(2.397)	-0.051(1.568)	-0.143(2.07)
TBT	-0.282(0.687)	-0.022(0.88)	-0.056(0.672)	0.008(0.2)	KOSPI	0.333(1.117)	0.45(1.144)	-0.391(1.259)	-0.38(1.276)
TBM	0.69(1.039)	0.997(1.047)	0.262(1.027)	-0.116(1.789)	ASX	-0.221(1.191)	-0.166(1.317)	-0.013(1.118)	-0.128(1.641)
DOD	-0.186(1.873)	-0.184(1.926)	-0.122(1.742)	-0.114(2.118)	JCI	-0.027(1.309)	-0.073(2.106)	-0.02(1.514)	-0.067(2.215)
UBA	-0.143(2.471)	-0.297(1.138)	-0.072(1.802)	-0.146(2.819)	SMI	0.14(1.755)	0.087(1.605)	-0.12(1.895)	-0.249(1.787)
DBT	-0.472(1.909)	-0.354(2.087)	-0.162(2.2)	-0.452(1.876)	SSE	-0.231(0.457)	-0.033(1.189)	-0.056(0.664)	-0.011(0.351)
EPU	-0.117(0.59)	-0.028(0.828)	-0.032(0.494)	-0.02(0.432)	RTS	0.042(0.679)	0.101(0.468)	-0.054(0.619)	-0.058(0.691)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each one of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 (main text) respectively. We report the R^2_{os} (%) and the MSFE-adj statistics from testing the null hypothesis that the historical average forecast MSFE is less than or equal to the actual forecast MSFE. The historical average (HA) forecast is given by $\hat{r}^{HA}_{t+1} = (1/t)\sum_{s=1}^{t} r_s$. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. 50% IS corresponds to period 1, as outlined in Table 5.13 (main text), keeping 50% of the total dataset out-of-sample. The equivalent Sharpe Ratio results are shown in Panels A of Tables 5.13-5.17 of the main text.

Table B. 28: Out-of-sample Predictive Regression Estimation Results (Sharpe Ratio –50%, 75%, and 90%)

F1

	BYTE	CAS	DASH	DOGE
NTs	0.002(0.402)	0.077(1.652)	0.029(1.488)	0.039(1.523)
NPs	0.021(1.102)	0.085(1.256)	0.02(1.045)	0.036(1.32)
NUs	0(0.419)	0.038(1.105)	-0.015(0.953)	0.014(0.923)
PVs	-0.048(1.15)	-0.063(1.397)	-0.036(0.982)	0.032(1.346)
Btc-W	-0.007(0.266)	-0.066(0.187)	-0.971(0.157)	-0.011(0.311)
Eth-W	-0.015(0.259)	-0.036(0.367)	-0.021(0.377)	-0.014(0.314)
Xrp-W	-0.011(0.301)	-0.013(0.388)	-0.208(0.16)	-0.017(0.364)
Btc-GT	-0.028(0.434)	-0.183(0.169)	-0.014(0.359)	-0.192(0.166)
Eth-GT	-0.007(0.27)	-0.036(0.295)	-0.254(0.175)	-0.006(0.259)
Xrp-GT	-0.025(0.319)	-0.016(0.446)	-0.014(0.349)	-0.016(0.237)

F2

	BYTE	CAS	DASH
NTs	0.097(1.634)	0.086(1.85)	0.065(1.485)
NPs	0.099(1.43)	0.066(1.945)	0.084(1.301)
NUs	0.079(1.407)	0.047(1.89)	0.054(1.103)
PVs	0.153(1.311)	0.08(1.539)	0.058(1.998)
Btc-W	-0.027(0.542)	-0.031(0.474)	-0.079(0.381)
Eth-W	-1.96(0.224)	-0.108(0.299)	-0.226(0.38)
Xrp-W	-0.076(0.451)	-1.594(0.223)	-0.046(0.575)
Btc-GT	-0.215(0.313)	-0.043(0.714)	-0.079(0.494)
Eth-GT	-0.03(0.382)	-0.032(0.759)	-0.174(0.321)
Xrp-GT	-0.35(0.316)	-0.7(0.232)	-0.357(0.223)

F3

	BYTE	CAS	DASH	DOGE
NTs	0.218(2.649)	0.267(1.701)	-0.134(3.036)	-0.135(2.199)
NPs	0.036(1.423)	0.074(2.467)	-0.013(1.592)	-0.166(1.777)
NUs	0(-0.948)	0(0.538)	-0.013(2.205)	-0.022(1.623)
PVs	0.374(1.474)	0.491(1.368)	-0.109(1.438)	-0.127(2.25)
Btc-W	-0.157(0.945)	-0.02(0.475)	-0.054(0.623)	-0.044(0.659)
Eth-W	-0.147(0.656)	-0.021(0.411)	-0.055(0.632)	-0.058(0.618)
Xrp-W	-0.561(0.492)	-0.017(0.828)	-0.051(0.595)	-0.059(0.629)
Btc-GT	-0.056(0.602)	-0.042(0.984)	-0.061(0.713)	-0.011(0.34)
Eth-GT	-1.388(0.364)	-0.032(1.41)	-0.073(0.785)	-0.022(0.335)
Xrp-GT	-0.124(0.798)	-0.027(1.38)	-0.054(0.626)	-0.019(0.385)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_t + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ where r_{t+1} is the cryptocurrency returns and $X_{i,t}$ the relevant predictor. Panel A and Panels B-F are the regression results for each one of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 (main text) respectively. We report the R^2_{os} (%) and the MSFE-adj statistics from testing the null hypothesis that the historical average forecast MSFE is less than or equal to the actual forecast MSFE. The historical average (HA) forecast is given by $\hat{r}^{HA}_{t+1} = (1/t)\sum_{s=1}^{t} r_s$. *, ** and *** indicate significance at the 10%, 5% and 1% levels respectively. 50% IS corresponds to period 1, as outlined in Table 4 (main text), keeping 50% of the total dataset out-of-sample. The equivalent Sharpe Ratio results are shown in Panels A of Tables 5.13-5.17 of the main text.

Table B. 29: Out-of-sample Profitability Performance Results (Sharpe Ratio –50%)

Panel A: Traditional Fundamental Factors					Panel B: Multiple Currency Factors				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
3mBill	0.871(0.027)	0.757(0.031)	0.33(0.019)	0.669(0.02)	AUD	0.701(0.019)	0.849(0.041)	0.235(0.015)	1.074(0.023)
10yBill	1.267(0.026)	0.525(0.034)	0.146(0.013)	0.566(0.017)	EUR	0.905(0.025)	0.574(0.032)	0.232(0.015)	0.719(0.019)
DJIA	1.009(0.03)	0.364(0.032)	0.373(0.017)	0.486(0.016)	YEN	1.57(0.02)	0.656(0.038)	0.096(0.013)	0.946(0.018)
GLD	1.193(0.02)	0.644(0.035)	0.187(0.014)	1.07(0.023)	CAD	0.829(0.019)	0.518(0.037)	0.049(0.012)	0.674(0.018)
MAAA	0.853(0.026)	0.53(0.042)	0.021(0.011)	0.434(0.02)	BRL	1.059(0.022)	0.514(0.032)	0.072(0.01)	1.016(0.022)
MBaa	1.074(0.027)	0.704(0.039)	0.02(0.011)	0.465(0.02)	RMB	0.888(0.024)	0.574(0.039)	0.385(0.016)	0.869(0.022)
MSCI	1.115(0.033)	0.386(0.032)	0.26(0.016)	0.488(0.017)	CHF	0.951(0.025)	0.598(0.038)	0.11(0.013)	0.782(0.021)
NSQ	0.831(0.031)	0.325(0.036)	0.381(0.018)	0.357(0.018)	IDR	1.915(0.028)	0.644(0.03)	0.608(0.02)	1.012(0.021)
OIL	1.16(0.021)	0.61(0.031)	0.264(0.014)	0.624(0.016)	KRW	1.183(0.025)	0.676(0.036)	0.022(0.011)	0.746(0.017)
MER	1.072(0.031)	0.82(0.039)	0.041(0.011)	0.935(0.017)	VEF	1.497(0.018)	0.749(0.031)	0.155(0.013)	0.769(0.015)
VIX	0.77(0.02)	0.759(0.035)	0.02(0.011)	0.867(0.016)	GBP	0.769(0.023)	0.771(0.034)	0.091(0.012)	0.901(0.016)
VXN	1.009(0.023)	0.4(0.038)	0.103(0.013)	0.646(0.02)	RUB	0.844(0.022)	0.791(0.036)	0.087(0.013)	0.659(0.024)
VXD	1.069(0.019)	0.642(0.035)	0.046(0.012)	0.769(0.017)	TRY	1.122(0.021)	0.568(0.032)	0.463(0.019)	0.682(0.015)
SP500	1.063(0.032)	0.465(0.032)	0.333(0.016)	0.479(0.016)	-				
Panel C: Blockchain Technology-based Factors					Panel D: Multiple Stock Indices				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
BZ	0.325(0.022)	0.067(0.049)	0.138(0.018)	0.091(0.023)	NI225	1.561(0.032)	0.467(0.029)	0.175(0.015)	0.606(0.018)
BSV	1.389(0.024)	0.639(0.027)	0.118(0.013)	0.553(0.014)	IBVC	0.818(0.036)	0.725(0.037)	0.566(0.022)	0.965(0.029)
HSH	0.794(0.029)	0.454(0.035)	0.134(0.014)	0.594(0.023)	BRA	0.999(0.017)	0.354(0.029)	0.141(0.014)	0.788(0.019)
MD	0.756(0.034)	0.711(0.031)	0.461(0.021)	0.799(0.022)	TSX	1.127(0.027)	0.493(0.038)	0.046(0.01)	0.603(0.023)
TBT	1.196(0.021)	0.705(0.039)	0.036(0.011)	0.766(0.019)	KOSPI	1.195(0.027)	0.326(0.037)	0.224(0.015)	0.681(0.022)
TBM	0.817(0.023)	0.822(0.031)	0.596(0.021)	0.669(0.02)	ASX	1.29(0.026)	0.552(0.035)	0.21(0.009)	0.596(0.018)
DOD	0.871(0.021)	0.419(0.04)	0.036(0.012)	0.73(0.019)	JCI	1.18(0.026)	0.385(0.044)	0.039(0.012)	0.541(0.018)
UBA	0.994(0.015)	0.76(0.04)	0.066(0.01)	0.605(0.015)	SMI	1.18(0.026)	0.385(0.044)	0.039(0.012)	0.541(0.018)
DBT	1.158(0.018)	0.796(0.042)	0.031(0.011)	0.58(0.016)	SSE	0.642(0.02)	0.558(0.037)	0.535(0.018)	0.752(0.025)
EPU	1.44(0.019)	0.657(0.043)	0.027(0.012)	0.721(0.017)	RTS	0.924(0.025)	0.832(0.034)	0.216(0.009)	0.639(0.019)

Note: This table reports the Sortino ratio and mean returns (in parentheses) and the benchmark is the buy-and-hold strategy. Panel A and Panels B-F are the results for each one of the top fifteen technical rules selected in the previous step and the selected factors listed in the Table 3 (main text), respectively. 50% IS corresponds to period 1, as outlined in Table 4 (main text), keeping 50% of the total dataset out-of-sample.

Table B. 30: Out-of-sample Profitability Performance Results (Sharpe Ratio –75%)

Panel A: Traditional Fundamental Factors					Panel B: Multiple Currency Factors				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
3mBill	0.265(0.006)	0.261(0.007)	0.21(0.004)	0.583(0.004)	AUD	0.321(0.005)	0.275(0.008)	0.231(0.004)	0.261(0.003)
10yBill	0.183(0.006)	0.127(0.007)	0.239(0.003)	0.247(0.003)	EUR	0.27(0.007)	0.28(0.009)	0.129(0.005)	0.226(0.003)
DJIA	0.915(0.01)	0.234(0.006)	0.111(0.006)	0.428(0.003)	YEN	0.201(0.007)	0.21(0.008)	0.272(0.004)	0.162(0.005)
GLD	0.452(0.007)	0.211(0.007)	0.09(0.005)	0.329(0.004)	CAD	0.47(0.008)	0.185(0.006)	0.093(0.004)	0.437(0.003)
MAAA	0.417(0.011)	0.216(0.008)	0.026(0.006)	0.408(0.004)	BRL	0.25(0.008)	0.236(0.008)	0.115(0.005)	0.274(0.003)
MBaa	0.288(0.008)	0.165(0.007)	0.095(0.005)	0.623(0.004)	RMB	0.441(0.008)	0.475(0.01)	0.002(0.006)	0.304(0.003)
MSCI	0.091(0.013)	0.057(0.01)	0.05(0.008)	0.197(0.004)	CHF	0.275(0.006)	0.186(0.006)	0.379(0.004)	0.231(0.003)
NSQ	0.657(0.008)	0.196(0.006)	0.072(0.005)	0.354(0.004)	IDR	0.376(0.008)	0.259(0.008)	0.114(0.005)	0.206(0.003)
OIL	0.226(0.01)	0.15(0.011)	0.008(0.006)	0.317(0.004)	KRW	0.467(0.007)	0.264(0.007)	0.004(0.006)	0.246(0.003)
MER	0.454(0.012)	0.216(0.007)	0.088(0.006)	0.25(0.003)	VEF	0.389(0.006)	0.199(0.005)	0.386(0.003)	3.527(0.009)
VIX	0.613(0.011)	0.325(0.01)	0.009(0.006)	0.402(0.003)	GBP	0.401(0.007)	0.251(0.007)	0.207(0.004)	0.382(0.004)
VXN	0.387(0.013)	0.182(0.01)	0.086(0.007)	0.337(0.004)	RUB	0.365(0.007)	0.209(0.007)	0.139(0.004)	0.28(0.003)
VXD	0.561(0.01)	0.342(0.01)	0.023(0.005)	0.338(0.003)	TRY	0.439(0.008)	0.316(0.008)	0.173(0.004)	0.284(0.003)
SP500	0.696(0.009)	0.179(0.005)	0.031(0.005)	0.461(0.004)	-				
Panel C: Blockchain Technology-based Factors					Panel D: Multiple Stock Indices				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
BZ	0.109(0.011)	0.075(0.012)	0.037(0.007)	0.082(0.005)	NI225	0.389(0.009)	0.155(0.006)	0.063(0.005)	0.383(0.004)
BSV	0.349(0.01)	0.105(0.007)	0.027(0.005)	0.376(0.003)	IBVC	0.299(0.011)	0.182(0.01)	0.159(0.008)	0.219(0.004)
HSH	0.179(0.01)	0.098(0.009)	0.019(0.005)	0.224(0.003)	BRA	0.516(0.01)	0.241(0.007)	0.027(0.006)	0.498(0.005)
MD	0.373(0.008)	0.272(0.008)	0.043(0.005)	0.373(0.003)	TSX	0.465(0.008)	0.199(0.006)	0.061(0.005)	0.411(0.003)
TBT	0.328(0.009)	0.118(0.007)	0.046(0.005)	0.349(0.003)	KOSPI	0.227(0.008)	0.149(0.009)	0.015(0.006)	0.356(0.003)
TBM	0.2(0.008)	0.222(0.009)	0.135(0.004)	0.403(0.004)	ASX	0.301(0.01)	0.108(0.007)	0.066(0.006)	0.555(0.004)
DOD	0.455(0.009)	0.16(0.007)	0.121(0.008)	0.471(0.004)	JCI	0.538(0.009)	0.205(0.006)	0.162(0.005)	0.238(0.003)
UBA	0.481(0.01)	0.186(0.007)	0.082(0.005)	0.169(0.002)	SMI	0.538(0.009)	0.205(0.006)	0.162(0.005)	0.238(0.003)
DBT	0.463(0.011)	0.228(0.009)	0.101(0.005)	0.155(0.002)	SSE	0.258(0.009)	0.112(0.007)	0.041(0.006)	0.281(0.003)
EPU	0.523(0.01)	0.213(0.007)	0.13(0.005)	0.206(0.002)	RTS	0.297(0.007)	0.166(0.006)	0.239(0.004)	0.407(0.004)

Note: This table reports the Sortino ratio and mean returns (in parentheses) and the benchmark is the buy-and-hold strategy. Panel A and Panels B-F are the results for each one of the top fifteen technical rules selected in the previous step and the selected factors listed in the Table 3 (main text), respectively. 50% IS corresponds to period 1, as outlined in Table 4 (main text), keeping 50% of the total dataset out-of-sample.

Table B. 31: Out-of-sample Profitability Performance Results (Sharpe Ratio –90%)

Panel A: Traditional Fundamental Factors					Panel B: Multiple Currency Factors				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
3mBill	0.533(0.006)	0.253(0.008)	0.302(0.004)	0.583(0.004)	AUD	0.357(0.004)	0.223(0.007)	0.183(0.003)	0.261(0.003)
10yBill	0.296(0.002)	0.232(0.005)	0.192(0.003)	0.247(0.003)	EUR	0.265(0.003)	0.162(0.006)	0.207(0.003)	0.226(0.003)
DJIA	0.362(0.003)	0.287(0.008)	0.07(0.002)	0.428(0.003)	YEN	0.095(0.005)	0.081(0.01)	0.05(0.003)	0.162(0.005)
GLD	0.253(0.003)	0.208(0.005)	0.105(0.002)	0.329(0.004)	CAD	0.455(0.004)	0.272(0.006)	0.256(0.003)	0.437(0.003)
MAAA	0.552(0.005)	0.322(0.008)	0.149(0.002)	0.408(0.004)	BRL	0.299(0.003)	0.153(0.005)	0.195(0.003)	0.274(0.003)
MBaa	0.613(0.005)	0.425(0.009)	0.221(0.003)	0.623(0.004)	RMB	0.265(0.002)	0.218(0.005)	0.106(0.002)	0.304(0.003)
MSCI	0.174(0.004)	0.144(0.007)	0.163(0.003)	0.197(0.004)	CHF	0.307(0.004)	0.173(0.005)	0.11(0.002)	0.231(0.003)
NSQ	0.383(0.003)	0.212(0.006)	0.181(0.003)	0.354(0.004)	IDR	0.475(0.005)	0.219(0.008)	0.176(0.003)	0.206(0.003)
OIL	0.12(0.003)	0.152(0.009)	0.063(0.003)	0.317(0.004)	KRW	0.343(0.002)	0.398(0.008)	0.054(0.002)	0.246(0.003)
MER	0.383(0.004)	0.373(0.006)	0(0.002)	0.25(0.003)	VEF	2.162(0.001)	2.389(0.001)	3.272(0.008)	3.527(0.009)
VIX	0.325(0.005)	0.164(0.007)	0.082(0.003)	0.402(0.003)	GBP	0.251(0.004)	0.162(0.006)	0.093(0.003)	0.382(0.004)
VXN	0.265(0.005)	0.129(0.007)	0.065(0.003)	0.337(0.004)	RUB	0.141(0.003)	0.112(0.007)	0.066(0.003)	0.28(0.003)
VXD	0.49(0.005)	0.246(0.006)	0.082(0.002)	0.338(0.003)	TRY	0.231(0.003)	0.22(0.007)	0.092(0.003)	0.284(0.003)
SP500	0.434(0.004)	0.217(0.008)	0.142(0.003)	0.461(0.004)	-				
Panel C: Blockchain Technology-based Factors					Panel D: Multiple Stock Indices				
	BYTE	CAS	DASH	DOGE		BYTE	CAS	DASH	DOGE
BZ	0.08(0.008)	0.062(0.011)	0.052(0.004)	0.082(0.005)	NI225	0.419(0.003)	0.183(0.008)	0.094(0.002)	0.383(0.004)
BSV	0.569(0.005)	0.209(0.005)	0.056(0.002)	0.376(0.003)	IBVC	0.411(0.006)	0.213(0.009)	0.246(0.004)	0.219(0.004)
HSH	0.375(0.004)	0.186(0.004)	0.036(0.002)	0.224(0.003)	BRA	0.277(0.003)	0.222(0.006)	0.146(0.003)	0.498(0.005)
MD	0.441(0.003)	0.5(0.008)	0.191(0.003)	0.373(0.003)	TSX	0.425(0.004)	0.289(0.006)	0.377(0.004)	0.411(0.003)
TBT	0.578(0.005)	0.222(0.005)	0.016(0.002)	0.349(0.003)	KOSPI	0.45(0.003)	0.169(0.006)	0.204(0.003)	0.356(0.003)
TBM	0.541(0.006)	0.276(0.008)	0.402(0.004)	0.403(0.004)	ASX	0.464(0.005)	0.389(0.007)	0.227(0.003)	0.555(0.004)
DOD	0.433(0.005)	0.235(0.01)	0.059(0.003)	0.471(0.004)	JCI	0.415(0.004)	0.185(0.005)	0.129(0.003)	0.238(0.003)
UBA	0.374(0.003)	0.211(0.004)	0.169(0.001)	0.169(0.002)	SMI	0.415(0.004)	0.185(0.005)	0.129(0.003)	0.238(0.003)
DBT	0.489(0.003)	0.256(0.005)	0.171(0.001)	0.155(0.002)	SSE	0.554(0.004)	0.354(0.007)	0.009(0.002)	0.281(0.003)
EPU	0.402(0.003)	0.222(0.005)	0.003(0.002)	0.206(0.002)	RTS	0.21(0.003)	0.189(0.006)	0.068(0.002)	0.407(0.004)

Note: This table reports the Sortino ratio and mean returns (in parentheses) and the benchmark is the buy-and-hold strategy. Panel A and Panels B-F are the results for each one of the top fifteen technical rules selected in the previous step and the selected factors listed in the Table 3 (main text), respectively. 50% IS corresponds to period 1, as outlined in Table 4 (main text), keeping 50% of the total dataset out-of-sample.

Table B. 32: Out-of-sample Profitability Performance Results (Sharpe Ratio –50%, 75%, and 90%)

F1					F2			
	BYTE	CAS	DASH	DOGE	BYTE	CAS	DASH	DOGE
NTs	1.014(0.019)	0.659(0.038)	0.041(0.012)	0.755(0.018)	0.177(0.007)	0.189(0.008)	0.204(0.004)	0.406(0.004)
NPs	0.775(0.023)	0.557(0.033)	0.735(0.021)	0.748(0.022)	0.215(0.008)	0.231(0.009)	0.104(0.005)	0.425(0.004)
NUs	0.937(0.023)	0.758(0.042)	0.101(0.013)	0.821(0.022)	0.17(0.007)	0.167(0.007)	0.243(0.003)	0.387(0.004)
PVs	0.722(0.02)	0.8(0.043)	0.035(0.011)	0.66(0.02)	0.171(0.007)	0.177(0.007)	0.227(0.003)	0.397(0.004)
Btc-W	0.105(0.022)	0.098(0.047)	0.044(0.014)	0.076(0.022)	0.224(0.006)	0.334(0.009)	0.462(0.003)	0.219(0.003)
Eth-W	0.724(0.016)	0.658(0.032)	0.12(0.013)	0.656(0.018)	0.323(0.009)	0.165(0.007)	0.03(0.005)	0.315(0.003)
Xrp-W	0.885(0.021)	0.437(0.042)	0.01(0.011)	0.778(0.02)	0.265(0.008)	0.131(0.007)	0.107(0.004)	0.154(0.003)
Btc-GT	1.357(0.02)	0.721(0.036)	0.075(0.013)	0.856(0.018)	0.628(0.01)	0.275(0.009)	0.007(0.006)	0.179(0.003)
Eth-GT	0.9(0.014)	0.516(0.025)	0.06(0.012)	0.493(0.014)	0.605(0.009)	0.245(0.007)	0.005(0.006)	0.29(0.003)
Xrp-GT	0.533(0.015)	0.952(0.036)	0.098(0.01)	0.635(0.016)	0.748(0.008)	0.138(0.004)	0.187(0.005)	0.315(0.003)

F2				
	BYTE	CAS	DASH	DOGE
NTs	0.554(0.006)	0.281(0.008)	0.399(0.004)	0.406(0.004)
NPs	0.547(0.006)	0.294(0.008)	0.41(0.004)	0.425(0.004)
NUs	0.555(0.006)	0.268(0.008)	0.39(0.004)	0.387(0.004)
PVs	0.555(0.006)	0.275(0.008)	0.395(0.004)	0.397(0.004)
Btc-W	0.141(0.003)	0.119(0.006)	0.062(0.003)	0.219(0.003)
Eth-W	0.33(0.003)	0.308(0.008)	0.001(0.002)	0.315(0.003)
Xrp-W	0.164(0.004)	0.139(0.009)	0.001(0.002)	0.154(0.003)
Btc-GT	0.138(0.003)	0.131(0.007)	0.1(0.003)	0.179(0.003)
Eth-GT	0.249(0.003)	0.202(0.006)	0.053(0.002)	0.29(0.003)
Xrp-GT	0.558(0.002)	0.152(0.003)	0.014(0.002)	0.315(0.003)

Note: This table reports the Sortino ratio and mean returns (in parentheses) and the benchmark is the buy-and-hold strategy. Panel A and Panels B-F are the results for each one of the top fifteen technical rules selected in the previous step and the selected factors listed in the Table 3 (main text), respectively. 50% IS corresponds to period 1, as outlined in Table 4 (main text), keeping 50% of the total dataset out-of-sample.

Appendix C (Chapter 6)

Latent Dirichlet Allocation (LDA)

C.1 Background

Developed by Blei et al. (2003), LDA is one of the most prevalent algorithms in topic modelling area. As a generative probabilistic model, LDA is used to identify latent topics in a large corpus of texture where each topic is characterized by a distribution over words. Given a corpus organized by D documents with T topic where each document d has N_i $(i \in 1, \dots, N)$words, we apply LDA algorithm to C in the following generative process:

1. For each topic t $(t \in 1, \dots, T)$ we draw a Dirichlet distribution over words $\beta_t^{iid} \sim Dirchilet\ (\eta)$, which is the probability of a word in topic t and η denotes the hyperparameter for prior distribution of β_i.
2. For each document d $(d \in 1, \dots, D)$, we draw a Dirichlet distribution over topics $\theta_d^{iid} \sim Dirchilet\ (\alpha)$,, indicating the distribution on the topics for document d. α denotes the hyperparameter for prior distribution of θ_d.
3. For each word w_{di} in document d, we have $d \in 1, \dots, D$,
   i. Choose a topic from $z_{di} \sim Multinomial(\theta_d)$, where z_{di} denote the topic from which w_{di} is drawn.
   ii. Choose an observed word from $w_{di} \sim Multinomial(\beta_{z_{di}})$,

In the above process, only words are observed variables and the rest parameters are latent variables. The probability of observed data is obtained as the product of marginal probability as follows:

$$p(D \mid \alpha, \beta) = \prod_{d=1}^{M} \int p(\theta_d \mid \alpha) \left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn} \mid \theta_d) p(w_{dn} \mid z_{dn}, \beta) \right) d\theta_d \qquad \textbf{(C. 1)}$$

C.2 Implement of LDA

Consistent with previous studies in NLP, we use nltk Python library (Joakim, 2012) to preprocess the data, including converting words to lower cases, removing special characters (e.g., horizontal Tab, space and comma) and stopping words (e.g., me, you and I), stemming (tracking back the root of words, e.g., stopping back to stop) and transforming the cleaned corpus into term-document matrix. As pointed by Chen and Doss (2019), it is difficult to specify an optimal topic number using LDA in advance, we thus use 10 as the number of topics. Similar to Gavaldon (2020), we want to give an interpretable picture so that fewer topics can give a more concise result. Another reason is because we do not seek for specific topic tasks but to retrieve the sentiment scores, therefore 10 topics are adequate.

C.3 Result of LDA

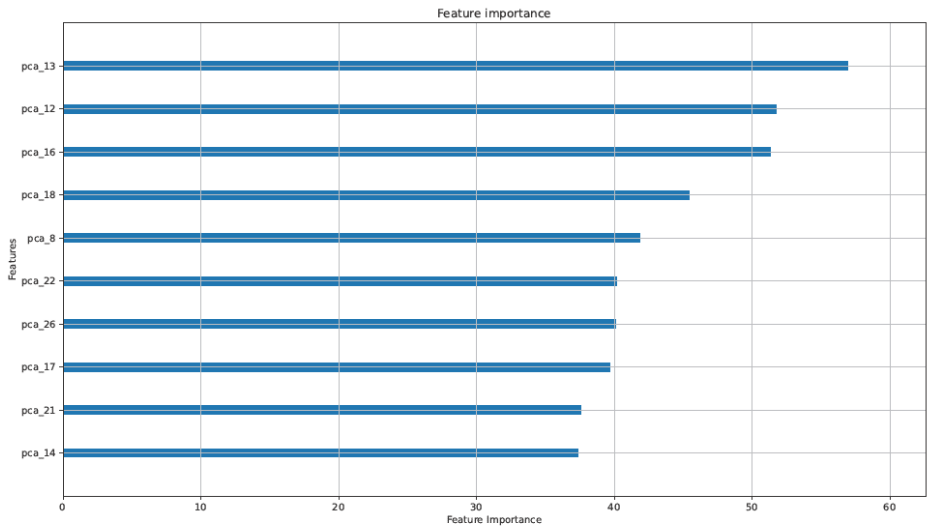
Table OA.1 displays ten topics produced by LDA. As suggested by Larsen and Thorsrud (2019), LDA is an unsupervised learning algorithm, and it does not generate labels through the computation procedure. In order to explicitly demonstrate results, we subjectively label each topic based on our understanding. Unsurprisingly, the largest topic corresponding to our corpus is about Finance and Economy, taking up 35.9% of all cryptocurrency narratives. Technology, the second largest topic contains words associated with technical development, such as *digit*, *blockchain*, *future*, *system*, *data*, etc. Media and Politics are the next two topics, having 12.1% and 9.7% proportions, respectively. For Media, we have words like *press*, *report*, *journal*, *magazine* and Politics has words associated with politicians and governments, such as *trump*, *nation*, *regulator*. In the end, we have three topics, including Crim (7.97%), Accountancy (6,58%) and Corporation (6.44%). Additional topics are not worth mentioning, since related narratives are not the main targets in this study.

C.4 RFE-RF Process:

Jiang et al. (2004) and Svetnik et al. (2004) suggests the combination of RFE and RF to perform feature selection through the iteration of model training, feature ranking and eliminating the ranked features below threshold. Similar evidence is also found in the occasion of correlated features (Gregorutti, Michel and Saint-Pierre, 2016). Generally, the process of RFE-RF in feature screening can be described as follows:

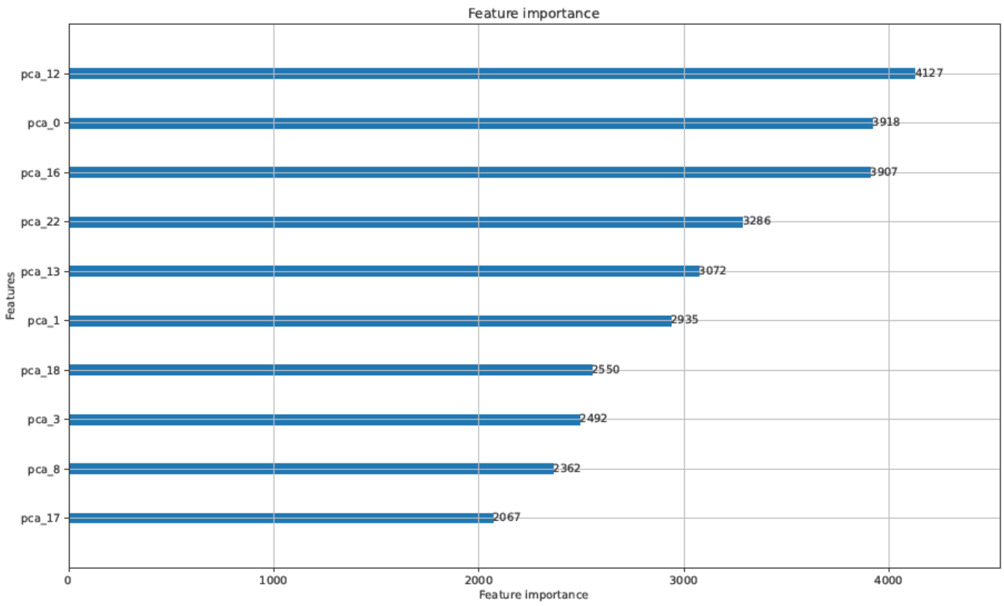
For target series y and a set of features x_m (m denotes the number of features and m = 1,2, …, m), RF algorithm is fit and exclude the features under the importance threshold (e.g., the least 25% important features are dropped). After the first round of model fit with RF, we obtain the reduced set of features x_k^1 (k < m) and fit with RF algorithm for the second time. After t-th iteration, we have the further reduced subset of x_j^t (j < k) features. In the manner of feature elimination, a user-specified stopping criterion is set so that necessary rounds of selection or a certain number of rules can be defined at start.

Figure C. 1 Top 10 features' contribution of PCA factors in the construction of XGB



Note: Factors reported are all principal components.

Figure C. 2 Top 10 features' contribution of PCA factors in the construction of LBM



Note: Factors reported are all principal components.

Figure C. 3 Hybrid strategy leverages PCA factors (F1)

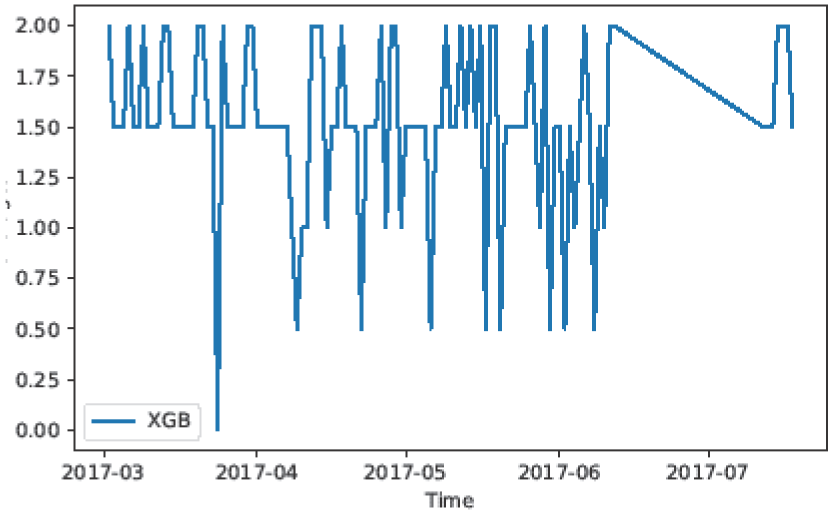


Figure C. 4 Hybrid strategy leverages PCA factors (F2)

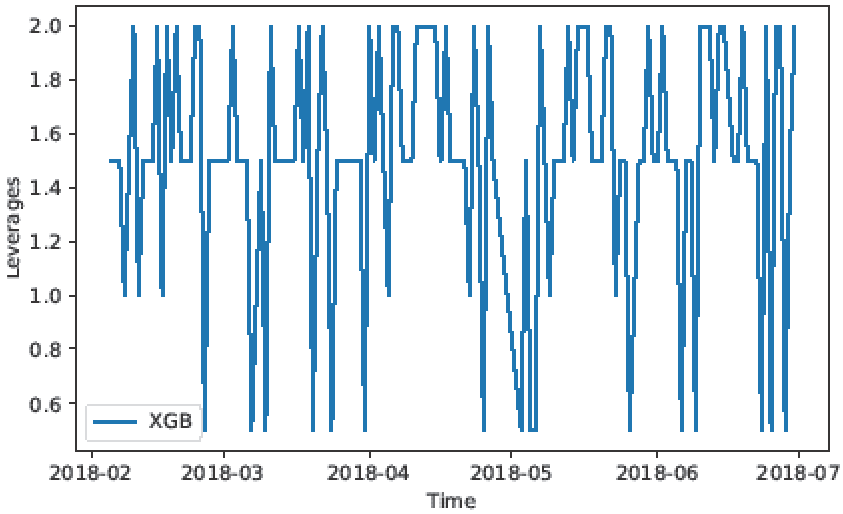
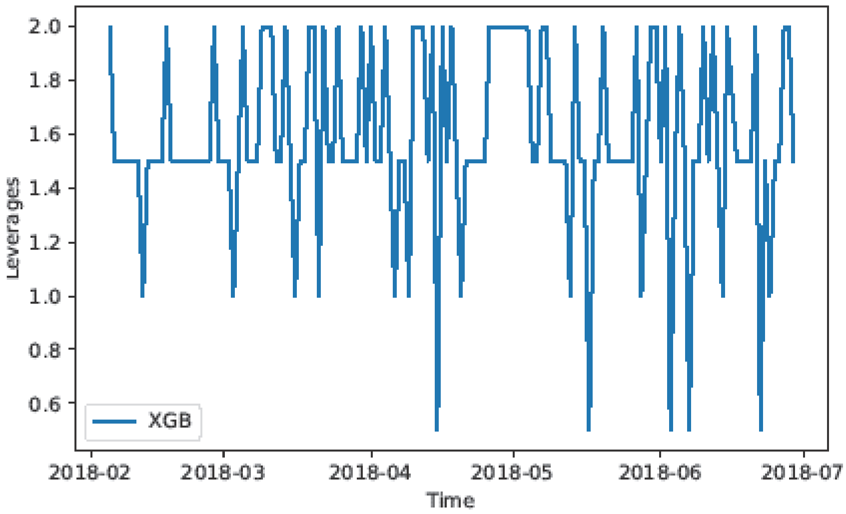


Figure C. 5 Hybrid strategy leverages PCA factors (F3)



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