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Cryptocurrencies and Lucky Factors: The value of technical and fundamental analysis

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Abstract

This study explores the effectiveness of technical and fundamental analysis in predicting and trading the returns of 12 cryptocurrencies, namely Bitcoin, Ethereum, Ripple, Dash, Cardano, Avalanche, Binance Coin, Dogecoin, Polkadot, Litecoin, Terra and Solana. A universe of 7846 technical rules, five log moving average-based ratios and 59 fundamental factors are used to test predictability and profitability through the Lucky Factors methodology and Superior Predictive Ability test. We observe predictability for a small set of technical and fundamental rules, while only the short-term log moving average-based ratio and Hashrate Index demonstrate genuine in-sample and out-of-sample profitability. Our findings question the value of both technical and fundamental analysis on cryptocurrencies.

KEYWORDS

cryptocurrencies, fundamental analysis, multiple hypothesis testing, technical analysis

1 | INTRODUCTION

The Financial Technology (FinTech) revolution is driven by valuable technological innovation applied in the financial industry. Chen et al. (2019) position Bitcoin (BTC) and Blockchain (BCH) within FinTech's seven most innovatory drivers. This should not come as a surprise, as investment in cryptocurrencies has grown largely in recent years and has brought BCH technology to the forefront of the researchers' and practitioners' attention.

The highest global market value of cryptocurrencies is currently above 1 trillion US dollars, having reached its highest peak of almost 3 trillion dollars in late 2021. BTC has the highest market capitalization, exceeding 1.2 trillion US dollars in 2021, while despite the recent downturn it is still currently valued at more than 440 million US dollars. It is quite astounding that the highest approximate return on BTC investment, if purchased at the time of launch, is above 60,700%. BTC is currently dominating the cryptocurrency market by more than 40%, but it did suffer a price crash of around 65% in early 2018 and a significant downturn from its highest point in November 2021. BTC's price has fluctuated around 16,000 US dollars in 2017, it has also skyrocketed around 40,000 US dollars in 2021 and reach its peak above 63,000 US dollars in its last bullish run in 2021, before crushing to below 25,000 US dollars within 2022.[1] Similar booms, rapid downfalls and periods of extreme volatility are commonly observed in alternative cryptocurrencies (cryptocoins) every year.

This poses a clear dilemma. On the one hand, researchers, investors and policymakers recognise the

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potential attractiveness of cryptocurrencies, mainly due to their popularity and commercial expansion. On the other hand, they are concerned about their risk management and lack of a clear underlying economic mechanism, which makes their utility controversial. For this reason, the cryptocurrency literature, although fast-growing, generally stands divided on the true value of cryptocoins.

There are two pathways to establish or contest this true value. First, attempting to explore ways to accurately forecast cryptocurrency returns, as is common with every other asset in financial markets. Second, identifying underlying risk or technology factors that can explain their price movements and tie them with specific stylised facts (Liu et al., 2022) and economically driven theories (Chen et al., 2022). For that reason, when observing the conflicting empirical evidence around cryptocoins' profitability and predictability, it is expected that researchers should turn to technical and fundamental analysis (TFA). This study's motivation is to resolve this dilemma by being the first to offer a holistic evaluation of the genuine merit of technical analysis (TA) and fundamental analysis (FA) for cryptocurrencies.

The literature on cryptocurrencies is gradually becoming richer and richer when it comes to forecasting applications of cryptocurrency returns. For example, Antonakakis et al. (2019) propose a neuro-fuzzy model for BTC prediction, while Zhang et al. (2021) illustrate that convolutional neural networks are particularly successful in forecasting the returns of six popular cryptocoins. Gradojevic et al. (2023) revisit BTC predictability and identify random forest as the best model for forecasting BTC returns. Parvini et al. (2022) propose a novel model also for BTC daily prediction through LSTM models and wavelet decomposition. All these studies promote the idea that advanced machine learning models can be very successful in predicting cryptocurrency returns. Recently, Yae and Tian (2022) provide a comparison of cryptocurrency forecasting methods, linear and non-linear, in order to identify the best predicting model out-of-sample. Their results suggest that simpler models can perform better than advanced ones. But this argument comes with constraints around the selection of factors that can be used to that end.

That is why the cryptocurrency literature becomes more intriguing when the predictability and profitability of cryptocurrencies is approached through the lens of the utility of technical indicators and fundamental factors. Several studies declare that TFA is crucial to the cryptocurrencies' pricing (Chen et al., 2022; Liu & Tsyvinski, 2021; Liu et al., 2022). More precisely, related research focuses on either TA or FA alone, uses strict and conservative measures that can distort the results of luck, or completely ignores data snooping. To better illustrate the above, we summarise in Table 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 TA and FA's predictability and profitability, unlike our complete, multi-dimensional approach.

The table provides some further insights. We can project that the use of TA around cryptocurrencies is becoming mainstream; however, the technical indicators used are limited, either in number, cryptocoins or time periods under study. Additionally, we observe that common controls against data-snooping bias, often applied in other financial markets applications (Bajgrowicz & Scaillet, 2012), are a rare occurrence in cryptocurrencies. While there are an increasing number of studies utilising fundamental factors, they usually suffer from availability of fundamentals that can be collected across multiple periods or cryptocurrencies. This provides further motivation to look at the literature for a robust selection of technical indicators and fundamental factors.

Markets' inefficiency is a crucial characteristic for the utility of technical rules. Researchers believe that BTC's market efficiency is not established (Hudson & Urquhart, 2021; Urquhart, 2016) as in traditional stock markets. Unlike conventional financial markets, cryptocurrency markets have skyrocketed in market capitalization and attractiveness, but continue to lack regulation and supervision. Although smart contracts and other contemporary infrastructures provide financial access to developing economies, flash loans and other financial transactions can still result in losses of users' assets, infusing the feeling of insecurity in these markets (Härdle et al., 2020; Kshetri, 2017; Zou et al., 2019). In addition, cryptocurrencies do not possess the same accounting features as equities and other traditional financial assets. This can lead to a greater reliance on technical analysis than evaluation of fundamentals.

In terms of technical indicators, the traditional universe of trading rules of Sullivan et al. (1999) (STW) provides a larger pool of rules generally acceptable in the TA literature. Recent research papers also focus on the utility of TA and provide direct evidence of high profitability in the BTC market. Atsalakis et al. (2019), Huang et al. (2019), Grobys et al. (2020) and Detzel et al. (2021) show that the moving average strategy and momentum indicators are powerful and can generate high profitability in the cryptocurrency market. Similar results of weekly momentum effects are also found to be significant in cryptocurrency returns (Liu & Tsyvinski, 2021). On the contrary, Hudson and Urquhart (2021) perform an extensive TA analysis and challenge the genuine value of

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TABLE 1 Cryptocurrency literature summary.

Research work	Dataset	Technical analysis	Fundamental analysis	Forecasting ability examination	Control of luck
This study	BTC, XRP, and ETH	Yes (7851)	Yes (59)	Empirical and wild bootstrap/ regression	k-Familywise Error Rate, Lucky Factors
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 and BTS	Yes (6)	No	Empirical	No
Grobys et al. (2020)	BTC, ETH, XRP, BCC, EOS, LTC, ADA, XLM and 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), and Ciaian et al. (2016)	BTC	No	Yes (17)	Regression	No
Wang and Vergne (2017)	BTC, LTC, PPC, XRP and XLM	No	Yes (7)	Regression	No
Kraaijeveld and De Smedt (2020)	BTC, ETH, XRP, BCC, EOS, LTC, ADA, XLM and TRX	No	Yes (3)	Regression	No
Detzel et al. (2021)	BTC, ETH and XRP	Yes (5)	Yes (4)	Empirical / Regression	No
Bhambhwani et al. (2019)	BTC, ETH, LTC, DSH and XMR	Yes (1)	Yes (3)	Regression	No
Liu and Tsyvinski (2021)	All cryptocurrencies from Coinmarketcap.com	No	Yes (29)	Regression	No
Hudson and Urquhart (2021)	BTC, LTC, XRP and 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) and Tron (TRX). The value in parentheses of the third and fourth columns 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.

technical indicators. Specifically, after accounting for data-snooping bias, no genuine profitability is achieved in cryptocurrency markets through TA.

From a diversification perspective, several recent studies highlight the benefits associated with cryptocurrency investment (Liu, 2019; 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 (Dyhrberg, 2016). Investigation into the efficiency of the 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 (Antonakakis et al., 2019; Tiwari et al., 2018; Urquhart, 2016) and mainly corroborate that weak efficiency conditions apply. Other studies, such as Gandal et al. (2018), find evidence of market inefficiencies and random walk deviations (e.g., potential suspicious trading on Mt Gox or mispricing in the BTC Investment Trust).

In terms of FA, the picture is vastly more complicated, as there is no theoretical or empirical consensus on what can be used for this niche market. A logical argument against FA for cryptocurrencies could be that there are no underlying assets or firms supporting their intrinsic value. Many researchers feel this is a superficial argument, as it is a stylised fact that cryptocurrency prices are influenced by factors endogenously or exogenously associated with cryptocurrencies. Consequently, to be on the safe side, one should probe information value in financial markets, underlying technology, sentiment analysis and search engine mechanics.

The expansion of cryptocoin markets across the globe and the uneven geographical concentration of coin miners can serve as justification for the utility of macroeconomic and financial indicators from different markets. Traditional fundamental factors such as commodity prices, volatility indices, stock market indices, and currency exchange rates should be evaluated. Studies on cryptocurrencies, such as Ciaian et al. (2016), Baur et al. (2018) and Detzel et al. (2021), also support this argument. Demir et al. (2018) also suggest that a Traditional Uncertainty Index, such as the Economic Policy Uncertainty (EPU) Index, is negatively related to BTC returns. Salisu et al. (2019) show that macroeconomic variables, such as country-specific interest rates, can be used to predict BTC returns to a certain extent. Global equity, bonds and commodity prices can affect BTC movements, as illustrated by Fang et al. (2019).

BCH technology, transactional and mining characteristics should also provide potential driving forces for cryptocurrency price movements. For example, Ciaian et al. (2016) show that BTC prices can be significantly influenced by the demand and supply of coins. 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 also be influential. 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. Nonetheless, it is vital to consider factors in terms of BCH information, since not all production-based factors are found to be useful (Liu & Tsyvinski, 2021). Hence, BTC and BCH technology-based factors, such as block size, transaction time between blocks, the Hashrate (HSH) and other factors related to computing power, should be considered.

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 and other cryptocoin return series. Matta et al. (2015) and Kraaijeveld and De Smedt (2020) show that online sentiment factors, such as number of searches, online community posts, tweets and news, affect the prices of BTC and other cryptocurrencies. Researchers have also explored issues related to usage, technological property, and political and social influence (Yermack, 2017). 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.

The above clearly illustrates the complexity of the quest for valuable technical rules and fundamental factors capturing cryptocoin price dynamics. More importantly, though, it highlights the need for an empirical framework that allows the practitioner to test the genuine utility of TFA in this market. We propose an elaborate empirical design in an attempt to answer this puzzle. In doing so, we utilise a novel exercise for the cryptocurrency literature. This combines studying a large universe of technical rules along with a robust pool of traditional fundamental factors (e.g., commodities, stock indices, currencies) infused with 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 fully up-to-date view compared to current cryptocurrency research.

We focus on 12 cryptocurrencies, namely BTC, Ethereum (ETH), Ripple (XRP), DASH, Cardano (ADA), Avalanche (AVAX), Binance Coin (BNB), Dogecoin (Doge), Polkadot (DOT), Litecoin (LTC), Terra (LUNA) and Solana (SOL), over the period 2015–2022. First, we apply the TA universe 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.[2]

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In addition, we employ a new MA-style indicator, the log-Price Moving Average (PMA), proposed by Detzel et al. (2021) and found to be successful in BTC prediction. Thus, we generate 7851 technical rules for each series under study, and our computations are performed with transaction costs. We estimate the trading performance of these rules in the in-sample, and we select the 15 outperformers.

Then, we examine the predictability of these TA rules along with 59 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 is to identify the rules and factors that also demonstrate genuine in-sample profitability. Finally, we examine the predictability of our selected TA and FA and their trading performance in our out-of-sample periods. Our empirical framework is implemented for three different forecasting horizons, each based on 50%, 75% and 90% of our total sample as in-sample and the remainder as out-of-sample.

We contribute to the literature as follows. First, 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 is true of a handful of the FA rules. Second, we show that traditional technical analysis rules have no value in cryptocurrencies, and only the recently introduced short-term PMA seems valuable. Finally, HSH, which is a measure of the computing power used in mining BTC, seems to be the only fundamental factor that demonstrates predictability and profitability. This finding contradicts the literature suggesting that capturing BTC and BCH news can provide a solid FA framework for the cryptocurrency universe.

The rest of the article is organised as follows. Section 2 presents the dataset and related factors used in this study, while Section 3 summarizes our empirical design. The empirical results are provided in Section 4. Finally, our concluding remarks are given in Section 5. Technical information relevant to our design and further analysis and results are made available in the online Appendix.

2 | CRYPTOCURRENCIES AND RELEVANT FACTORS DATASET

In this section, we provide a summary of the dataset used in this study. The main focus is four main cryptocurrencies, namely BTC, ETH, XRP, and DASH over the period 8 August 2015 to 5 March 2022.[3] However, for further robustness, we also examine another eight cryptocurrencies that belong in the top 10 list of Coinmarketcap in terms of market capitalization. These are ADA, AVAX, BNB, Doge, DOT, LTC, LUNA, and SOL.

We acquire cryptocurrency prices from Bitstamp and Binance. Our selection of cryptocurrencies is based on data availability, longevity and relatively large intraday transactions. Many cryptocurrencies introduced in the earlier periods have dissolved, while other cryptocoins with large capitalization are only available after 2017. Our current selection is consistent across the time periods under study. The summary statistics of the cryptocurrency return series and the relevant fundamental factors are presented in Tables 2 and 3, respectively.

The Jarque–Bera (JB) statistic reported in Table 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 DASH are stationary. As shown in Table 3, we consider 59 factors that 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 online Appendix OA.2. Our factor selection is motivated by the TA and FA literature along with the growing literature on cryptocurrency news and BCH technology.

More specifically, the FA approach is initially built upon a set of 14 fundamental indicators, including commodity prices, volatility, and main stock and volatility indices, along with market measures such as 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 BTC, the BCH technology evolution and the related sentiment. We attempt to capture this with 12 trend factors based on search engine results, news and discussion in crypto-forums. The motivation behind this selection of factors is supported by the literature, as explained in the introduction.

3 | METHODOLOGY

This section summarizes the empirical design of this study. Initially, we describe the TA approach along with the application of the LF method for extracting the genuine value of the top performing rules. Then, the regression framework based on the selected factors is examined, along with their utility in predicting cryptocurrency movements.

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TABLE 2 Summary statistics of cryptocurrency returns.

Statistics	BTC	ETH	XRP	DASH	ADA	AVAX
N	2460	2460	2460	2460	1477	588
Mean	0.003	0.003	0.005	0.004	0.006	0.008
SD	0.039	0.068	0.051	0.077	0.063	0.085
Maximum	−0.144	−0.379	−0.277	−0.416	−0.268	−0.375
Minimum	0.195	0.596	0.263	0.568	0.332	0.713
Skewness	0.216	1.149	0.034	1.493	0.824	1.435
Kurtosis	2.096	11.96	3.877	11.88	3.109	10.225
JB (p-value)	0	0	0	0	0	0
ADF (p-value)	0	0	0	0	0	0
Statistics	BNB	DOGE	DOT	LTC	LUNA	SOL
N	1639	1032	618	2460	619	629
Mean	0.007	0.015	0.005	0.003	0.014	0.009
SD	0.065	0.189	0.069	0.059	0.094	0.079
Maximum	−0.341	−0.384	−0.383	−0.368	−0.395	−0.375
Minimum	0.703	3.924	0.366	0.301	0.874	0.363
Skewness	2.428	15.608	0.667	−0.236	2.149	0.56
Kurtosis	25.495	316.117	5.22	4.876	16.523	3.075
JB (p-value)	0	0	0	0	0	0
ADF (p-value)	0	0	0	0	0	0

Abbreviations: N, number of observations; SD, the standard deviation.
Note: *, ** and *** indicate 10%, 5% and 1% levels, respectively.

3.1 | Technical analysis and trading performance

In terms of our TA framework, we follow STW and Detzel et al. (2021) to generate the specifications of the STW universe and the relevant PMA ratios. As suggested by Detzel et al. (2021), cryptocurrency returns can be predicted by applying the difference between the log price of the cryptocurrency and a simple weighted average of its corresponding lag price. To this end, we simplify the equilibrium model proposed by Detzel et al. (2021) in two ways. First, we apply equal weighting in the moving averages, which suffices for predicting cryptocurrency returns. Second, we use fixed time horizons for the MAs. Then, the log price to MA ratios, denoted as $PMA_t(L)$, is calculated as follows:

$$PMA_t(L) = p_t - ma_t(L), \tag{1}$$

where p_t is the log-price of each cryptocurrency, $ma_t(L) = \frac{1}{nL}\sum_{l=0}^{nL-1} p_{t-l}$ and n the number of days per week in $L = 1$, 2, 4, 10 and 20 weeks.[4] For more details on these rules and their parameters, we refer readers to the online Appendix OA.3. To evaluate the performance of the trading strategies, we provide the ranking results of each cryptocurrency's returns based on the Sharpe ratio.[5] The performance of the technical strategies is benchmarked to a Buy-and-Hold (BH) strategy. BH is a widely used passive investment strategy where investors realise returns at the end of their investment horizon. Its popularity is well supported by studies such as Shilling (1992), Shiryaev et al. (2008) and Hui and Kevin Chan (2014). It is also considered a way of testing market efficiency; as compared to other strategies, BH can fully reflect the natural performance of the financial asset during the horizon of interest.

We evaluate the trading performance of each technical indicator over three different periods in our sample with transaction costs. Since transaction costs of cryptocurrencies using exchanges are inconstant, we use average transaction costs from Binance.[6] More specifically, we consider the three in-sample periods 8 August 2015 to 9 May 2018, 8 August 2015 to 25 August 2020 and 8 August 2015 to 29 August 2021 as well as the out-of-sample periods 9 May 2018 to 5 March 2022, 25 August 2020 to 5 March 2022 and 29 August 2021 to 5 March 2022. These correspond to 50:50, 75:25 and 90:10 splits of the total sample in in-sample and out-of-sample, respectively. These time-spans include prominent bull and bear phases of the

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TABLE 3 Summary of 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) and 10-year treasury bill rate (10yBill)	Detzel et al. (2021)	Wharton Research Data Services
S&P500 (SP500), Moody's Baa-bond index (MBaa) and Moody's AAA-bond index (MAAA)	Detzel et al. (2021)	Federal Research Bank of St. Louis
Market Excess Return (MER)	Detzel et al. (2021)	Website of Kenneth French
Dow Jones Industrial Average (DJIA) and Nasdaq Composite Market index (NSQ) and 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
Economic Policy Uncertainty (EPU)	Demir et al. (2018), Jiang et al. (2021)	policyuncertainty.com
Currency factors		
AUD/USD, EURO/USD, YEN/USD, CAD/USD, BRL/USD, RMB/USD, CHF/USD, IDR/USD, KRW/USD, VEF/USD, RUB/USD and 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) and Russian Trading System Stock Index (RTS)	Baur et al. (2018))	DataStream
Blockchain technology-based factors		
Daily bitcoin transactions (DBT), Hashrate (HSH) and mining difficulty (MD)	Li and Wang (2017)	Blockchain.com
Block size (BZ), Time between transaction (TBT) and 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
Bitcoin and blockchain trend-based factors		
Search Number on Wikipedia (BTC-W, ETH-W and XRP-W)	Kristoufek (2013)	Wikipedia
Search Number on Google Trends (BTC-GT, ETH-GT and XRP-GT)	Kristoufek (2013)	Google
Number of new topics (NTs), new posts (NPs), new users (NUs) and page views (PVs)	Ciaian et al. (2016)	bitcointalk.org

Note: The table summarizes all the relevant factors used in the regression specifications. There are 59 factors in total under consideration. The selection is based on studies that utilise similar factors to explain cryptocurrency returns. These studies are matched to each factor and the relevant data resource.

cryptocurrency market. Observing this performance over these periods adds robustness to our results. Once the trading performance of all rules is obtained, we rank them according to their Sharpe ratios in descending order and select the top 15 performing strategies. The mathematical details of our trading algorithm are presented in the online Appendix OA.4.

3.2 | Predictive regressions and Lucky Factors: Consolidating technical and fundamental analysis

In order to design a framework for testing TA and FA factors, we follow Neely et al. (2014) and set up regressions between cryptocurrency returns, the top performing technical rules and 59 fundamental factors. In other words, we form the predictive bivariate regression as

$$r_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1}, \tag{2}$$

where r_{t+1} is the return on cryptocurrency on day $(t+1)$; X_t a predictor (a TA or FA factor) at time t; and ε_{t+1} a zero-mean disturbance term. This procedure allows us to explore the predictive power of each individual factor against one return series.

For the in-sample analysis, we set a one-sided alternative hypothesis, following Inoue and Kilian (2005), to increase the predictive power of the test. Our null hypothesis is that the predictor has no forecasting ability $(\beta_i = 0)$. Using a heteroskedasticity-consistent t-statistic, we test $H_0 : \beta_i = 0$ against $H_1 : \beta_i \geq 0$ for the Ordinary Least Squares (OLS) estimates of each β_i.[7] When testing a number of popular predictors (e.g., treasury bills, long-term government bond yield and other commonly used economic indicators), the Stambaugh (1999) bias may inflate the t-statistic for the β in Equation (2) and contort the test size for highly persistent X_t. For this reason, we use a heteroskedasticity-robust test for each bivariate model. Taking the persistence in regressors and the correlations between cryptocurrency returns and innovation terms into account, we calculate the p-values by means of a wild bootstrap procedure.[8]

Through the in-sample analysis, we may find more than one factor with forecasting ability in cryptocurrency returns. This motivates us to further check the order of the importance of the multiple factors. To avoid the data-snooping bias in multiple hypotheses testing (MHT) and examine the superiority of statistically significant factors during in-sample periods, we apply the LFs framework and the SPA test. The LFs framework of Harvey and Liu (2021) is ideal for revealing the genuine performance of multiple factors, compared to other MHT approaches. The LF design aims to restrain the proliferation of factors seen in other studies, such as Harvey et al. (2016). This is crucial because an order of importance of the indicators selected at each stage of our tests can improve the interpretability for traders, a feature that is not available in other MHT and data-snooping techniques.

According to Harvey and Liu (2021), LFs is a highly compatible approach which can be put into either single or panel regression forms. Based on the task requirements, the test statistic for the R-squared and the median scaled intercept are designed to measure the performance in univariate or multiple target series, respectively. This is also important in our setting because the scaled intercept can be thought of as an information ratio proxy and can also account for return volatilities' heterogeneity. In addition, we provide SPA results as a robustness check. The mathematical details of the LF methodology are presented in the online Appendix OA.5.

For the out-of-sample analysis, we calculate the recursive estimated statistics for each of the bivariate models using a one-day-ahead horizon. In this article, we apply expanding windows in out-of-sample periods; that is, we predict returns on day $(t+1)$ using all the data ahead. We follow the three forecasting exercises mentioned earlier and apply two statistical measuring approaches. Our design is based on a well-known benchmark, the historical average forecast, which can perform better than the selected statistical measure (Campbell & Thompson, 2008). This is estimated as follows:

$$\hat{r}_{t+1}^{HA} = \frac{1}{t}\sum_{s=1}^{t} r_s. \tag{3}$$

where $\hat{r}_{t+1}^{HA}$ is the expectation of the average historical returns and r_s the cryptocurrency returns at time s.

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 given by

$$R_{os}^2 = 1 - \frac{SSR_P}{SST_T}, \tag{4}$$

where SSR_P is the difference between cryptocurrency returns and predictive returns in the predictive set and SST_T the difference between cryptocurrency returns and average returns in the 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. The MSFE-adj. further ensures an approximately standard normal asymptotic distribution for the comparison between the nested model and the predictive forecast. Following the procedure above, predictive regressions are obtained based on the selected top performing technical rules and the five sets of fundamental factors presented in Table 3. This creates a rather more complete portrayal of the value of the TA and FA analysis in cryptocurrencies, taking into consideration the results of the previous section. Figure 1 summarizes our empirical design.

Here, we should note that the proposed framework can easily adapt to new identified factors, regardless of their number. In other words, the motivation of this approach is not to justify the selection of this large pool of factors, but rather to examine which indicators proposed by the previous literature actually work and for which cryptocurrencies. This is because factors that are

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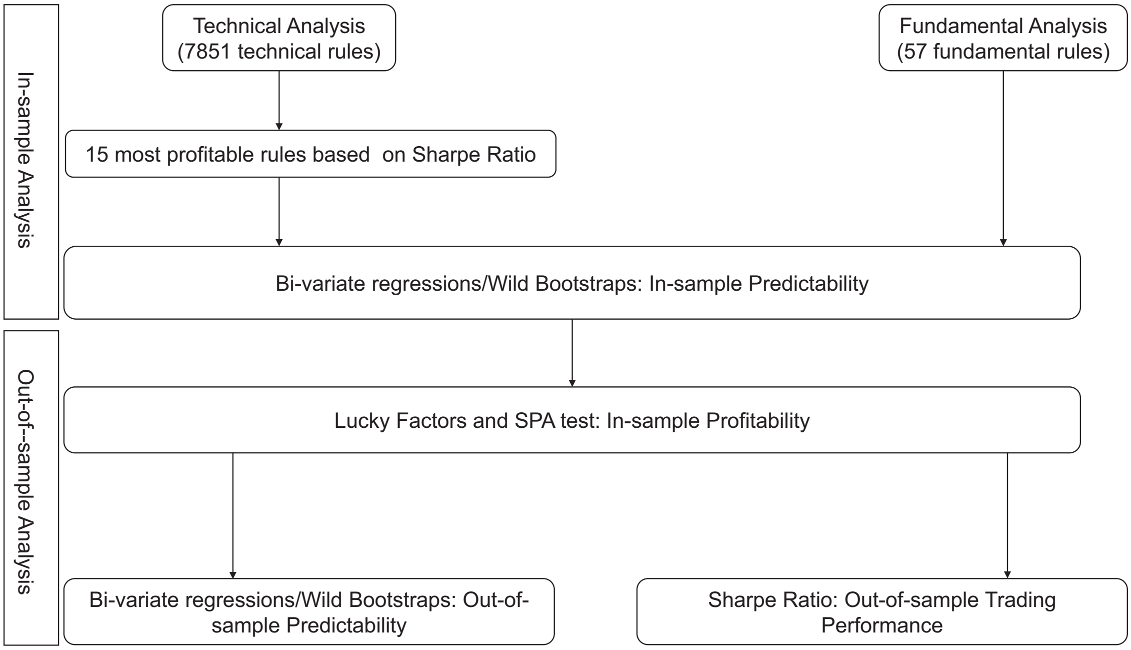

FIGURE 1 Methodology flowchart. The figure presents the methodology flowchart of this study.

not genuinely good predictors will be discarded and will not move to the out-of-sample analysis stage. The findings of this empirical framework are presented in the following section.

4 | EMPIRICAL RESULTS

4.1 | In-sample analysis

The first set of empirical findings relates to the profitability performance of the technical rules. We summarise the performance of the top 15 performing rules based on their Sharpe ratios across all periods and series under study in Table 4. 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 FRs and CBs are common in the rankings in terms of trading performance (the latter especially in the case of BTC). When evaluating the other cryptocurrencies across periods, momentum rules are usually the best or appear regularly in the top five performance ranking. Particularly, CB (10, 0.03, 10, 20) has the best performance for the most cryptocurrencies and periods 2 and 3 except in the case of BTC. FRs have their share of success too, as they perform better when modelled for shorter period and with small values 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 15 rankings, while PMA1 is consistently within the top three performing rules across the periods and cryptocurrencies under study. Focusing on period 1 of BTC, the best rule is the shortest PMA ratio (PMA1), and the remaining rank of rules is constructed CB rules with the shortest length (CB (5, 0.075, 5, 0.001))[9] and the shortest time of channel in CB (5 days).

Similar results are found in DASH, where good performance rules are mainly constituted by short days of rules, that is, 5-day or 10-day slow MA and 2-day or 5-day fast MA lines with fixed multiplicative band. Not surprisingly, the high volatility of the daily cryptocurrency 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 0.004, 0.006, 0.006 and 0.007 for BTC, XRP, ETH and DASH, respectively. Moreover, the highest observed Sharpe ratios are 0.570 (DASH—period 2), 1.350 (BTC—period 2), 0.670 (ETH—period 2) and 0.650 (XRP—period 2).

For further robustness, we investigate the performance under the Sortino ratio metric for our four main cryptocurrencies. The top 15 performing rules for the Sortino ratio are presented in the online Appendix

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

BTC							DASH					
Rank	Technical Rule	Period 1 (50%IS) 8 August 2015 to 9 May 2018	Technical Rule	Period 2 (75% IS) 8 August 2015 to 25 August 2020	Technical Rule	Period 3 (90% IS) 8 August 2015 to 29 August 2021	Technical rule	Period 1 (50%IS) 8 August 2015 to 9 May 2018	Technical Rule	Period 2 (75% IS) 8 August 2015to 25 August 2020	Technical Rule	Period 3 (90% IS) 8 August 2015to 29 August 2021
1	PMA1	0.410 (0.004)	CB (15, 0.1, 25, 100)	1.350 (0.004)	CB (15, 0.1, 25, 100)	1.040 (0.003)	MA (5, 2, 0)	0.400 (0.006)	CB (10, 0.03, 10, 20)	0.570 (0.007)	CB (10, 0.03, 10, 20)	0.300 (0.006)
2	CB (5,0.075,5,0.01)	0.400 (0.004)	FR (0.01, 5)	1.340 (0.004)	FR (0.01, 5)	1.030 (0.003)	MA (5, 2, 0.05)	0.390 (0.005)	MA (10, 5, 0.01)	0.560 (0.007)	MA (10, 5, 0.01)	0.290 (0.006)
3	CB (5,0.075,5,0.005)	0.390 (0.004)	MA (50, 5, 0.03)	1.330(0.003)	PMA1	1.020 (0.003)	MA (15, 2, 0.04)	0.380 (0.005)	PMA1	0.550 (0.007)	MA (10, 2, 0.005)	0.280 (0.006)
4	MA (200, 25, 0.001)	0.380 (0.004)	MA (50, 2, 0.02)	1.320 (0.003)	CB (5,0.075,5,0.01)	1.010 (0.003)	PMA1	0.360 (0.005)	MA (10, 5, 0.02)	0.540 (0.007)	MA (5, 1, 0.01)	0.270 (0.006)
5	MA (150, 30, 25)	0.370 (0.004)	MA (50, 20, 25)	1.310 (0.003)	CB (5, 0.075, 5, 0.015)	1.000 (0.003)	MA (5, 1, 0.01)	0.350 (0.005)	MA (5, 2, 0.05)	0.520 (0.007)	MA (10, 5, 0.04)	0.260 (0.005)
6	MA (10, 2, 0)	0.360 (0.004)	PMA1	1.300 (0.003)	MA (200, 125, 25)	0.990 (0.003)	MA (5, 2, 0.05)	0.340 (0.005)	MA (10, 5, 0.04)	0.510 (0.007)	MA (5, 2, 0.015)	0.250 (0.005)
7	MA (150, 30, 5)	0.350 (0.004)	CB (5, 0.075, 5, 0.01)	1.290 (0.003)	FR (0.03, 3)	0.980 (0.003)	FR (0.02, 5)	0.330 (0.005)	MA (10, 2, 0)	0.500 (0.007)	FR (0.005, 3)	0.240 (0.005)
8	MA (200, 1, 0.02)	0.340 (0.004)	CB (5, 0.075, 5, 0)	1.280 (0.003)	FR (0.035, 1)	0.970 (0.003)	FR (0.045, 5)	0.320 (0.005)	MA (15, 10, 0.02)	0.490 (0.007)	FR (0.04, 15)	0.230 (0.005)
9	MA (75, 1, 5)	0.330 (0.004)	FR (0.02, 0.015)	1.270 (0.003)	FR (0.04, 1)	0.960 (0.003)	MA (10, 5, 0.01)	0.300 (0.005)	MA (15, 1, 0.015)	0.480 (0.006)	FR (0.01, 3)	0.220 (0.005)
10	MA (200, 25, 0.01)	0.320 (0.004)	MA (50, 15, 25)	1.260 (0.003)	MA (5,1,0.015)	0.950 (0.003)	MA (10, 2, 0.005)	0.280 (0.005)	MA (5, 1, 0.01)	0.470 (0.006)	FR (0.005, 3)	0.210 (0.005)
11	FR (0.035,1)	0.310 (0.004)	PMA2	1.250 (0.003)	MA (10,5,0.05)	0.940 (0.003)	FR (0.01, 5)	0.270 (0.005)	MA (15, 10, 0.04)	0.460 (0.006)	PMA1	0.200 (0.005)
12	MA (75, 30, 25)	0.300 (0.003)	MA (2,1,0.05)	1.210 (0.003)	FR (0.005, 1)	0.920 (0.003)	MA (10, 2, 0.005)	0.260 (0.006)	MA (20, 1, 0.015)	0.450 (0.006)	FR (0.01, 1)	0.190 (0.005)
13	MA (75, 40, 5)	0.290 (0.003)	MA (10,1,0.01)	1.170 (0.003)	MA (2,1,0.05)	0.910 (0.003)	FR0.005	0.240 (0.006)	MA (10, 2, 0.005)	0.440 (0.006)	FR (0.045, 1)	0.180 (0.005)
14	MA (40, 1, 5)	0.280 (0.003)	FR (0.025, 0.025)	1.140 (0.003)	FR (0.005, 5)	0.850 (0.003)	MA (5, 2, 0.015)	0.230 (0.006)	MA (5, 2, 0.015)	0.430 (0.006)	FR (0.045, 15)	0.170 (0.005)
15	MA (200, 20, 0.05)	0.270 (0.003)	FR (0.01, 15)	1.042 (0.002)	MA (10, 1, 0.01)	0.841 (0.003)	MA (2, 1, 0)	0.211 (0.005)	FR (0.025, 5)	0.420 (0.006)	FR (0.01, 5)	0.165 (0.005)
	Benchmark	0.043		0.034		0.037	Benchmark	0.043		0.028		0.029

ETH							XRP					
Rank	Technical Rule	Period 1 (50%IS) 8 August 2015 to 9 May 2018	Technical Rule	Period 2 (75% IS) 8 August 2015 to 25 August 2020	Technical Rule	Period 3 (90% IS) 8 August 2015 to 29 August 2021	Technical Rule	Period 1 (50% IS) 8 August 2015 to 9 May 2018	Technical rule	Period 2 (75% IS) 8 August 2015 to 25 August 2020	Technical rule	Period 3 (90% IS) 8 August 2015–29 August 2021
1	MA (75, 20, 0.03)	0.590 (0.006)	CB (10, 0.03, 10, 20)	0.670 (0.006)	CB (10, 0.03, 10, 20)	0.450 (0.005)	MA (20, 1, 3)	0.600 (0.004)	CB (10, 0.03, 10, 20)	0.650(0.006)	CB (10, 0.03, 10, 20)	0.460(0.004)
2	MA (50, 20, 0.04)	0.580 (0.005)	MA (75, 20, 0.03)	0.640 (0.006)	MA (200, 5, 0.04)	0.440 (0.004)	MA (20, 10, 3)	0.590 (0.004)	PMA1	0.640 (0.006)	MA (10, 2, 0.005)	0.450 (0.004)
3	MA (75, 20, 0.015)	0.570 (0.004)	MA (50, 20, 0.04)	0.630 (0.006)	MA (50, 5, 0.03)	0.430 (0.004)	MA (30, 5, 3)	0.580 (0.004)	FR (0.14, 10)	0.630 (0.006)	MA (15, 1, 0.005)	0.440 (0.004)
4	PMA1	0.560 (0.004)	PMA1	0.620 (0.006)	MA (50, 20, 0.04)	0.420 (0.004)	MA (30, 10, 3)	0.570 (0.004)	FR (0.005,3)	0.620 (0.006)	PMA1	0.430 (0.004)
5	MA (200, 15, 0.02)	0.550 (0.005)	FR (0.01,1)	0.610 (0.006)	MA (75, 20, 0.03)	0.410 (0.004)	MA (30, 5, 5)	0.560 (0.004)	MA (40, 25, 0.05)	0.610 (0.006)	MA (2, 1, 0.02)	0.420 (0.004)
6	MA (50, 25, 0)	0.540(0.005)	MA (75, 20, 0.05)	0.600 (0.006)	MA (75, 1, 0.001)	0.400 (0.005)	MA (30, 2, 5)	0.550 (0.004)	MA (15, 1, 0.005)	0.600 (0.006)	MA (2, 1, 0.015)	0.410 (0.004)
7	MA (75, 40, 0.02)	0.530 (0.005)	MA (50, 15, 0.015)	0.590 (0.005)	MA (50, 2, 0.02)	0.390 (0.005)	MA (20, 10, 5)	0.540 (0.004)	MA (50, 20, 0.02)	0.590 (0.006)	MA (2, 1, 0.02)	0.400 (0.004)
8	MA (50, 30, 0.01)	0.520 (0.005)	MA (75, 30, 0)	0.580 (0.006)	MA (100, 30, 0.015)	0.380 (0.005)	MA (20, 15, 5)	0.530 (0.005)	MA (75, 10, 0.005)	0.580 (0.006)	MA (40, 20, 5)	0.390 (0.004)
9	MA (75, 50, 0)	0.510 (0.005)	MA (75, 25, 0.001)	0.570 (0.006)	FR (0.07, 0.15)	0.370 (0.005)	PMA1	0.520 (0.005)	MA (40, 20, 0.02)	0.570 (0.005)	MA (40, 1, 0.05)	0.380 (0.004)
10	MA (50, 25, 0.005)	0.500 (0.005)	MA (40, 25, 0.03)	0.560 (0.005)	MA (100, 30, 0.005)	0.360 (0.005)	PMA4	0.510 (0.005)	MA (40, 20, 0.001)	0.560 (0.006)	MA (75, 1, 0.01)	0.370 (0.004)
11	MA (50, 40, 0.03)	0.490 (0.005)	MA (40, 30, 0.04)	0.550 (0.005)	FR (0.035, 0.04)	0.350 (0.005)	MA (5, 2,5)	0.500 (0.005)	MA (10, 5, 0.001)	0.550 (0.005)	MA (10, 5, 0.02)	0.360 (0.004)
12	MA (50, 40, 0.015)	0.480 (0.005)	MA (50, 5, 0.05)	0.540 (0.005)	FR (0.04, 0.025)	0.340 (0.005)	FR (0.005,5)	0.490 (0.005)	MA (50, 15, 0.015)	0.540 (0.005)	MA (40, 20, 0.02)	0.350 (0.005)
13	FR (0.035, 1)	0.460 (0.005)	MA (50, 1, 0)	0.530 (0.005)	PMA1	0.330 (0.005)	MA (75, 20, 5)	0.480 (0.005)	MA (40, 20, 0.04)	0.530 (0.005)	MA (15, 1, 0.03)	0.340 (0.005)

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TABLE 4 (Continued)

	ETH						XRP					
Rank	Technical Rule	Period 1 (50%IS) 8 August 2015 to 9 May 2018	Technical Rule	Period 2 (75% IS) 8 August 2015 to 25 August 2020	Technical Rule	Period 3 (90% IS) 8 August 2015 to 29 August 2021	Technical Rule	Period 1 (50% IS) 8 August 2015 to 9 May 2018	Technical rule	Period 2 (75% IS) 8 August 2015 to 25 August 2020	Technical rule	Period 3 (90% IS) 8 August 2015–29 August 2021
14	MA (75, 40, 0.001)	0.440 (0.005)	MA (75, 40, 0.01)	0.520 (0.005)	PMA2	0.320 (0.005)	MA (75, 10, 3)	0.470 (0.005)	MA (75, 1, 0.001)	0.520 (0.005)	MA (100, 25, 0.04)	0.320 (0.005)
15	MA (125, 5, 0)	0.414 (0.005)	MA (50, 1, 0.015)	0.510 (0.005)	FR (0.4, 0.04)	0.310 (0.005)	MA (40, 30, 3)	0.469 (0.005)	MA (50, 40, 0.03)	0.510 (0.005)	MA (40, 15, 25)	0.031 (0.004)
	Benchmark	0.052		0.04		0.029	Benchmark	0.039		0.026		0.043

Note: This table presents the Sharpe ratios and mean returns (in parentheses) of the top 15 technical rules for BTC, ETH, XRP and DASH. 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). F 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 the difference between the high and low channels, 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). A BH strategy is used as a benchmark. Indications 50%, 75% and 90% IS refer to use as in-sample 50%, 75% and 90% of the total dataset in period 1, period 2 and period 3, respectively.

OA.7 (Table A.3.3). Similar to our findings using the Sharpe ratio, we see that the top 15 TA factors have good performance across three forecasting exercises during in-sample periods and beat the benchmark. CB, FR and MA are again in the top rankings, but, more importantly, PMA1 factors continue to be within the top 15 performing rules. Regarding the remaining eight cryptocurrencies, our findings are also consistent across the Sortino (online Appendix OA.7, Tables A.3.1–A.3.2) and the Sharpe (online Appendix OA.8, Tables A.7.1–A.7.2) ratios. In conclusion, across the 12 cryptocurrencies and under two performance metrics we observe that PMA factors, along with momentum and CB strategies, are consistently among the top performing rules.

Technical rules consistently performing better than the BH strategy indicate that there is utility of TA in the cryptocurrency market. We therefore move to explore the predictability of the high-performing rules and the selected fundamental factors through the bivariate regression framework and the wild bootstrap (see Equation (2)). The in-sample examination and the corresponding results are given in Tables 5–7. The tables present the in-sample analysis for BTC, ETH, XRP and DASH for three different lengths of forecasting exercises (F1, F2 and F3). Focusing on 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. (2021), where PMA ratios have both high trading performance and predictive power in cryptocurrencies.

In the cases of ETH, XRP and DASH, we observe FRs with short periods and MAs with long periods having predictive power in cryptocurrency returns, but this performance is not as consistent as it appears to be for PMA1.[10] In terms of fundamental factors, the HSH (Panel E) is notably robust across all cases within all forecasting exercises. OIL (Panel B) and RMB (Panel C) are also found to be statistically significant in most cases in-sample. For BTC and ETH, another factor from BCH-related information, MD (Panel E), is useful in prediction. Conventional financial indicators such as 3mBilll (Panel B), GLD (Panel B) and NSQ (Panel B) also show forecasting ability in BTC, ETH and XRP. Popular online media factors, like Google Trends and Wikipedia search numbers of BTC (Btc-GT and Btc-W from Panel D), seem to have forecasting ability only in F1. This can be explained by the fact that access to relevant

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TABLE 5 In-sample predictive regression estimation results (F1: 50% IS).

Panel A: Technical rules

	BTC		ETH		XRP		DASH
PMA1	**−0.053* (1.887)**	MA (75, 20, 0.03)	−0.006 (1.082)	MA (20, 1, 3)	−0.01 (1.099)	MA (5, 2, 0)	0.013 (0.886)
CB (5, 0.075, 5, 0.01)	**−0.041* (1.999)**	MA (50, 20, 0.04)	−0.005 (1.09)	MA (20, 10, 3)	−0.005 (1.094)	MA (5, 2, 0.05)	0.001 (1.022)
CB (5, 0.075, 5, 0.005)	**0.042* (1.842)**	MA (75, 20, 0.015)	0.002 (1.693)	MA (30, 5, 3)	0 (1.097)	MA (15, 2, 0.04)	0.021 (0.473)
MA (200, 25, 0.001)	0.021 (1.613)	**PMA1**	**0.001* (1.837)**	MA (30, 10, 3)	0.013 (1.677)	PMA1	**0.042* (1.988)**
MA (150, 30, 25)	−0.004 (1.545)	MA (200, 15, 0.02)	−0.007 (1.608)	MA (30, 5, 5)	0.004 (0.718)	**MA (5, 1, 0.01)**	**−0.019* (1.887)**
MA (10, 2, 0)	0.001 (0.636)	MA (50, 25, 0)	−0.003 (0.825)	MA (30, 2, 5)	0.002 (0.187)	**MA (5, 2, 0.05)**	**−0.001* (1.845)**
MA (150, 30, 5)	0.02 (1.691)	MA (75, 40, 0.02)	0.015 (0.864)	MA (20, 10, 5)	−0.002 (1.06)	FR (0.02, 5)	0.001 (0.513)
MA (200, 1, 0.02)	0.011 (0.743)	MA (50, 30, 0.01)	0.013 (0.876)	MA (20, 15, 5)	0.512 (1.09)	FR (0.045, 5)	0 (0.604)
MA (75, 1, 5)	0.024 (0.872)	MA (75, 50, 0)	0.001 (0.785)	**PMA1**	**0.001* (1.999)**	MA (10, 5, 0.01)	0 (1.541)
MA (200, 25, 0.01)	0.002 (0.302)	MA (50, 25, 0.005)	0.004 (0.098)	**PMA4**	**0.003** (2.285)**	MA (10, 2, 0.005)	0.001 (0.769)
FR (0.035,1)	−0.001 (0.922)	MA (50, 40, 0.03)	−0.001 (0.958)	**MA (5,2,5)**	**−0.001* (1.908)**	FR (0.01, 5)	−0.002 (0.997)
MA (75, 30, 25)	−0.001 (0.978)	MA (50, 40, 0.015)	−0.001 (0.99)	**FR (0.005,5)**	**−0.001* (1.828)**	MA (10, 2, 0.005)	−0.002 (0.097)
MA (75, 40, 5)	−0.001 (0.929)	FR (0.035,1)	−0.001 (0.971)	MA (75, 20, 5)	−0.001 (1.612)	FR0.005	−0.002 (0.906)
MA (40, 1, 5)	−0.027 (1.535)	MA (75, 40, 0.001)	0.017 (0.791)	MA (75, 10, 3)	0 (1.098)	MA (5, 2, 0.015)	0 (0.455)
MA (200, 20, 0.05)	−0.029 (1.371)	MA (125, 5, 0)	0.023 (0.791)	MA (40, 30, 3)	−0.104 (1.708)	MA (2, 1, 0)	0.127 (0.209)

Panel B: Traditional fundamental factors

BTC	ETH	XRP	DASH	BTC
3mBill	−0.049 (1.287)	−0.073 (1.182)	−0.101 (1.219)	0.003 (0.886)
10yBill	−0.017 (1.399)	−0.054 (1.19)	−0.042 (1.094)	−0.001 (1.022)
DJIA	−0.038 (1.642)	−0.042 (1.593)	−0.105 (1.097)	0.019 (0.473)
GLD	−0.036 (1.713)	**−0.028* (1.937)**	−0.035 (1.677)	0.015 (0.488)
MAAA	−0.024 (1.545)	−0.025 (1.608)	0.011 (0.718)	−0.044 (0.87)
MBaa	0.015 (0.636)	−0.048 (1.625)	0.034 (0.187)	−0.007 (1.345)
MSCI	−0.034 (1.691)	−0.051 (1.664)	−0.098 (1.096)	0.017 (0.513)
NSQ	**−0.035* (1.843)**	**−0.049* (1.876)**	**−0.111* (1.999)**	**0.012*** (2.304)**
OIL	−0.045 (1.072)	**−0.04* (1.985)**	−0.118 (1.199)	−0.017 (1.541)
MER	0.035 (0.302)	0.053 (0.098)	0.038 (0.285)	0.007 (0.769)
VIX	−0.073 (0.922)	−0.079 (0.958)	−0.034 (1.608)	−0.087 (0.997)
VXN	−0.081 (0.978)	−0.097 (0.99)	−0.054 (0.828)	−0.112 (0.997)
VXD	−0.069 (0.929)	−0.084 (0.971)	−0.033 (1.612)	−0.091 (0.996)
SP500	−0.036 (1.075)	−0.041 (1.091)	−0.107 (1.081)	0.019 (0.455)

Panel C: Multiple currency factors

BTC	ETH	XRP	DASH	BTC
AUD	−0.019 (1.371)	0.009 (0.791)	−0.037 (1.708)	0.033 (0.209)
EUR	−0.06 (0.863)	−0.078 (0.962)	−0.096 (0.998)	−0.037 (1.64)
YEN	−0.036 (1.573)	−0.024 (1.652)	−0.07 (0.919)	0.007 (0.696)
CAD	−0.046 (0.762)	−0.043 (0.707)	−0.095 (0.995)	−0.037 (1.735)
BRL	0.039 (0.196)	0.055 (0.121)	0.029 (0.397)	0.079 (0.031)
RMB	**0.063* (1.915)**	**0.043* (1.875)**	**0.011** (2.231)**	**0.064* (1.919)**
CHF	−0.058 (0.842)	−0.056 (0.878)	−0.056 (0.927)	−0.045 (0.853)
IDR	0.051 (0.042)	0.08 (0.005)	0.098 (0.694)	0.053 (0.034)
KRW	−0.036 (1.675)	−0.04 (1.738)	−0.084 (0.977)	0.049 (0.089)
VEF	0.068 (0.038)	0.079 (0.015)	0.14 (0.1453)	0.031 (0.141)
GBP	−0.03 (1.664)	−0.04 (0.816)	0.038 (0.388)	−0.066 (0.97)
RUB	0.004 (0.002)	0.012 (0)	−0.012 (0.2)	−0.003 (1.192)
TRY	0.033 (0.214)	0.049 (0.1)	0.104 (0.002)	−0.006 (1.212)

Panel D: Bitcoin and blockchain trend-based factors

	BTC	ETH	XRP	DASH
NTs	−0.524 (1.12)	−0.381 (1.099)	−0.524 (1.42)	−0.475 (1.312)
NPs	−0.334 (1.097)	−0.294 (1.192)	−0.4 (1.298)	−0.323 (1.494)
NUs	−0.019 (1.29)	−0.003 (1.059)	0.024 (0.485)	0.065 (0.264)
PVs	0.411 (0.002)	0.28 (0.012)	0.416 (0.001)	0.403 (0.002)
Btc-W	0.108 (0.104)	0.048 (0.224)	0.037 (0.272)	0.093 (0.081)
Eth-W	**0.07* (1.94)**	0.066 (0.077)	0.08 (0.017)	0.059 (0.15)
Xrp-W	−0.005 (1.09)	0.004 (0.913)	0.058 (0.022)	0.177 (0.002)
Doge-W	0.03 (0.535)	0.048 (0.28)	0.055 (0.082)	0.086 (0.114)
Btc-GT	0.019 (0.801)	−0.033 (1.58)	−0.041 (1.77)	0.063 (0.311)
Eth-GT	**0.022** (2.059)**	0.019 (0.646)	0.042 (0.258)	0.055 (0.289)
Xrp-GT	−0.043 (1.667)	−0.009 (1.156)	0.022 (0.475)	0.183 (0.009)
Doge-GT	0.004 (0.93)	0.011 (0.786)	0.003 (0.926)	0.059 (0.217)

Panel E: Blockchain technology-based factors

	BTC	ETH	XRP	DASH
BZ	0.058 (0.083)	0.046 (0.115)	0.014 (0.697)	0.09 (0.01)
BSV	−0.041 (1.727)	−0.028 (1.597)	0.003 (0.929)	−0.06 (1.962)
HSH	**0.07* (1.998)**	**0.082* (1.999)**	**0.097** (2.201)**	**0.029* (1.815)**
MD	**0.074* (1.999)**	**0.084* (1.999)**	**0.097** (2)**	**0.032* (1.861)**
TBT	−0.05 (1.906)	−0.021 (1.563)	0.019 (0.496)	−0.043 (1.79)
TBM	−0.029 (1.437)	−0.034 (1.523)	−0.073 (1.072)	0.017 (0.359)
DOD	0.018 (0.439)	0.012 (0.636)	0.007 (0.739)	0.048 (0.071)
UBA	0.054 (0.171)	0.04 (0.236)	0.025 (0.464)	0.108 (0.011)
DBT	0.08 (0.018)	0.085 (0.006)	0.063 (0.064)	0.135 (0.001)
EPU	−0.003 (1.089)	0.002 (0.938)	0.007 (0.781)	0.028 (0.253)

Panel F: Multiple stock indices

	BTC	ETH	XRP	DASH
NI225	−0.015 (1.286)	−0.009 (1.193)	−0.055 (1.221)	0.063 (0.039)
IBVC	−0.025 (1.6)	−0.05 (1.038)	−0.061 (1.091)	−0.044 (1.298)
BRA	−0.024 (1.455)	−0.024 (1.47)	−0.076 (1.964)	0.03 (0.268)
TSX	−0.012 (1.274)	−0.024 (1.452)	−0.099 (1.092)	0.026 (0.335)
KOSPI	0.009 (0.831)	0 (1.009)	−0.046 (1.099)	0.038 (0.209)
ASX	−0.007 (1.186)	−0.023 (1.487)	−0.065 (1.232)	0.046 (0.105)
JCI	−0.015 (1.287)	−0.009 (1.189)	−0.055 (1.182)	0.062 (0.04)
SMI	0.009 (0.803)	−0.011 (1.262)	−0.037 (1.664)	0.049 (0.115)
SSE	0.02 (0.592)	0.035 (0.309)	0.074 (0.132)	0.011 (0.727)
RTS	−0.018 (1.404)	−0.033 (1.628)	−0.1 (1.087)	0.025 (0.368)

Note: We report the estimation of the slope coefficient and the heteroskedasticity-consistent t-statistic (in parentheses) for bivariate predictive regression model $r_{t+1} = \alpha_i + \beta_i X_{i,t} + \varepsilon_{i,t+1}$, 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 15 technical rules selected in the previous step and the selected factors in Table 3, respectively. 50% IS corresponds to period 1 as explained in Table 4.

*Significance at the 10% level based on one-sided (upper-tail) wild bootstrapped p-value.

**Significance at the 5% level based on one-sided (upper-tail) wild bootstrapped p-value.

***Significance at the 1% level based on one-sided (upper-tail) wild bootstrapped p-value.

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TABLE 6 In-sample predictive regression estimation results (F2: 75% IS).

Panel A: Technical rules

	BTC		ETH		XRP		DASH
CB (15, 0.1, 25, 100)	−0.001 (1.16)	CB (10, 0.03, 10, 20)	−0.004 (1.072)	CB (10, 0.03, 10, 20)	−0.006 (1.098)	CB (10, 0.03, 10, 20)	−0.002 (1.626)
FR (0.01, 5)	−0.001 (1.301)	MA (75, 20, 0.03)	−0.001 (1.47)	**PMA1**	**0.002* (1.841)**	MA (10, 5, 0.01)	0.001 (0.781)
MA (50, 5, 0.03)	0.002 (1.584)	MA (50, 20, 0.04)	0 (1.459)	**FR (0.14, 10)**	**0.001* (1.994)**	PMA1	**0.004* (1.917)**
MA (50, 2, 0.02)	0 (1.045)	**PMA1**	**0.02* (1.855)**	**FR (0.005, 3)**	**0.013* (1.847)**	MA (10, 5, 0.02)	0.021 (1.492)
MA (50, 20, 25)	−0.001 (1.24)	**FR (0.01,1)**	**0.002* (1.924)**	**MA (40, 25, 0.05)**	**0.003* (1.733)**	MA (5, 2, 0.05)	0.001 (0.845)
PMA1	**0.001* (1.925)**	MA (75, 20, 0.05)	−0.001 (1.58)	MA (15, 1, 0.005)	0.002 (0.1)	**MA (10, 5, 0.04)**	**0.012* (1.836)**
CB (5, 0.075, 5, 0.01)	**0.013* (1.991)**	MA (50, 15, 0.015)	0 (1.089)	MA (50, 20, 0.02)	0 (1.091)	**MA (10, 2, 0)**	**0.014* (1.773)**
CB (5, 0.075, 5,0)	**0.003* (1.872)**	MA (75, 30, 0)	0 (1.139)	MA (75, 10, 0.005)	0 (1.186)	MA (15, 10, 0.02)	0 0.013 (1.494)
FR (0.02, 0.015)	0 (1.088)	MA (75, 25, 0.001)	0.017 (1.553)	MA (40, 20, 0.02)	−0.001 (1.298)	MA (15, 1, 0.015)	−0.004 (1.69)
MA (50, 15, 25)	0.005 (0.012)	MA (40, 25, 0.03)	0 (1.07)	MA (40, 20, 0.001)	0.007 (0.003)	MA (5, 1, 0.01)	0.005 (0.007)
PMA2	0.021 (1.223)	MA (40, 30, 0.04)	0.005 (1.525)	MA (10, 5, 0.001)	−0.001 (1.34)	MA (15, 10, 0.04)	0 (1.436)
MA (2, 1, 0.05)	0 (1.315)	MA (50, 5, 0.05)	0.113 (1.643)	MA (50, 15, 0.015)	0.002 (1.525)	MA (20, 1, 0.015)	−0.001 (1.028)
MA (10, 1, 0.01)	0 (1.128)	MA (50, 1, 0)	0 (1.605)	MA (40, 20, 0.04)	0 (1.266)	MA (10, 2, 0.005)	0 (1.223)
FR (0.025, 0.025)	0 (1.403)	MA (75, 40, 0.01)	0 (1.209)	MA (75, 1, 0.001)	0 (1.099)	MA (5, 2, 0.015)	0 (1.39)
FR (0.01, 15)	−0.029 (1.541)	MA (50, 1, 0.015)	0.031 (0.592)	MA (50, 40, 0.03)	−0.015 (1.231)	FR (0.025, 5)	0.073 (0.205)

Panel B: Traditional fundamental factors

	BTC	ETH	XRP	DASH
3mBill	−0.03 (1.176)	−0.054 (1.072)	−0.081 (1.098)	−0.016 (1.626)
10yBill	−0.011 (1.301)	−0.017 (1.47)	−0.021 (1.641)	0.005 (0.781)
DJIA	−0.019 (1.584)	−0.038 (1.659)	−0.084 (1.594)	−0.008 (1.317)
GLD	−0.001 (1.045)	**−0.022* (1.855)**	−0.023 (1.647)	−0.011 (1.492)
MAAA	−0.008 (1.24)	0.019 (0.429)	0.022 (0.373)	0.004 (0.845)
MBaa	0.028 (0.255)	−0.021 (1.58)	0.037 (0.1)	0.003 (0.836)
MSCI	−0.019 (1.591)	−0.044 (1.189)	−0.076 (1.291)	−0.007 (1.273)
NSQ	**−0.005* (1.972)**	**−0.034* (1.839)**	−0.068 (1.086)	−0.012 (1.494)
OIL	−0.047 (1.288)	**−0.022* (1.953)**	−0.093 (1.998)	**−0.02* (1.869)**
MER	0.149 (0.012)	−0.004 (1.07)	0.132 (0.003)	0.077 (0.007)
VIX	−0.018 (1.223)	−0.034 (1.525)	−0.02 (1.34)	−0.044 (1.836)
VXN	−0.023 (1.315)	−0.042 (1.643)	−0.031 (1.525)	−0.06 (1.928)
VXD	−0.009 (1.128)	−0.038 (1.605)	−0.014 (1.266)	−0.04 (1.823)
SP500	−0.012 (1.403)	−0.034 (1.009)	−0.075 (1.199)	−0.009 (1.39)

Panel C: Multiple currency factors

	BTC	ETH	XRP	DASH
AUD	−0.028 (1.541)	0.02 (0.592)	−0.009 (1.231)	0.035 (0.205)
EUR	−0.052 (1.088)	−0.059 (1.037)	−0.08 (1.098)	−0.029 (1.592)
YEN	−0.031 (1.076)	−0.037 (1.099)	−0.074 (1.059)	−0.007 (1.313)
CAD	−0.051 (1.046)	−0.028 (0.569)	−0.075 (0.988)	−0.026 (1.663)
BRL	0.003 (0.932)	0.038 (0.18)	0.021 (0.419)	0.055 (0.081)
RMB	**−0.048* (1.874)**	**−0.009* (1.84)**	**0.001* (1.977)**	**−0.027* (1.756)**
CHF	−0.044 (1.148)	−0.039 (1.44)	−0.04 (1.089)	−0.033 (0.824)
IDR	0.002 (0.941)	0.05 (0.084)	0.064 (0.021)	0.043 (0.09)
KRW	−0.035 (1.711)	−0.008 (1.196)	−0.048 (1.091)	0.048 (0.1)
VEF	0.033 (0.216)	0.066 (0.015)	0.108 (0.001)	0.041 (0.073)
GBP	−0.033 (1.482)	−0.015 (1.453)	0.037 (0.346)	−0.043 (0.946)
RUB	0.003 (0.02)	0.011 (0.024)	−0.011 (0.02)	−0.003 (0.761)
TRY	0.005 (0.828)	0.044 (0.071)	0.074 (0.014)	0.017 (0.352)

Panel D: Bitcoin and blockchain trend-based factors

	BTC	ETH	XRP	DASH
NTs	−0.03 (1.445)	−0.055 (1.104)	−0.059 (1.554)	−0.029 (1.383)
NPs	−0.002 (1.027)	0.008 (0.83)	−0.003 (1.05)	−0.016 (1.296)
NUs	−0.011 (1.212)	0.002 (0.951)	0.025 (0.414)	0.065 (0.244)
PVs	0.084 (0.051)	0.085 (0.013)	0.074 (0.076)	0.055 (0.184)
Btc-W	0.088 (0.106)	0.046 (0.177)	0.038 (0.201)	0.094 (0.062)
Eth-W	**0.062* (1.872)**	0.068 (0.029)	0.077 (0.008)	0.063 (0.089)
Xrp-W	−0.007 (1.16)	0.006 (0.855)	0.053 (0.021)	0.169 (0.002)
Doge-W	0.032 (0.395)	0.046 (0.186)	0.055 (0.034)	0.091 (0.059)
Btc-GT	0.022 (0.724)	−0.03 (1.612)	−0.034 (1.742)	0.061 (0.299)
Eth-GT	**0.019* (1.843)**	0.021 (0.56)	0.044 (0.181)	0.06 (0.226)
Xrp-GT	−0.033 (1.629)	−0.004 (1.085)	0.024 (0.377)	0.178 (0.008)
Doge-GT	0.009 (0.797)	0.018 (0.567)	0.008 (0.72)	0.063 (0.124)

Panel E: Blockchain technology-based factors

	BTC	ETH	XRP	DASH
BZ	0.043 (0.084)	0.017 (0.396)	0.022 (0.992)	0.046 (0.028)
BSV	−0.028 (1.677)	−0.017 (1.493)	0.014 (0.549)	−0.038 (1.089)
HSH	**0.037* (1.881)**	**0.041* (1.918)**	**0.051* (1.979)**	**0.039* (1.959)**
MD	**0.032* (1.815)**	**0.041* (1.913)**	**0.048* (1.965)**	**0.037* (1.944)**
TBT	−0.015 (1.463)	−0.012 (1.373)	0.022 (0.339)	−0.029 (1.69)
TBM	−0.019 (1.64)	−0.033 (0.888)	−0.056 (0.959)	−0.016 (0.713)
DOD	0.01 (0.615)	0.002 (0.919)	0.001 (0.948)	0.043 (0.065)
UBA	0.049 (0.084)	0.022 (0.359)	0.017 (0.537)	0.077 (0.012)
DBT	0.054 (0.029)	0.038 (0.077)	0.027 (0.311)	0.072 (0.004)
EPU	0.023 (0.312)	0.002 (0.943)	0.015 (0.446)	0.011 (0.434)

Panel F: Multiple stock indices

	BTC	ETH	XRP	DASH
NI225	−0.028 (1.604)	−0.019 (1.454)	−0.059 (0.929)	0.028 (0.214)
IBVC	−0.022 (1.638)	−0.037 (0.903)	−0.048 (0.984)	−0.034 (0.966)
BRA	−0.031 (1.645)	−0.017 (1.39)	−0.064 (0.967)	0.006 (0.755)
TSX	−0.022 (1.482)	−0.024 (1.491)	−0.086 (0.988)	0.005 (0.837)
KOSPI	−0.015 (1.317)	0.007 (0.859)	−0.038 (1.765)	0.032 (0.279)
ASX	−0.019 (1.539)	−0.033 (1.732)	−0.061 (1.068)	−0.004 (1.174)
JCI	−0.028 (1.604)	−0.019 (1.45)	−0.059 (1.929)	0.028 (0.217)
SMI	0.011 (0.651)	−0.013 (1.365)	−0.028 (1.172)	0.002 (0.913)
SSE	0.011 (0.716)	0.038 (0.213)	0.063 (0.129)	0.018 (0.522)
RTS	−0.013 (1.407)	−0.028 (1.632)	−0.073 (0.979)	−0.004 (1.195)

Note: We report the estimation of the slope coefficient and the heteroskedasticity-consistent t-statistic (in parentheses) for the bivariate predictive regression model $r_{t+1} = \alpha_i + \beta_i X_{i,t} + \varepsilon_{i,t+1}$, 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 15 technical rules selected in the previous step and the selected factors in Table 3 respectively. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, based on one-sided (upper-tail) wild bootstrapped p-values. 75% IS corresponds to period 2 as explained in Table 4.

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TABLE 7 In-sample predictive regression estimation results (F3: 90% IS).

Panel A: Technical rules

BTC		ETH		XRP		DASH	
CB (15, 0.1, 25, 100)	−0.002 (1.083)	CB (10, 0.03, 10, 20)	−0.004 (1.061)	CB (10, 0.03, 10, 20)	−0.005 (1.096)	CB (10, 0.03, 10, 20)	−0.002 (1.644)
FR (0.01, 5)	−0.001 (1.658)	MA (200, 5, 0.04)	−0.001 (1.393)	MA (10, 2, 0.005)	−0.001 (1.589)	MA (10, 5, 0.01)	0.001 (0.784)
PMA1	**0.206* (1.868)**	MA (50, 5, 0.03)	0.002 (1.14)	MA (15, 1, 0.005)	0.003 (1.503)	MA (10, 2, 0.005)	0.014 (0.853)
CB (5, 0.075, 5, 0.01)	**0.034* (1.932)**	MA (50, 20, 0.04)	0.004 (1.103)	**PMA1**	**0.001* (1.812)**	MA (5, 1, 0.01)	0.013 (1.184)
CB (5,0.075,5,0.015)	**0.002* (1.831)**	MA (75, 20, 0.03)	0.001 (0.845)	**MA (2,1,0.02)**	**0.002* (1.884)**	MA (10, 5, 0.04)	0.013 (0.997)
MA (200, 125, 25)	0.031 (0.599)	MA (75, 1, 0.001)	−0.001 (1.598)	**MA (2, 1, 0.015)**	**0.002* (1.927)**	MA (5, 2, 0.015)	0.014 (0.915)
FR (0.03, 3)	0 0.014 (0.896)	MA (50, 2, 0.02)	0.216 (1.115)	**MA (2, 1, 0.02)**	**−0.012 (1.85)**	FR (0.005, 3)	0.022 (0.752)
FR (0.035, 1)	0.012 (0.511)	MA (100, 30, 0.015)	−0.102 (0.852)	MA (40, 20, 5)	0.013 (1.497)	FR (0.04, 15)	0.112 (0.846)
FR (0.04, 1)	0.021 (1.228)	FR (0.07, 0.15)	−0.031 (1.175)	MA (40, 1, 0.05)	0.002 (1.398)	FR (0.01, 3)	0.01 (1.599)
MA (5,1,0.015)	0.006 (0.001)	MA (100, 30, 0.005)	−0.001 (1.259)	MA (75, 1, 0.01)	0.008 (0.749)	FR (0.005, 3)	0.007 (0.519)
MA (10,5,0.05)	0.001 (1.181)	FR (0.035, 0.04)	−0.005 (1.586)	MA (10, 5, 0.02)	0 0.002 (1.451)	PMA1	**0.031* (1.899)**
FR (0.005, 1)	0.017 (1.269)	FR (0.04, 0.025)	0.001 (1.708)	MA (40, 20, 0.02)	0.001 (1.654)	**FR (0.01, 1)**	**−0.041* (1.946)**
MA (2,1,0.05)	0 (1.032)	**PMA1**	**0.211* (1.83)**	MA (15, 1, 0.03)	0.004 (1.308)	**FR (0.045, 1)**	**0.047* (1.866)**
FR (0.005, 5)	0 (0.755)	**PMA2**	**0.182* (1.892)**	MA (100, 25, 0.04)	0.103 (1.273)	FR (0.045, 15)	0.071 (0.82)
MA (10,1,0.01)	−0.023 (1.475)	FR (0.4, 0.04)	−0.034 (0.515)	MA (40, 15, 25)	−0.009 (1.159)	FR (0.01, 5)	0.075 (0.159)

Panel B: Traditional fundamental factors

	BTC	ETH	XRP	DASH
3mBill	**−0.033* (1.983)**	**−0.048* (1.961)**	**−0.067* (1.996)**	−0.017 (1.644)
10yBill	−0.024 (1.658)	−0.012 (1.393)	−0.017 (1.589)	0.006 (0.784)
DJIA	−0.002 (1.068)	−0.005 (1.14)	−0.059 (1.053)	0.004 (0.853)
GLD	0.016 (0.532)	**−0.003* (1.903)**	−0.017 (1.512)	−0.006 (1.184)
MAAA	−0.026 (1.731)	0.005 (0.845)	0.017 (0.484)	0.024 (0.997)
MBaa	0.013 (0.599)	−0.02 (1.598)	0.027 (0.227)	0.002 (0.915)
MSCI	0.003 (0.896)	−0.004 (1.115)	−0.039 (1.285)	0.008 (0.752)
NSQ	**0.017* (1.811)**	0.005 (0.852)	−0.034 (0.797)	0.005 (0.846)
OIL	**−0.048** (2.128)**	**−0.006* (1.875)**	**−0.083* (1.898)**	**−0.015* (1.799)**
MER	0.17 (0.001)	−0.013 (1.259)	0.148 (0.906)	0.09 (0.647)
VIX	−0.012 (1.181)	−0.033 (1.586)	−0.025 (1.451)	−0.047 (1.299)
VXN	−0.016 (1.269)	−0.039 (1.708)	−0.035 (1.654)	−0.059 (1.146)
VXD	−0.002 (1.032)	−0.035 (1.637)	−0.015 (1.308)	−0.04 (1.166)
SP500	0.008 (0.755)	0.004 (0.892)	−0.042 (0.873)	0.006 (0.82)
–				

Panel C: Multiple currency factors

	BTC	ETH	XRP	DASH
AUD	−0.021 (1.475)	0.02 (0.515)	−0.005 (1.159)	0.034 (0.159)
EUR	−0.027 (1.662)	−0.038 (1.05)	−0.062 (1.187)	−0.021 (1.494)
YEN	−0.007 (1.224)	−0.029 (1.25)	−0.061 (1.28)	−0.007 (1.274)
CAD	−0.042 (1.016)	−0.01 (1.227)	−0.06 (1.064)	−0.014 (1.397)
BRL	−0.014 (1.398)	0.016 (0.552)	0.014 (0.591)	0.028 (0.369)
RMB	**−0.033* (1.748)**	**0.003* (1.908)**	**0.001* (1.976)**	**−0.02* (1.825)**
CHF	0.002 (0.943)	−0.011 (1.308)	−0.021 (1.626)	−0.017 (1.464)
IDR	0.002 (0.922)	0.04 (0.115)	0.058 (0.024)	0.035 (0.152)
KRW	−0.017 (1.45)	0.001 (0.975)	−0.038 (1.085)	0.045 (0.075)
VEF	0.02 (0.404)	0.05 (0.043)	0.095 (0.002)	0.032 (0.173)
GBP	−0.03 (1.074)	−0.009 (1.289)	0.033 (0.348)	−0.033 (0.882)
RUB	0.002 (0.177)	0.009 (0.203)	−0.01 (0.519)	−0.003 (1.215)
TRY	−0.006 (1.196)	0.025 (0.288)	0.058 (0.04)	0.008 (0.716)
–				

Panel D: Bitcoin and blockchain trend-based factors

	BTC	ETH	XRP	DASH
NTs	−0.026 (1.527)	0.029 (0.421)	0.002 (0.95)	0.015 (0.741)
NPs	−0.009 (1.137)	0.055 (0.305)	0.022 (0.599)	−0.027 (1.433)
NUs	−0.006 (1.15)	0.012 (0.712)	0.017 (0.507)	0.041 (0.281)
PVs	−0.037 (1.587)	0.075 (0.067)	−0.02 (1.343)	0.08 (0.305)
Btc-W	0.078 (0.112)	0.041 (0.166)	0.036 (0.203)	0.082 (0.063)
Eth-W	**0.035* (1.935)**	0.058 (0.062)	0.068 (0.012)	0.055 (0.063)
Xrp-W	−0.005 (1.129)	0.007 (0.801)	0.051 (0.018)	0.15 (0.002)
Doge-W	0.006 (0.838)	0.035 (0.115)	0.018 (0.329)	0.021 (0.525)
Btc-GT	0.027 (0.555)	−0.009 (1.209)	−0.022 (1.583)	0.052 (0.224)
Eth-GT	**0.011* (1.872)**	0.029 (0.399)	0.024 (0.426)	0.025 (0.428)
Xrp-GT	−0.033 (1.682)	0.001 (0.979)	0.023 (0.36)	0.161 (0.006)
Doge-GT	−0.01 (1.259)	0.023 (0.354)	0 (1.009)	−0.017 (1.503)

Panel E: Blockchain technology-based factors

	BTC	ETH	XRP	DASH
BZ	0.048 (0.025)	0.027 (0.162)	0.021 (0.398)	0.05 (0.009)
BSV	−0.03 (1.765)	−0.015 (1.476)	0.008 (0.705)	−0.029 (1.218)
HSH	**0.012* (1.815)**	**0.011* (1.941)**	**0.02* (1.847)**	**0.008* (1.876)**
MD	**0.013* (1.843)**	**0.02* (1.959)**	**0.025* (1.927)**	**0.011* (1.859)**
TBT	−0.019 (1.565)	−0.035 (1.455)	−0.001 (1.037)	−0.033 (1.317)
TBM	−0.005 (1.19)	−0.017 (1.6)	−0.036 (1.045)	−0.002 (1.104)
DOD	0.008 (0.65)	−0.002 (1.108)	0.004 (0.841)	0.028 (0.184)
UBA	0.048 (0.036)	0.03 (0.171)	0.028 (0.263)	0.067 (0.006)
DBT	0.06 (0.007)	0.047 (0.012)	0.034 (0.166)	0.069 (0.001)
EPU	0.029 (0.15)	0.008 (0.68)	0.021 (0.258)	0.008 (0.59)

Panel F: Multiple stock indices

	BTC	ETH	XRP	DASH
NI225	−0.02 (1.519)	−0.01 (1.289)	−0.052 (1.027)	0.023 (0.249)
IBVC	−0.022 (1.687)	−0.035 (1.116)	−0.044 (1.082)	−0.03 (1.265)
BRA	−0.03 (1.696)	−0.004 (1.095)	−0.059 (1.058)	0.005 (0.807)
TSX	−0.012 (1.307)	0.01 (0.759)	−0.058 (1.51)	0.01 (0.685)
KOSPI	0.001 (0.964)	0.017 (0.587)	−0.012 (1.332)	0.027 (0.28)
ASX	−0.008 (1.259)	−0.01 (1.279)	−0.047 (1.415)	0.001 (0.96)
JCI	−0.02 (1.519)	−0.01 (1.282)	−0.052 (1.22)	0.023 (0.249)
SMI	0.011 (0.652)	0.011 (0.669)	−0.025 (1.678)	−0.004 (1.143)
SSE	0.013 (0.649)	0.031 (0.271)	0.044 (0.188)	0.015 (0.54)
RTS	−0.005 (1.174)	−0.004 (1.116)	−0.059 (1.245)	0.002 (0.932)

Note: We report the estimation of the slope coefficient and the heteroskedasticity-consistent *t*-statistic (in parentheses) 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 respectively. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, based on one-sided (upper-tail) wild bootstrapped *p*-values. 90% IS corresponds to period 3 as explained in Table 4. Bold indicates the factors that are found to be significant (at any level).

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TABLE 8 Lucky Factors and SPA test summary (50% IS).

BTC											
Panel 1: Baseline = No factor (Period1)				**Panel 2: Baseline = NSQ Factor (Period 1)**				**Panel 3: Baseline = NSQ + HSH Factor (Period 1)**			
	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	0.079	0.086	0.228	**Eth-W**	0.015	0.936	0.790	**Eth-W**	0.066	0.532	0.826
Eth-GT	0.197	0.096	0.201	**Eth-GT**	0.058	0.971	0.707	**Eth-GT**	0.071	0.728	0.319
RMB	0.105	0.049	0.428	**RMB**	0.058	0.460	0.372	**RMB**	0.054	0.562	0.771
HSH	0.255	0.055	0.041	**HSH**	**0.124**	**0.017**	**0.007**	**MD**	0.059	0.841	0.723
NSQ	**0385**	**0.011**	**0.003**	**MD**	0.088	0.349	0.591	**PMA1**	0.075	0.221	0.425
MD	0.155	0.178	0.866	**PMA1**	0.04	0.143	0.963	**CB (5, 0.075, 5, 0.01)**	0.07	0.477	0.118
PMA1	0.147	0.527	0.236	**CB (5, 0.075, 5, 0.01)**	0.027	0.041	0.467	**CB (5, 0.075, 5, 0.005)**	0.057	0.262	0.363
CB (5, 0.075, 5, 0.01)	0.084	0.173	0.364	**CB (5, 0.075, 5, 0.005)**	0.075	0.942	0.098				
CB (5, 0.075, 5, 0.005)	0.033	0.470	0.682								
ETH											
Panel 1: Baseline = no factor (Period 1)				**Panel 2: Baseline = NSQ factor (Period 1)**				**Panel 3: Baseline = NSQ + HSH factor (Period 1)**			
	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	0.074	0.738	0.672	**GLD**	0.033	0.489	0.911	**GLD**	0.075	0.853	0.69
NSQ	**0.268**	**0.007**	**0.005**	**HSH**	**0.159**	**0.008**	**0.006**	**NSQ**	0.042	0.178	0.215
OIL	0.056	0.681	0.782	**OIL**	0.005	0.786	0.781	**OIL**	0.073	0.515	0.865
HSH	0.231	0.069	0.731	**MD**	0.099	0.505	0.698	**MD**	0.063	0.889	0.972
MD	0.102	0.989	0.703	**RMB**	0.046	0.726	0.484	**RMB**	0.087	0.263	0.521
RMB	0.118	0.494	0.337	**PMA1**	0.017	0.838	0.87				
PMA1	0.235	0.423	0.731								
XRP											
Panel 1: Baseline = No factor (Period 1)				**Panel 2: Baseline = NSQ Factor (Period 1)**				**Panel 3: Baseline = NSQ + HSH factor (Period 1)**			
	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	0.117	0.369	0.025	**RMB**	0.039	0.566	0.327	**RMB**	0.034	0.427	0.602
NSQ	**0.258**	**0.009**	**0.011**	**HSH**	**0.203**	**0.011**	**0.008**	**NSQ**	0.069	0.618	0.775

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TABLE 8 (Continued)

Panel 1: Baseline = No factor (Period 1)				Panel 2: Baseline = NSQ Factor (Period 1)				Panel 3: Baseline = NSQ + HSH factor (Period 1)			
	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	0.246	0.008	0.061	**PMA1**	0.093	0.674	0.648	**PMA1**	0.056	0.01	0.298
MD	0.185	0.181	0.271	**MD**	0.051	0.272	0.662	**PMA4**	0.015	0.63	0.331
PMA1	0.126	0.880	0.806	**PMA4**	0.099	0.270	0.984	**MA (5, 2, 5)**	0.062	0.05	0.274
PMA4	0.026	0.950	0.495	**MA (5, 2, 5)**	0.085	0.126	0.51	**FR (0.005,5)**	0.068	0.939	0.59
MA (5, 2, 5)	0.088	0.609	0.584	**FR (0.005,5)**	0.012	0.775	0.250				
FR (0.005,5)	0.048	0.301	0.284								
DASH											
Panel 1: Baseline = No factor (Period 1)				**Panel 2: Baseline = NSQ factor (Period 1)**				**Panel 3: Baseline = NSQ + HSH factor (Period 1)**			
	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	0.112	0.084	0.018	**HSH**	**0.107**	**0.023**	**0.022**	**MD**	0.052	0.232	0.146
MD	0.059	0.541	0.393	**MD**	0.084	0.659	0.065	**RMB**	0.053	0.895	0.642
RMB	0.031	0.304	0.371	**RMB**	0.067	0.071	0.812	PMA1	0.042	0.764	0.837
NSQ	**0.206**	**0.011**	**0.008**	PMA1	0.036	0.205	0.448	MA (**5**, **1**, **0.01**)	0.028	0.961	0.846
PMA1	0.086	0.251	0.077	**MA (5, 1, 0.01)**	0.086	0.946	0.401	MA (**5**, **2**, **0.05**)	0.045	0.696	0.119
MA (5, 1, 0.01)	0.086	0.255	0.086	**MA (5, 2, 0.05)**	0.095	0.096	0.843				
MA (5, 2, 0.05)	0.081	0.825	0.294								

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 to be significant in each step of the process. 50% IS corresponds to period 1 as explained in Table 4. The baseline model refers to the model that includes the pre-selected factors.

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TABLE 9 Lucky factors and SPA test summary (75% IS).

BTC											
Panel 1: Baseline = No Factor (Period2)				**Panel 2: Baseline = HSH Factor (Period2)**				**Panel 3: Baseline = RMB + HSH Factor (Period 2)**			
	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	0.009	0.556	0.700	**Eth-W**	0.097	0.097	0.512	**Eth-W**	0.046	0.573	0.217
Eth-GT	0.075	0.526	0.762	**Eth-GT**	0.082	0.561	0.29	**Eth-GT**	0.027	0.93	0.913
RMB	0.159	0.084	0.107	**RMB**	**0.141**	**0.032**	**0.009**	**MD**	0.019	0.619	0.538
NSQ	0.103	0.045	0.095	**NSQ**	0.056	0.124	0.017	**NSQ**	0.074	0.969	0.905
HSH	**0.169**	**0.020**	**0.012**	**MD**	0.016	0.919	0.439	**PMA1**	0.013	0.488	0.897
MD	0.015	0.544	0.970	**PMA1**	0.087	0.032	0.484	**CB (5, 0.075, 5, 0.01)**	0.019	0.222	0.341
PMA1	0.156	0.245	0.007	**CB (5, 0.075, 5, 0.01)**	0.057	0.562	0.144	**CB (5, 0.075, 5, 0)**	0.003	0.236	0.341
CB (5, 0.075, 5, 0.01)	0.088	0.590	0.989	**CB (5, 0.075, 5, 0)**	0.016	0.689	0.938				
CB (5, 0.075, 5, 0)	0.052	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
NSQ	0.119	0.201	0.092	**NSQ**	0.061	0.094	0.068	**NSQ**	0.009	0.862	0.922
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 (Period 2)				**Panel 2: Baseline = HSH factor (Period 2)**				**Panel 3: Baseline = PMA1 + RMB factor (Period 2)**			
	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	0.189	0.089	0.1	**RMB**	**0.144**	**0.012**	**0.007**	**PMA1**	0.004	0.656	0.366
HSH	**0.203**	**0.007**	**0.528**	**PMA1**	0.038	0.684	0.258	**MD**	0.067	0.715	0.638

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TABLE 9 (Continued)

XRP											
Panel 1: Baseline = No factor (Period 2)				**Panel 2: Baseline = HSH factor (Period 2)**				**Panel 3: Baseline = PMA1 + RMB factor (Period 2)**			
	R^2	**LF (*p*-value)**	**SPA (*p*-value)**		R^2	**LF (*p*-value)**	**SPA (*p*-value)**		R^2	**LF (*p*-value)**	**SPA (*p*-value)**
MD	0.143	0.851	0.666	**MD**	0.076	0.992	0.14	**FR (0.14, 10)**	0.075	0.223	0.637
PMA1	0.164	0.344	0.177	**FR (0.14, 10)**	0.023	0.681	0.087	**FR (0.005, 3)**	0.007	0.366	0.962
FR (0.14, 10)	0.056	0.162	0.984	**FR (0.005, 3)**	0.048	0.957	0.653	**MA (40, 25, 0.05)**	0.024	0.575	0.752
FR (0.005, 3)	0.093	0.874	0.639	**MA (40, 25, 0.05)**	0.071	0.873	0.081				
MA (40, 25, 0.05)	0.063	0.922	0.902								
DASH											
Panel 1: Baseline = No factor (Period 2)				**Panel 2: Baseline = MD Factor (Period 2)**				**Panel 3: Baseline = HSH + MD Factor (Period 2)**			
	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	0.258	0.094	0.054	**RMB**	0.096	0.075	0.069	**RMB**	0.088	0.27	0.199
MD	**0.301**	**0.006**	**0.008**	**HSH**	**0.114**	**0.011**	**0.026**	**OIL**	0.049	0.333	0.304
RMB	0.077	0.058	0.633	**OIL**	0.007	0.186	0.234	PMA1	0.031	0.612	0.23
OIL	0.166	0.696	0.988	PMA1	0.08	0.335	0.162	**MA (10, 5, 0.04)**	0.04	0.032	0.072
PMA1	0.052	0.079	0.03	**MA (10, 5, 0.04)**	0.028	0.255	0.263	**MA (10, 2, 0)**	0.019	0.919	0.528
MA (10, 5, 0.04)	0.012	0.428	0.117	**MA (10, 2, 0)**	0.019	0.391	0.994				
MA (10, 2, 0)	0.075	0.335	0.737								

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 to be significant in each step of the process. 75% IS corresponds to period 2 as explained in Table 4. The baseline model refers to the model that includes the pre-selected factors.

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TABLE 10 Lucky Factors and SPA test summary (90% IS).

BTC											
Panel 1: Baseline = No factor (Period 3)				**Panel 2: Baseline = HSH Factor (Period 3)**				**Panel 3: Baseline = NSQ + HSH Factor (Period 3)**			
	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	0.117	0.078	0.035	**Eth-W**	0.095	0.829	0.141	**Eth-W**	0.009	0.863	0.908
Eth-GT	0.129	0.445	0.671	**Eth-GT**	0.058	0.274	0.67	**Eth-GT**	0.002	0.815	0.844
RMB	0.187	0.106	0.291	**NSQ**	**0.134**	**0.012**	**0.004**	**3mBill**	**0.088**	**0.086**	**0.865**
3mBill	0.101	0.309	0.524	**3mBill**	0.092	0.563	0.982	**RMB**	0.064	0.192	0.521
NSQ	0.193	0.018	0.048	**RMB**	0.042	0.956	0.438	**OIL**	0.017	0.942	0.865
OIL	0.093	0.403	0.425	**OIL**	0.044	0.989	0.901	**MD**	0.074	0.165	0.975
HSH	**0.201**	**0.008**	**0.008**	**MD**	0.075	0.994	0.497	**PMA1**	0.013	0.951	0.299
MD	0.057	0.284	0.183	**PMA1**	0.033	0.128	0.448	**CB (5, 0.075, 5, 0.01)**	0.005	0.934	0.563
PMA1	0.088	0.245	0.360	**CB (5,0.075,5,0.01)**	0.085	0.774	0.609	**CB (5, 0.075, 5, 0.015)**	0.008	0.934	0.858
CB (5, 0.075, 5, 0.01)	0.092	0.466	0.472	**CB (5, 0.075, 5, 0.015)**	0.041	0.244	0.942				
CB (5, 0.075, 5, 0.015)	0.088	0.805	0.554								
BTC											
Panel 4: Baseline = PMA1 + NSQ + HSH (Period 3)				**Panel 5: Baseline = 3mBill + PMA1 + NSQ + HSH (Period 3)**				**Panel 6: Baseline = 3mBill + PMA1 + NSQ + HSH + MD (Period 3)**			
	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	0.077	0.095	0.738	**Eth-W**	0.049	0.699	0.539	**Eth-W**	0.911	0.112	0.625
Eth-GT	0.088	0.177	0.877	**Eth-GT**	0.013	0.859	0.985	**Eth-GT**	0.707	0.854	0.555
RMB	0.073	0.311	0.315	**RMB**	0.009	0.155	0.657	**RMB**	0.739	0.993	0.834
OIL	0.066	0.888	0.262	**OIL**	0.056	0.475	0.248	**OIL**	0.027	0.929	0.481
MD	0.154	0.056	0.052	**MD**	**0.124**	**0.044**	**0.014**	**CB (5, 0.075, 5, 0.01)**	0.893	0.312	0.201
PMA1	**0.172**	**0.018**	**0.005**	**CB (5, 0.075, 5, 0.01)**	0.072	0.945	0.072	**CB (5, 0.075, 5, 0.015)**	0.042	0.639	0.816
CB (5, 0.075, 5, 0.01)	0.043	0.038	0.284	**CB (5, 0.075, 5, 0.015)**	0.043	0.031	0.522				
CB (5, 0.075, 5, 0.015)	0.037	0.254	0.016								

TABLE 10 (Continued)

(Continues)

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ETH											
Panel 1: Baseline = No Factor (Period 3)				Panel 2: Baseline = HSH Factor (Period 3)				Panel 3: Baseline = OIL + HSH Factor (Period 3)			
	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	0.147	0.236	0.137	GLD	0.074	0.408	0.571	GLD	0.044	0.111	0.485
3mBill	0.093	0.531	0.666	3mBill	0.078	0.141	0.439	3mBill	0.057	0.739	0.879
OIL	0.151	0.096	0.071	OIL	**0.169**	**0.013**	**0.014**	MD	0.075	0.509	0.203
HSH	**0.238**	**0.014**	**0.012**	MD	0.016	0.264	0.663	RMB	0.083	0.329	0.616
MD	0.046	0.736	0.193	RMB	0.028	0.496	0.247	PMA1	0.047	0.115	0.558
RMB	0.005	0.824	0.543	PMA1	0.002	0.818	0.398	PMA2	0.060	0.237	0.342
PMA1	0.081	0.468	0.161	PMA2	0.053	0.849	0.177				
PMA2	0.092	0.914	0.148								
XRP											
Panel 1: Baseline = No Factor (Period 3)				Panel 2: Baseline = HSH Factor (Period 3)				Panel 3: Baseline = RMB + HSH Factor (Period 3)			
	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	0.199	0.056	0.034	RMB	**0.193**	**0.033**	**0.029**	MD	0.011	0.264	0.532
3mBill	0.108	0.662	0.653	3mBill	0.089	0.902	0.858	3mBill	0.078	0.713	0.966
OIL	0.058	0.382	0.229	OIL	0.081	0.313	0.238	OIL	0.067	0.192	0.911
HSH	**0.208**	**0.018**	**0.014**	MD	0.101	0.161	0.114	PMA1	0.044	0.553	0.252
MD	0.123	0.203	0.527	PMA1	0.072	0.225	0.541	MA (2, 1, 0.02)	0.04	0.541	0.584
PMA1	0.054	0.712	0.807	MA (2, 1, 0.02)	0.027	0.209	0.541	MA (2, 1, 0.015)	0.015	0.241	0.265
MA (2, 1, 0.02)	0.095	0.794	0.377	MA (2, 1, 0.015)	0.044	0.531	0.674	MA (2, 1, 0.02)	0.002	0.622	0.688
MA (2, 1, 0.015)	0.054	0.209	0.571	MA (2, 1, 0.02)	0.045	0.346	0.865				
MA (2, 1, 0.02)	0.025	0.462	0.373								
DASH											
Panel 1: Baseline = No Factor (Period3)				Panel 2: Baseline = HSH Factor (Period3)				Panel 3: Baseline = OIL+ HSH Factor (Period3)			
	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	**0.269**	**0.001**	**0.011**	RMB	0.104	0.115	0.719	RMB	0.089	0.136	0.121
RMB	0.041	0.761	0.359	OIL	**0.198**	**0.007**	**0.019**	MD	0.008	0.189	0.717
OIL	0.168	0.062	0.066	MD	0.068	0.246	0.111	PMA1	0.081	0.504	0.629

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TABLE 10 (Continued)

DASH											
Panel 1: Baseline = No Factor (Period3)				Panel 2: Baseline = HSH Factor (Period3)				Panel 3: Baseline = OIL+ HSH Factor (Period3)			
	R^2	LF (*p*-value)	SPA (p-value)		R^2	LF (*p*-value)	SPA (p-value)		R^2	LF (*p*-value)	SPA (*p*-value)
MD	0.146	0.688	0.981	PMA1	0.081	0.432	0.738	**FR (0.01, 1)**	0.056	0.221	0.692
PMA1	0.015	0.627	0.825	**FR (0.01, 1)**	0.047	0.701	0.894	**FR (0.045, 1)**	0.093	0.175	0.298
FR (0.01, 1)	0.086	0.294	0.451	**FR (0.045, 1)**	0.047	0.715	0.914				
FR (0.045, 1)	0.017	0.91	0.098								

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 to be significant in each step of the process. 90% IS corresponds to period 1 as explained in Table 4. The baseline model refers to the model that includes the pre-selected factors.

information in the early stages of BCH is mainly narrative-based in online resources; therefore, 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 about 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 D seem to have predictability over BTC but not the other cryptocurrencies. Finally, RMB (Panel C), HSH (Panel E) and MD (Panel E) are found to be significant in terms of DASH predictability. Regarding the remaining eight cryptocurrencies, in terms of the Sharpe ratio we present the in-sample predictive performance in the online Appendix OA.8 (Tables A.8–A.10 and A.17–A19). We again find several cases of PMAs and several fundamental factors (VXN, TBT, OIL, VEF, MD, HSH, 3mBill) to be significant across different cryptocurrencies and exercises. 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.

Given the largely utilised 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 8–10.

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 summarise 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 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 to be as small as possible (see online Appendix OA.5 and the LF description). Nonetheless, the hurdle rate of significance level is rather a subjective decision (Harvey et al., 2016); we apply 5% as a cut-off point in this article. 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 BTC and period 1, the largest R^2 (0.385) is matched to the NSQ and the corresponding *p*-value of the LFs is 0.011. In addition, the *p*-value (0.003) of the SPA test further affirms our conclusion that the profitability of NSQ is genuine and free from data-snooping bias. The second largest R^2 (0.255) is from the HSH factor, and the corresponding LFs and SPA *p*-values

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are 0.055 and 0.041. Thus, we can declare both the NSQ and HSH 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 HSH 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 PMA1 and HSH have true value in cryptocurrency trading in an 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 six fundamental factors (3mBill, HSH, MD, RMB, NSQ and OIL) seem to consistently predict cryptocurrency returns while having genuine profitability across all cryptocurrencies and forecasting exercises in-sample.

The Lucky Factors analysis for the remaining eight cryptocurrencies is presented in the online Appendix OA.9. The results showcase that only PMA ratios and three fundamental factors (3mBill, HSH and OIL) preserve genuine predictive power and are free from data-snooping bias across our forecasting exercises. Finally, we construct equal-weighted portfolios with the top 5 and top 10 technical rules based on Sharpe and Sortino ratios. The relevant performances are presented in the online Appendix OA.10 (Figures A.1–A.4). These results show that the overall performance of the equal-weighted portfolios across periods, cryptocurrencies, selected rules and metrics varies, but there are cases where consistently high Sharpe and Sortino ratios can be achieved (BTC, LTC, LUNA). It will be interesting to see if this is borne out in our out-of-sample analysis that follows.

4.2 | Out-of-sample analysis

Our in-sample analysis revealed only one TA rule and six FA factors that possess both predictability and statistical significance in trading cryptocurrencies. In this section, we extend our analysis in the out-of-sample, and we present our results for all the TA and FA elements that possess in-sample predictability (see Tables 8–10). We investigate their 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. Positive (negative) R_{OS}^2 implies that the bivariate predictive model performs better (worse) than the historical average.

We summarize our results in Tables 11–13. 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, and hence possess predictability in the out-of-sample. Our in-sample and out-of-sample analysis confirms that only one out of 59 FA factors and one out of the 15 top performing TA rules possess genuine forecasting ability in the cryptocurrency market that can be exploited in the out-of-sample. An interesting finding is that several fundamental factors (3mBil, HSH, MD, RMB, NSQ, OIL and SSE) show persistent forecasting ability for BTC and ETH in F3 (period 3). However, this is not consistent across F1-F3. Regarding the remaining eight cryptocurrencies (Sharpe ratio), we present the out-of-sample predictive performance in the online Appendix OA.8 (Tables A.11–A.13 and A.20–A22). Once again, the results show that only PMA1 and HSH are found to have persistent forecasting ability in the out-of-sample.

Overall, our in-sample analysis on the predictability of the factors employed shows that there is a value in TA and FA when it comes to cryptocurrency prediction. 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 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 all the HSH capacity; hence, HSH reflects the overall health of the cryptocurrency market. In other words, higher HSH implies a healthier BTC market, which in turn positively influences cryptocurrency investment.

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 Tables 14–16 both the Sharpe ratio and mean returns. With the BH strategy as the benchmark, the Sharpe ratio[11] of the TA factors ranges from 0.108 to 0.266, while the mean returns range from 0.004 to 0.005 in the case of the BTC (period 1). Compared with the in-sample results, we have a dramatic upturn in each cryptocurrency. By contrast, the

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TABLE 11 Out-of-sample predictive regression estimation results (F1: 50% IS).

Panel A: Technical rules

	BTC		ETH		XRP		DASH
PMA1	**0.016* (1.797)**	MA (75, 20, 0.03)	−0.156 (0.159)	MA (20, 1, 3)	−0.029 (0.278)	MA (5, 2, 0)	−0.014 (0.189)
CB (5, 0.075, 5, 0.01)	−0.017 (0.345)	MA (50, 20, 0.04)	−0.081 (0.239)	MA (20, 10, 3)	−0.051 (0.262)	MA (5, 2, 0.05)	−0.007 (0.41)
CB (5, 0.075, 5, 0.005)	−0.023 (0.246)	MA (75, 20, 0.015)	−0.117 (0.207)	MA (30, 5, 3)	−0.021 (0.295)	MA (15, 2, 0.04)	−0.01 (0.199)
MA (200, 25, 0.001)	−0.032 (0.225)	PMA1	**0.16* (1.851)**	MA (30, 10, 3)	−0.144 (0.152)	PMA1	−0.01 (0.259)
MA (150, 30, 25)	−0.015 (0.29)	MA (200, 15, 0.02)	−0.088 (0.246)	MA (30, 5, 5)	−0.026 (0.318)	MA (5, 1, 0.01)	−0.006 (0.229)
MA (10, 2, 0)	−0.015 (0.278)	MA (50, 25, 0)	−0.167 (0.17)	MA (30, 2, 5)	−0.021 (0.253)	MA (5, 2, 0.05)	−0.009 (0.307)
MA (150, 30, 5)	−0.016 (0.468)	MA (75, 40, 0.02)	−0.09 (0.234)	MA (20, 10, 5)	−0.029 (0.249)	FR (0.02, 5)	−0.01 (0.254)
MA (200, 1, 0.02)	−0.025 (0.266)	MA (50, 30, 0.01)	−0.12 (0.258)	MA (20, 15, 5)	−0.051 (0.232)	FR (0.045, 5)	−0.007 (0.371)
MA (75, 1, 5)	−0.019 (0.362)	MA (75, 50, 0)	−0.083 (0.246)	PMA1	**0.03* (1.937)**	MA (10, 5, 0.01)	−0.007 (0.332)
MA (200, 25, 0.01)	−0.016 (0.328)	MA (50, 25, 0.005)	−0.084 (0.223)	PMA4	−0.036 (0.23)	MA (10, 2, 0.005)	−0.012 (0.218)
FR (0.035,1)	−0.015 (0.387)	MA (50, 40, 0.03)	−0.082 (0.219)	MA (5, 2, 5)	−0.021 (0.376)	FR (0.01, 5)	−0.006 (0.307)
MA (75, 30, 25)	−0.023 (0.175)	MA (50, 40, 0.015)	−0.09 (0.218)	FR (0.005,5)	−0.024 (0.317)	MA (10, 2, 0.005)	−0.008 (0.297)
MA (75, 40, 5)	−0.014 (0.383)	FR (0.035,1)	−0.079 (0.25)	MA (75, 20, 5)	−0.028 (0.246)	FR0.005	−0.007 (0.316)
MA (40, 1, 5)	−0.026 (0.228)	MA (75, 40, 0.001)	−1.047 (0.117)	MA (75, 10, 3)	−0.026 (0.288)	MA (5, 2, 0.015)	−0.012 (0.245)
MA (200, 20, 0.05)	−0.02 (0.243)	MA (125, 5, 0)	−0.203 (0.152)	MA (40, 30, 3)	−0.127 (0.129)	MA (2, 1, 0)	−0.01 (0.363)

Panel B: Traditional fundamental factors

	BTC	ETH	XRP	DASH
3mBill	−0.019 (0.665)	−0.012 (0.878)	−0.028 (0.8)	−0.015 (0.726)
10yBill	−0.015 (0.6)	−0.01 (0.886)	−0.024 (0.75)	−0.014 (0.696)
DJIA	−0.021 (0.841)	−0.027 (0.759)	−0.038 (0.8)	−0.025 (0.877)
GLD	−0.025 (0.667)	−0.298 (0.28)	−0.079 (0.488)	−0.131 (0.317)
MAAA	−0.019 (0.797)	−0.018 (1.062)	−0.039 (0.712)	−0.023 (0.699)
MBaa	−0.012 (0.567)	−0.01 (0.893)	−0.023 (0.79)	−0.016 (0.712)
MSCI	−0.21 (0.286)	−0.031 (0.805)	−0.425 (0.285)	−0.353 (0.278)
NSQ	−0.016 (0.848)	−0.023 (0.945)	−0.035 (0.839)	−0.023 (0.894)
OIL	−0.028 (0.794)	−0.033 (0.684)	−0.05 (0.773)	−0.02 (0.823)
MER	0.054 (−0.09)	−0.016 (0.843)	0.058 (0.052)	0.029 (0.085)
VIX	−0.048 (0.63)	−0.031 (0.636)	−0.067 (0.678)	−0.03 (0.675)
VXN	−0.037 (0.67)	−0.028 (0.644)	−0.05 (0.854)	−0.024 (0.937)
VXD	−0.042 (0.617)	−0.031 (0.644)	−0.064 (0.681)	−0.03 (0.658)
SP500	−0.018 (0.872)	−0.025 (0.847)	−0.036 (0.8)	−0.025 (0.874)

Panel C: Multiple currency factors

	BTC	ETH	XRP	DASH
AUD	−0.112 (0.383)	−0.051 (0.488)	−0.23 (0.366)	−0.171 (0.32)
EUR	−0.088 (0.328)	−0.024 (0.981)	−0.184 (0.317)	−0.153 (0.295)
YEN	−0.016 (0.8)	−0.017 (1.043)	−0.046 (0.567)	−0.027 (0.558)
CAD	−0.052 (0.608)	−0.036 (0.685)	−0.095 (0.552)	−0.051 (0.649)
BRL	−0.119 (0.264)	−0.16 (0.318)	−0.319 (0.264)	−0.841 (0.264)
RMB	−0.023 (0.724)	−0.035 (0.703)	−0.045 (0.616)	−0.027 (0.894)
CHF	−0.656 (0.265)	−0.02 (0.667)	−0.636 (0.265)	−0.163 (0.265)
IDR	−0.027 (0.928)	−0.024 (0.658)	−0.052 (0.774)	−0.028 (0.685)
KRW	−0.09 (0.388)	−0.059 (0.349)	−0.144 (0.488)	−0.066 (0.547)
VEF	−0.01 (0.722)	−0.006 (0.745)	−0.019 (0.599)	−0.011 (0.469)
GBP	−0.042 (0.406)	−0.021 (0.836)	−0.076 (0.465)	−0.046 (0.482)
RUB	−0.34 (0.282)	−0.03 (0.583)	−0.517 (0.283)	−0.358 (0.278)
TRY	−0.147 (0.384)	−0.128 (0.297)	−0.371 (0.347)	−0.09 (0.459)

Panel D: Bitcoin and blockchain trend-based factors

	BTC	ETH	XRP	DASH
NTs	−0.978 (0.224)	−0.314 (0.223)	−0.106 (0.224)	−1.662 (0.229)
NPs	−0.039 (0.819)	−0.059 (0.509)	−0.051 (0.733)	−0.029 (0.723)
NUs	−0.024 (0.812)	−0.034 (0.608)	−0.035 (0.766)	−0.036 (0.501)
PVs	−0.027 (0.687)	−0.038 (0.514)	−0.039 (0.625)	−0.03 (0.723)
Btc-W	−0.019 (0.765)	−0.086 (0.377)	−0.032 (0.739)	−0.039 (0.358)
Eth-W	−0.052 (0.354)	−0.052 (0.331)	−0.123 (0.276)	−0.046 (0.303)
Xrp-W	−0.03 (0.765)	−0.052 (0.343)	−0.059 (0.636)	−0.026 (0.681)
Doge-W	−0.122 (0.345)	−0.043 (0.625)	−0.155 (0.311)	−0.036 (0.617)
Btc-GT	−0.138 (0.282)	−0.849 (0.229)	−0.188 (0.26)	−0.032 (0.462)
Eth-GT	−0.021 (0.768)	−0.03 (0.699)	−0.032 (0.842)	−0.025 (0.796)
Xrp-GT	−0.016 (0.723)	−0.021 (0.412)	−0.016 (0.838)	−0.01 (0.474)
Doge-GT	−0.137 (0.329)	−0.037 (0.58)	−0.124 (0.328)	−0.063 (0.434)

Panel E: Blockchain technology-based factors

	BTC	ETH	XRP	DASH
BZ	−0.021 (0.565)	−0.023 (0.492)	−0.035 (0.538)	−0.015 (0.489)
BSV	−0.019 (0.533)	−0.085 (0.262)	−0.032 (0.627)	−0.013 (0.643)
HSH	**0.225* (1.824)**	**0.843* (1.826)**	**0.299** (2.005)**	0.069 (0.274)
MD	0.016 (0.714)	0.017 (0.697)	0.023 (0.769)	0.011 (0.734)
TBT	−0.278 (0.231)	−2.321 (0.225)	−0.371 (0.237)	−0.079 (0.254)
TBM	−0.023 (0.675)	−0.029 (0.687)	−0.044 (0.556)	−0.019 (0.492)
DOD	−0.026 (0.582)	−0.073 (0.442)	−0.056 (0.547)	−0.018 (0.482)
UBA	−0.016 (0.589)	−0.033 (0.347)	−0.042 (0.481)	−0.016 (0.435)
DBT	−1.217 (0.225)	−9.939 (0.223)	−1.634 (0.226)	−0.281 (0.231)
EPU	−0.008 (0.714)	−0.015 (0.528)	−0.019 (0.617)	−0.007 (0.686)

Panel F: Multiple stock indices

	BTC	ETH	XRP	DASH
NI225	−0.043 (0.643)	−0.048 (0.694)	−0.081 (0.611)	−0.032 (0.586)
IBVC	−0.026 (0.647)	−0.046 (0.594)	−0.069 (0.562)	−0.025 (0.611)
BRA	−0.15 (0.426)	−0.096 (0.384)	−0.428 (0.412)	−0.156 (0.404)
TSX	−0.035 (0.776)	−0.026 (0.667)	−0.073 (0.611)	−0.042 (0.732)
KOSPI	−0.027 (0.794)	−0.039 (0.642)	−0.054 (0.702)	−0.036 (0.785)
ASX	−0.032 (0.55)	−0.02 (0.889)	−0.09 (0.427)	−0.048 (0.432)
JCI	−0.04 (0.639)	−0.047 (0.676)	−0.069 (0.659)	−0.028 (0.626)
SMI	−0.034 (0.722)	−0.02 (0.83)	−0.092 (0.599)	−0.04 (0.659)
SSE	−0.022 (0.654)	−0.022 (0.879)	−0.046 (0.759)	−0.029 (0.817)
RTS	−0.03 (0.9)	−0.024 (0.855)	−0.058 (0.594)	−0.034 (0.627)

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 of the top 15 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 explained in Table 4, keeping 50% of the total dataset out-of-sample.

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TABLE 12 Out-of-sample predictive regression estimation results (F2: 75% IS).

Panel A: Technical rules

	BTC		ETH		XRP		DASH
CB (15, 0.1, 25, 100)	−0.018 (0.372)	CB (10, 0.03, 10, 20)	−0.644 (0.16)	CB (10, 0.03, 10, 20)	−0.031 (0.389)	CB (10, 0.03, 10, 20)	−0.02 (0.395)
FR (0.01, 5)	−0.061 (0.217)	MA (75, 20, 0.03)	−0.019 (0.325)	PMA1	**0.02* (1.833)**	MA (10, 5, 0.01)	−0.016 (0.371)
MA (50, 5, 0.03)	−0.018 (0.295)	MA (50, 20, 0.04)	−0.068 (0.231)	FR (0.14, 10)	−0.026 (0.379)	PMA1	−0.012 (0.438)
MA (50, 2, 0.02)	−0.012 (0.472)	PMA1	**0.029* (1.929)**	FR (0.005, 3)	−0.076 (0.193)	MA (10, 5, 0.02)	−0.018 (0.366)
MA (50, 20, 25)	−0.026 (0.292)	FR (0.01,1)	−0.053 (0.193)	MA (40, 25, 0.05)	−0.071 (0.209)	MA (5, 2, 0.05)	−0.022 (0.435)
PMA1	**0.126* (1.834)**	MA (75, 20, 0.05)	−0.012 (0.432)	MA (15, 1, 0.005)	−0.046 (0.278)	MA (10, 5, 0.04)	−0.012 (0.562)
CB (5, 0.075, 5, 0.01)	−0.014 (0.489)	MA (50, 15, 0.015)	−0.011 (0.487)	MA (50, 20, 0.02)	−0.043 (0.238)	MA (10, 2, 0)	−0.013 (0.476)
CB (5, 0.075, 5, 0)	−0.075 (0.181)	MA (75, 30, 0)	−0.017 (0.482)	MA (75, 10, 0.005)	−0.03 (0.449)	MA (15, 10, 0.02)	−0.241 (0.168)
FR (0.02, 0.015)	−0.017 (0.471)	MA (75, 25, 0.001)	−0.011 (0.379)	MA (40, 20, 0.02)	−0.045 (0.3)	MA (15, 1, 0.015)	−1.31 (0.159)
MA (50, 15, 25)	−0.259 (0.167)	MA (40, 25, 0.03)	−0.008 (0.344)	MA (40, 20, 0.001)	−0.031 (0.322)	MA (5, 1, 0.01)	−0.035 (0.217)
PMA2	−0.013 (0.5)	MA (40, 30, 0.04)	−0.01 (0.436)	MA (10, 5, 0.001)	−0.058 (0.226)	MA (15, 10, 0.04)	−0.018 (0.383)
MA (2,1,0.05)	−0.019 (0.515)	MA (50, 5, 0.05)	−0.013 (0.482)	MA (50, 15, 0.015)	−0.021 (0.482)	MA (20, 1, 0.015)	−0.017 (0.432)
MA (10,1,0.01)	−0.15 (0.173)	MA (50, 1, 0)	−0.014 (0.318)	MA (40, 20, 0.04)	−0.096 (0.183)	MA (10, 2, 0.005)	−0.033 (0.273)
FR (0.025, 0.025)	−0.025 (0.336)	MA (75, 40, 0.01)	−2.946 (0.159)	MA(75, 1, 0.001)	−0.072 (0.25)	MA (5, 2, 0.015)	−0.019 (0.416)
FR (0.01, 15)	−0.015 (0.466)	MA (50, 1, 0.015)	−0.021 (0.434)	MA (50, 40, 0.03)	−0.021 (0.514)	FR (0.025, 5)	−0.012 (0.488)

Panel B: Traditional fundamental factors

	BTC	ETH	XRP	DASH
3mBill	−0.031 (1.128)	−0.112 (0.514)	−0.04 (0.981)	−0.028 (1.09)
10yBill	−0.754 (0.386)	−0.061 (0.911)	−0.691 (0.392)	−0.313 (0.40)
DJIA	−0.045 (1.046)	−0.085 (0.626)	−0.086 (0.699)	−0.042 (1.031)
GLD	−0.05 (0.917)	−0.091 (0.639)	−0.047 (0.99)	−0.026 (1.099)
MAAA	−0.048 (1.334)	−0.068 (0.829)	−0.078 (0.735)	−0.038 (1.265)
MBaa	−0.502 (0.375)	−0.312 (0.401)	−0.384 (0.375)	−0.738 (0.375)
MSCI	−0.098 (0.775)	−0.203 (0.51)	−0.159 (0.627)	−0.077 (0.85)
NSQ	−0.055 (1.035)	−0.091 (0.594)	−0.086 (0.953)	−0.049 (1.286)
OIL	−0.108 (0.5)	−0.175 (0.589)	−0.109 (0.495)	−0.066 (0.669)
MER	0.053 (0.545)	−0.036 (0.902)	0.015 (0.534)	0.009 (0.633)
VIX	−0.019 (0.945)	−0.042 (0.874)	−0.02 (1.172)	−0.008 (0.94)
VXN	−0.016 (0.832)	−0.039 (0.892)	−0.029 (1.09)	−0.016 (0.942)
VXD	−0.018 (1.024)	−0.042 (0.898)	−0.026 (1.237)	−0.016 (1.036)
SP500	−0.06 (1.112)	−0.103 (0.667)	−0.142 (0.569)	−0.054 (1.219)

Panel C: Multiple currency factors

	BTC	ETH	XRP	DASH
AUD	−0.059 (0.963)	−0.118 (0.558)	−0.059 (0.96)	−0.05 (1.06)
EUR	−0.059 (0.832)	−0.088 (0.584)	−0.095 (0.727)	−0.055 (0.828)
YEN	−0.023 (1.198)	−0.034 (1.58)	−0.049 (1.096)	−0.03 (1.169)
CAD	−0.067 (0.9)	−0.055 (0.752)	−0.086 (0.887)	−0.049 (1.092)
BRL	−0.031 (0.888)	−0.029 (1.065)	−0.043 (0.901)	−0.021 (1.012)
RMB	−0.021 (1.016)	−0.039 (1.177)	−0.043 (0.999)	−0.029 (1.197)
CHF	−0.274 (0.421)	−0.889 (0.388)	−0.203 (0.512)	−0.199 (0.434)
IDR	−0.084 (0.466)	−0.307 (0.404)	−0.045 (0.729)	−0.064 (0.507)
KRW	−0.022 (1.12)	−0.025 (1.264)	−0.038 (1.04)	−0.02 (1.107)
VEF	−0.013 (0.964)	−0.015 (1.118)	−0.019 (0.953)	−0.011 (1.124)
GBP	−0.045 (0.735)	−0.091 (0.544)	−0.078 (0.836)	−0.035 (1.1)
RUB	−0.04 (1.076)	−0.044 (1.131)	−0.042 (1.17)	−0.024 (1.228)
TRY	−0.027 (0.708)	−0.056 (0.834)	−0.048 (0.904)	−0.028 (0.915)

Panel D: Bitcoin and blockchain trend-based factors

	BTC	ETH	XRP	DASH
NTs	−0.03 (1.064)	−0.066 (0.634)	−0.032 (1.021)	−0.041 (0.862)
NPs	−0.076 (0.723)	−0.067 (0.565)	−0.075 (0.688)	−0.055 (0.951)
NUs	−0.707 (0.35)	−0.098 (0.6)	−1.66 (0.329)	−0.46 (0.381)
PVs	−0.051 (0.929)	−0.031 (1.128)	−0.047 (0.659)	−0.053 (1.128)
Btc-W	−0.021 (0.918)	−0.026 (0.82)	−0.036 (0.927)	−0.028 (0.854)
Eth-W	−0.017 (0.775)	−0.024 (0.742)	−0.039 (1.001)	−0.03 (0.851)
Xrp-W	−0.038 (0.801)	−0.045 (0.626)	−0.06 (0.799)	−0.055 (0.762)
Doge-W	−0.162 (0.383)	−0.086 (0.634)	−0.254 (0.405)	−0.11 (0.691)
Btc-GT	−0.025 (0.85)	−0.028 (0.767)	−0.042 (0.809)	−0.027 (0.782)
Eth-GT	−0.02 (0.776)	−0.022 (0.892)	−0.045 (0.936)	−0.039 (0.829)
Xrp-GT	−0.015 (0.959)	−0.015 (0.777)	−0.03 (0.659)	−0.038 (0.819)
Doge-GT	−0.263 (0.394)	−0.097 (0.552)	−0.351 (0.509)	−0.088 (0.812)

Panel E: Blockchain technology-based factors

	BTC	ETH	XRP	DASH
BZ	−0.02 (1.059)	−0.017 (0.92)	−0.022 (1.138)	−0.013 (0.977)
BSV	−0.02 (0.964)	−0.024 (0.713)	−0.022 (0.966)	−0.017 (0.911)
HSH	**0.019* (1.856)**	**0.02* (1.915)**	**0.025* (1.813)**	0.017 (0.982)
MD	0.028 (0.628)	0.041 (0.599)	0.026 (0.963)	0.021 (0.889)
TBT	−0.02 (0.894)	−0.016 (0.767)	−0.026 (0.791)	−0.014 (0.893)
TBM	−0.028 (0.945)	−0.033 (0.84)	−0.05 (0.934)	−0.026 (1.005)
DOD	−0.022 (1.091)	−0.017 (1.189)	−0.027 (1.074)	−0.019 (0.876)
UBA	−0.016 (0.875)	−0.011 (0.765)	−0.022 (1.001)	−0.013 (0.862)
DBT	−0.011 (0.693)	−0.004 (0.55)	−0.02 (0.901)	−0.012 (0.906)
EPU	−0.018 (0.6)	−0.023 (0.764)	−0.034 (0.502)	−0.015 (0.901)

Panel F: Multiple stock indice

	BTC	ETH	XRP	DASH
NI225	−0.039 (0.636)	−0.048 (1.108)	−0.058 (0.782)	−0.036 (0.837)
IBVC	−0.05 (0.683)	−0.067 (0.853)	−0.089 (0.846)	−0.044 (0.922)
BRA	−0.027 (1.186)	−0.035 (1.223)	−0.037 (1.065)	−0.033 (1.073)
TSX	−0.068 (0.826)	−0.091 (0.525)	−0.099 (0.939)	−0.054 (1.091)
KOSPI	−0.042 (1.215)	−0.044 (1.095)	−0.055 (1.211)	−0.049 (1.118)
ASX	−0.078 (0.582)	−0.23 (0.445)	−0.082 (0.81)	−0.074 (0.62)
JCI	−0.037 (0.668)	−0.047 (1.078)	−0.059 (0.831)	−0.035 (0.867)
SMI	−0.061 (0.7)	−0.087 (0.607)	−0.209 (0.452)	−0.069 (0.563)
SSE	−0.099 (0.466)	−0.141 (0.472)	−0.115 (0.5)	−0.06 (0.591)
RTS	−0.04 (0.883)	−0.055 (1.156)	−0.045 (1.115)	−0.033 (1.149)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_i + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ 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 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. 75% IS corresponds to period 2, as explained in Table 4, keeping 25% of the total dataset out-of-sample.

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TABLE 13 Out-of-sample predictive regression estimation results (F3: 90% IS).

Panel A: Technical rules

	BTC		ETH		XRP		DASH
CB (15, 0.1, 25, 100)	0.154 (0.794)	CB (10, 0.03, 10, 20)	−0.046 (0.665)	CB (10, 0.03, 10, 20)	−0.069 (0.555)	CB (10, 0.03, 10, 20)	−0.062 (0.67)
FR (0.01, 5)	−0.443 (0.297)	MA (200, 5, 0.04)	−0.084 (0.463)	MA (10, 2, 0.005)	−0.734 (0.408)	MA (10, 5, 0.01)	−0.058 (0.444)
PMA1	**0.07*(1.816)**	MA (50, 5, 0.03)	−0.071 (0.564)	MA (15, 1, 0.005)	−0.144 (0.423)	MA (10, 2, 0.005)	−0.061 (0.55)
CB (5, 0.075, 5, 0.01)	−0.039 (0.602)	MA (50, 20, 0.04)	−0.093 (0.639)	**PMA1**	**0.09* (1.828)**	MA (5, 1, 0.01)	−0.06 (0.546)
CB (5, 0.075, 5, 0.015)	−0.036 (0.617)	MA (75, 20, 0.03)	−0.05 (0.791)	MA (2,1,0.02)	−0.071 (0.476)	MA (10, 5, 0.04)	−0.073 (0.537)
MA (200, 125, 25)	−0.073 (0.562)	MA (75, 1, 0.001)	−0.072 (0.58)	MA (2,1,0.015)	−0.446 (0.349)	MA (5, 2, 0.015)	−0.075 (0.409)
FR (0.03, 3)	−0.041 (0.694)	MA (50, 2, 0.02)	−0.05 (0.764)	MA (2,1,0.02)	−0.103 (0.531)	FR (0.005, 3)	−0.068 (0.568)
FR (0.035, 1)	−0.126 (0.446)	MA (100, 30, 0.015)	−0.053 (0.651)	MA (40, 20, 5)	−0.099 (0.501)	FR (0.04, 15)	−0.088 (0.597)
FR (0.04, 1)	−0.094 (0.553)	FR (0.07, 0.15)	−0.155 (0.278)	M A(40, 1, 0.05)	−0.09 (0.548)	FR (0.01, 3)	−0.067 (0.746)
MA (5, 1, 0.015)	−0.227 (0.337)	MA (100, 30, 0.005)	−0.09 (0.446)	MA (75, 1, 0.01)	−0.111 (0.55)	FR (0.005, 3)	−0.085 (0.552)
MA (10, 5, 0.05)	−0.101 (0.664)	FR (0.035, 0.04)	−0.076 (0.592)	MA (10, 5, 0.02)	−0.228 (0.343)	PMA1	−0.071 (0.543)
FR (0.005, 1)	−0.075 (0.455)	FR (0.04, 0.025)	−0.123 (0.364)	MA (40, 20, 0.02)	−0.067 (0.632)	FR (0.01, 1)	−0.061 (0.713)
MA (2, 1, 0.05)	−0.059 (0.504)	**PMA1**	**0.06* (1.791)**	MA (15, 1, 0.03)	−0.346 (0.311)	FR (0.045, 1)	−0.071 (0.644)
FR (0.005, 5)	−0.059 (0.629)	PMA2	−0.106 (0.55)	MA (100, 25, 0.04)	−0.173 (0.523)	FR (0.045, 15)	−0.068 (0.592)
MA (10,1,0.01)	−0.056 (0.606)	FR (0.4, 0.04)	−0.062 (0.8)	MA (40, 15, 25)	−0.127 (0.431)	FR (0.01, 5)	−0.062 (0.631)

Panel B: Traditional fundamental factors

	BTC	ETH	XRP	DASH
3mBill	**0.089*** (2.468)**	**0.099*** (2.368)**	**0.16*(1.914)**	−0.114 (1.428)
10yBill	−0.24 (0.824)	−0.687 (0.595)	−0.272 (0.612)	−0.85 (0.659)
DJIA	−0.252 (1.512)	−0.168 (1.132)	−0.668 (0.894)	−0.339 (1.394)
GLD	−0.194 (1.417)	−0.18 (1.668)	−1.134 (0.73)	−0.204 (1.667)
MAAA	−0.178 (1.061)	−0.108 (1.42)	−0.462 (1.011)	−0.262 (1.002)
MBaa	−0.782 (0.598)	−0.132 (0.592)	−0.308 (0.593)	−0.146 (0.596)
MSCI	−0.108 (1.659)	−0.184 (1.325)	−0.222 (1.709)	−0.115 (1.539)
NSQ	**0.222* (1.813)**	**0.262* (1.856)**	−0.473 (1.678)	−0.276 (1.635)
OIL	**0.079* (1.796)**	**0.054* (1.812)**	**0.207* (1.817)**	**0.142* (1.935)**
MER	0.01 (0.119)	−0.134 (1.331)	−0.143 (1.562)	−0.104 (0.11)
VIX	−0.102 (1.751)	−0.169 (1.205)	−0.639 (0.84)	−0.134 (1.223)
VXN	−0.132 (1.666)	−0.36 (1.012)	−0.215 (1.076)	−0.172 (1.329)
VXD	−0.41 (0.882)	−0.187 (1.194)	−0.673 (1.182)	−0.611 (0.734)
SP500	−0.187 (1.679)	−0.281 (0.972)	−0.312 (1.175)	−0.261 (1.434)

Panel C: Multiple currency factors

BTC	ETH	XRP	DASH	BTC
AUD	−0.106 (1.648)	−0.112 (1.528)	−0.328 (1.143)	−0.118 (1.329)
EUR	−0.137 (1.586)	−0.138 (1.218)	−0.259 (1.396)	−0.172 (1.48)
YEN	−0.372 (0.905)	−0.296 (1.009)	−0.383 (0.626)	−0.336 (1.062)
CAD	−0.127 (1.235)	−0.094 (1.234)	−0.266 (1.236)	−0.166 (1.414)
BRL	−1.12 (0.641)	−0.296 (1.73)	−1.145 (0.681)	−1.42 (0.635)
RMB	**0.17* (1.916)**	−0.167 (1.331)	−0.8 (0.842)	**0.178** (2.029)**
CHF	−0.256 (1.293)	−0.18 (1.343)	−0.589 (1.112)	−0.376 (1.17)
IDR	−0.15 (1.227)	0.088 (1.091)	−0.264 (1.136)	−0.253 (0.858)
KRW	−0.252 (0.874)	−0.207 (1.143)	−0.348 (0.971)	−0.375 (0.764)
VEF	−0.051 (1.565)	−0.052 (1.445)	−0.109 (1.149)	−0.055 (0.914)
GBP	−0.126 (1.381)	0.12 (2.052)	−0.27 (1.436)	−0.158 (1.18)
RUB	−0.431 (1.268)	−0.295 (1.43)	−0.125 (0.644)	−0.362 (1.384)
TRY	−0.586 (0.961)	−0.182 (1.425)	−0.002 (0.704)	−0.835 (0.776)

Panel D: Bitcoin and blockchain trend-based factors

	BTC	ETH	XRP	DASH
NTs	−0.159 (0.622)	−0.507 (0.545)	−0.209 (0.523)	−0.216 (0.626)
NPs	−0.094 (0.828)	−0.202 (0.655)	−0.404 (0.898)	−0.309 (0.581)
NUs	−0.093 (1.776)	−0.069 (1.676)	−0.177 (1.377)	−0.192 (1.193)
PVs	−0.059 (1.679)	−0.048 (1.597)	−0.126 (1.159)	−0.076 (1.37)
Btc-W	−0.118 (1.355)	−0.127 (0.706)	−0.206 (1.237)	−0.295 (1.095)
Eth-W	−0.07 (1.606)	−0.074 (1.36)	−0.279 (0.902)	−0.082 (1.396)
Xrp-W	−0.618 (0.554)	−0.866 (0.505)	−0.547 (0.744)	−0.063 (0.507)
Doge-W	−0.155 (1.24)	−0.399 (0.604)	−0.636 (0.872)	−0.132 (1.35)
Btc-GT	−0.072 (1.439)	−0.065 (1.4)	−0.16 (1.515)	−0.259 (1.075)
Eth-GT	−0.073 (1.374)	−0.086 (0.965)	−0.469 (0.675)	−0.105 (1.663)
Xrp-GT	−0.116 (0.849)	−0.085 (1.65)	−0.812 (0.593)	−0.114 (1.096)
Doge-GT	−0.073 (1.677)	−0.053 (1.391)	−0.228 (1.032)	−0.111 (1.694)*

Panel E: Blockchain technology-based factors

	BTC	ETH	XRP	DASH
BZ	−0.064 (0.941)	−0.044 (1.455)	−0.407 (0.629)	−0.077 (1.026)
BSV	−0.069 (1.321)	−0.071 (1.244)	−0.137 (0.988)	−0.096 (0.86)
HSH	**0.06* (1.867)**	**0.054* (1.813)**	**0.136* (1.883)**	0.065 (1.363)
MD	**0.068* (1.881)**	0.145 (1.314)	0.123 (1.301)	0.072 (1.42)
TBT	−0.05 (1.492)	−0.059 (1.673)	−0.11 (1.711)	−0.059 (1.194)
TBM	−0.108 (1.206)	−0.11 (1.647)	−0.233 (1.366)	−0.142 (1.667)
DOD	−0.34 (0.86)	−0.332 (0.736)	−0.424 (0.586)	−0.315 (0.932)
UBA	−0.073 (0.802)	−0.037 (1.343)	−0.525 (0.589)	−0.081 (0.945)
DBT	−0.152 (0.633)	−0.156 (0.651)	−0.711 (0.524)	−0.169 (0.676)
EPU	−0.161 (0.626)	−0.316 (0.55)	−0.295 (0.522)	−0.264 (0.597)

Panel F: Multiple stock indices

	BTC	ETH	XRP	DASH
NI225	−0.142 (1.612)	−0.177 (1.456)	−0.719 (0.734)	−0.128 (1.424)
IBVC	−0.142 (1.572)	−0.135 (1.538)	−0.332 (1.172)	−0.23 (1.529)
BRA	−0.047 (1.551)	−0.166 (1.439)	−0.163 (1.667)	−0.054 (1.435)
TSX	−0.115 (1.227)	−0.111 (1.189)	−0.187 (1.488)	−0.121 (1.525)
KOSPI	−0.11 (1.672)	−0.272 (0.935)	−0.231 (0.762)	−0.151 (1.403)
ASX	−0.094 (1.444)	−0.095 (1.627)	−0.166 (1.547)	−0.132 (1.108)
JCI	−0.214 (1.231)	−0.21 (1.519)	−1.667 (0.656)	−0.181 (1.154)
SMI	−0.44 (0.599)	−0.866 (0.6)	−1.247 (0.599)	−0.697 (0.6)
SSE	**0.09* (1.859)**	**0.13* (1.839)**	**0.17* (1.807)**	**0.213* (1.841)**
RTS	−0.153 (1.069)	−0.124 (1.093)	−0.261 (1.31)	−0.14 (1.205)

Note: This table presents the out-of-sample estimation results for the bivariate regression model $r_{t+1} = \alpha_i + \beta_i X_{i,t} + \varepsilon_{i,t+1}$ 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, 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 $\hat{r}^{HA}_{t+1} = (1/t)\sum_{s=1}^{t} r_s$. 90% IS corresponds to period 3, as explained in Table 4, keeping 10% of the total dataset out-of-sample. Bold indicates the factors that are found to be significant (at any level).

*Significance at the 10% level.

**Significance at the 5% level.

***Significance at the 1% level.

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TABLE 14 Out-of-sample profitability performance results (50% IS).

Panel A: Technical rules

	BTC		ETH		XRP		DASH
PMA1	**0.189 (0.004)**	MA (75, 20, 0.03)	0.064 (0.005)	MA (20, 1, 3)	0.664 (0.006)	MA (5, 2, 0)	0.484 (0.003)
CB (5, 0.075, 5, 0.01)	0.165 (0.004)	MA (50, 20, 0.04)	0.113 (0.005)	MA (20, 10, 3)	0.508 (0.006)	M A(5, 2, 0.05)	0.449 (0.004)
CB (5, 0.075,5, 0.005)	0.116 (0.004)	MA (75, 20, 0.015)	0.109 (0.006)	MA (30, 5, 3)	0.778 (0.005)	MA (15, 2, 0.04)	0.447 (0.003)
MA (200, 25, 0.001)	0.127 (0.004)	**PMA1**	**0.086 (0.006)**	MA (30, 10, 3)	0.296 (0.006)	PMA1	0.385 (0.003)
MA (150, 30, 25)	0.108 (0.004)	MA (200, 15, 0.02)	0.119 (0.005)	MA (30, 5, 5)	0.729 (0.005)	MA (5, 1, 0.01)	1.075 (0.002)
MA (10, 2, 0)	0.164 (0.004)	MA (50, 25, 0)	0.095 (0.006)	MA (30, 2, 5)	0.883 (0.005)	MA (5, 2, 0.05)	0.403 (0.003)
MA (150, 30, 5)	0.266 (0.005)	MA (75, 40, 0.02)	0.083 (0.005)	MA (20, 10, 5)	0.835 (0.005)	FR (0.02, 5)	0.738 (0.003)
MA (200, 1, 0.02)	0.125 (0.004)	MA (50, 30, 0.01)	0.094 (0.005)	MA (20, 15, 5)	0.555 (0.006)	FR (0.045, 5)	0.289 (0.004)
MA (75, 1, 5)	0.148 (0.004)	MA (75, 50, 0)	0.176 (0.006)	PMA1	**0.974 (0.005)**	MA (10, 5, 0.01)	0.638 (0.003)
MA (200, 25, 0.01)	0.141 (0.004)	MA (50, 25, 0.005)	0.151 (0.006)	PMA4	0.673 (0.005)	MA (10, 2, 0.005)	0.627 (0.002)
FR (0.035,1)	0.258 (0.005)	MA (50, 40, 0.03)	0.096 (0.005)	MA (5, 2, 5)	0.545 (0.006)	FR (0.01, 5)	1.095 (0.002)
MA (75, 30, 25)	0.161 (0.004)	MA (50, 40, 0.015)	0.085 (0.005)	FR (0.005,5)	1.336 (0.005)	MA (10, 2, 0.005)	0.771 (0.002)
MA (75, 40, 5)	0.146 (0.004)	FR (0.035,1)	0.147 (0.006)	MA (75, 20, 5)	0.726 (0.005)	FR0.005	1.29 (0.002)
MA (40, 1, 5)	0.241 (0.005)	MA (75, 40, 0.001)	0.051 (0.006)	MA (75, 10, 3)	0.647 (0.006)	MA (5, 2, 0.015)	0.481 (0.003)
MA (200, 20, 0.05)	0.202 (0.005)	MA (125, 5, 0)	0.069 (0.005)	MA (40, 30, 3)	0.341 (0.005)	MA (2, 1, 0)	0.818 (0.002)

Panel B: Traditional fundamental factors

	BTC	ETH	XRP	DASH
3mBill	0.649 (0.005)	0.402 (0.002)	1.531 (0.006)	0.705 (0.004)
10yBill	0.435 (0.004)	0.465 (0.002)	1.035 (0.004)	1.42 (0.002)
DJIA	0.632 (0.006)	0.382 (0.006)	1.124 (0.005)	0.161 (0.005)
GLD	0.358 (0.006)	0.079 (0.006)	0.196 (0.007)	0.027 (0.006)
MAAA	0.417 (0.006)	0.304 (0.006)	0.991 (0.005)	0.289 (0.004)
MBaa	0.301 (0.004)	0.618 (0.002)	0.251 (0.004)	1.694 (0.002)
MSCI	0.814 (0.006)	0.334 (0.006)	0.972 (0.006)	0.292 (0.004)
NSQ	1.055 (0.007)	0.544 (0.007)	0.695 (0.008)	0.064 (0.006)
OIL	0.503 (0.005)	0.209 (0.005)	0.624 (0.006)	0.497 (0.003)
MER	0.495 (0.007)	0.151 (0.003)	0.212 (0.009)	0.375 (0.006)
VIX	0.406 (0.005)	0.036 (0.004)	0.881 (0.005)	0.356 (0.003)
VXN	0.453 (0.005)	0.019 (0.004)	1.097 (0.005)	0.472 (0.003)
VXD	0.542 (0.006)	0.167 (0.004)	0.942 (0.005)	0.379 (0.003)
SP500	0.771 (0.006)	0.487 (0.007)	0.926 (0.006)	0.617 (0.005)

Panel C: Multiple currency factors

	BTC	ETH	XRP	DASH
AUD	0.355 (0.005)	0.159 (0.004)	0.819 (0.005)	0.549 (0.004)
EUR	0.428 (0.006)	0.262 (0.005)	0.741 (0.006)	0.583 (0.003)
YEN	0.326 (0.004)	0.462 (0.006)	0.897 (0.005)	0.446 (0.004)
CAD	0.36 (0.005)	0.174 (0.005)	0.726 (0.006)	0.19 (0.004)
BRL	0.511 (0.006)	0.126 (0.005)	0.49 (0.007)	0.187 (0.005)
RMB	0.51 (0.007)	0.179 (0.005)	0.364 (0.007)	0.011 (0.005)
CHF	0.377 (0.005)	0.281 (0.005)	1.853 (0.005)	0.854 (0.003)
IDR	0.609 (0.006)	0.174 (0.004)	0.773 (0.006)	0.502 (0.003)
KRW	0.208 (0.007)	0.059 (0.004)	0.187 (0.006)	0.058 (0.004)
VEF	0.714 (0.005)	0.842 (0.002)	1.107 (0.004)	1.688 (0.002)
GBP	0.434 (0.004)	0.17 (0.004)	1.333 (0.005)	0.267 (0.004)
RUB	0.152 (0.009)	0.107 (0.004)	0.033 (0.008)	0.029 (0.006)
TRY	1.397 (0.008)	0.177 (0.004)	0.761 (0.008)	0.182 (0.005)

Panel D: Bitcoin and blockchain trend-based factors

	BTC	ETH	XRP	DASH
NTs	0.251 (0.005)	0.16 (0.005)	0.245 (0.008)	0.263 (0.01)
NPs	0.278 (0.005)	0.124 (0.005)	0.486 (0.006)	0.298 (0.003)
Nus	0.358 (0.006)	0.409 (0.008)	0.194 (0.009)	0.092 (0.007)
PVs	0.27 (0.006)	0.323 (0.007)	0.392 (0.007)	0.019 (0.006)
Btc-W	0.343 (0.006)	0.265 (0.006)	0.336 (0.008)	0.148 (0.004)
Eth-W	0.222 (0.006)	0.287 (0.006)	0.122 (0.008)	0.037 (0.005)
Xrp-W	0.376 (0.005)	0.034 (0.003)	0.496 (0.006)	0.359 (0.003)
Doge-W	0.187 (0.007)	0.182 (0.006)	0.028 (0.01)	0.027 (0.006)
Btc-GT	0.498 (0.008)	0.3 (0.006)	0.324 (0.008)	0.086 (0.006)
Eth-GT	0.351 (0.006)	0.389 (0.007)	0.053 (0.01)	0.159 (0.007)
Xrp-GT	0.158 (0.004)	0.046 (0.004)	0.682 (0.006)	0.147 (0.005)
Doge-GT	0.134 (0.006)	0.148 (0.006)	0.107 (0.008)	0.002 (0.005)

Panel E: Blockchain technology-based factors

	BTC	ETH	XRP	DASH
BZ	0.422 (0.006)	0.514 (0.003)	0.729 (0.006)	0.407 (0.003)
BSV	0.259 (0.004)	0.011 (0.003)	1.129 (0.006)	0.646 (0.003)
HSH	**0.152 (0.004)**	**0.425 (0.005)**	**0.704 (0.006)**	**0.705 (0.003)**
MD	0.123 (0.004)	0.551 (0.006)	1.358 (0.006)	0.507 (0.004)
TBT	0.243 (0.004)	0.036 (0.003)	0.891 (0.006)	2.308 (0.002)
TBM	0.271 (0.005)	0.488 (0.006)	0.684 (0.006)	0.289 (0.004)
DOD	0.185 (0.004)	0.123 (0.003)	1.296 (0.005)	0.698 (0.002)
UBA	0.918 (0.008)	0.159 (0.004)	0.39 (0.008)	0.069 (0.005)
DBT	0.21 (0.004)	0.316 (0.002)	0.878 (0.005)	0.869 (0.002)
EPU	0.264 (0.004)	0.169 (0.003)	1.382 (0.005)	0.918 (0.003)
–				

Panel F: Multiple stock indices

	BTC	ETH	XRP	DASH
NI225	0.616 (0.007)	0.078 (0.004)	0.236 (0.008)	0.178 (0.004)
IBVC	0.455 (0.006)	0.115 (0.005)	0.358 (0.007)	0.294 (0.003)
BRA	0.185 (0.006)	0.166 (0.007)	0.114 (0.007)	0.059 (0.004)
TSX	0.355 (0.005)	0.338 (0.005)	0.729 (0.005)	0.15 (0.004)
KOSPI	0.436 (0.005)	0.198 (0.005)	1.015 (0.006)	0.085 (0.005)
ASX	0.441 (0.006)	0.089 (0.004)	0.467 (0.005)	0.124 (0.004)
JCI	0.656 (0.007)	0.075 (0.004)	0.286 (0.008)	0.202 (0.004)
SMI	0.446 (0.006)	0.599 (0.007)	0.209 (0.008)	0.131 (0.004)
SSE	0.59 (0.006)	0.159 (0.004)	0.933 (0.005)	0.33 (0.003)
RTS	0.371 (0.005)	0.323 (0.006)	0.509 (0.005)	0.208 (0.004)
–				

Note: This table reports the Sharpe 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 of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 respectively. 50% IS corresponds to period 1, as explained in Table 4, keeping 50% of the total dataset out-of-sample. Bold indicates the factors that are found to be significant (at any level).

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TABLE 15 Out-of-sample profitability performance results (75% IS).

Panel A: Technical rules

	BTC		ETH		XRP		DASH
CB (15, 0.1, 25, 100)	0.023 (0.003)	CB (10, 0.03, 10, 20)	0.032 (0.004)	CB (10, 0.03, 10, 20)	0.383 (0.004)	CB (10, 0.03, 10, 20)	0.267 (0.004)
FR (0.01, 5)	0.033 (0.003)	MA (75, 20, 0.03)	0.009 (0.003)	**PMA1**	**0.248 (0.004)**	MA (10, 5, 0.01)	0.2 (0.004)
MA (50, 5, 0.03)	0.03 (0.003)	MA (50, 20, 0.04)	0.053 (0.003)	FR (0.14, 10)	0.381 (0.004)	PMA1	0.266 (0.004)
MA (50, 2, 0.02)	0.04 (0.003)	**PMA1**	**0.072 (0.003)**	FR (0.005, 3)	0.083 (0.005)	MA (10, 5, 0.02)	0.187 (0.004)
MA (50, 20, 25)	0.031 (0.003)	FR (0.01,1)	0.052 (0.003)	MA (40, 25, 0.05)	0.202 (0.004)	MA (5, 2, 0.05)	0.159 (0.004)
PMA1	**0.062 (0.003)**	MA (75, 20, 0.05)	0.061 (0.003)	MA (15, 1, 0.005)	0.182 (0.004)	MA (10, 5, 0.04)	0.245 (0.004)
CB (5, 0.075, 5, 0.01)	0.018 (0.003)	MA (50, 15, 0.015)	0.008 (0.003)	MA (50, 20, 0.02)	0.282 (0.004)	MA (10, 2, 0)	0.408 (0.003)
CB (5, 0.075, 5, 0)	0.029 (0.003)	MA (75, 30, 0)	0.051 (0.003)	MA (75, 10, 0.005)	0.523 (0.004)	MA (15, 10, 0.02)	0.027 (0.004)
FR (0.02, 0.015)	0.035 (0.003)	MA (75, 25, 0.001)	0.042 (0.003)	MA (40, 20, 0.02)	0.311 (0.004)	MA (15, 1, 0.015)	0.003 (0.004)
MA (50, 15, 25)	0.044 (0.003)	MA (40, 25, 0.03)	0.041 (0.003)	MA (40, 20, 0.001)	0.407 (0.004)	MA (5, 1, 0.01)	0.149 (0.004)
PMA2	0.011 (0.003)	MA (40, 30, 0.04)	0.08 (0.003)	MA (10, 5, 0.001)	0.183 (0.004)	MA (15, 10, 0.04)	0.138 (0.004)
MA (2, 1, 0.05)	0.055 (0.003)	MA (50, 5, 0.05)	0.153 (0.004)	MA (50, 15, 0.015)	0.589 (0.004)	MA (20, 1, 0.015)	0.195 (0.004)
MA (10, 1, 0.01)	0.032 (0.003)	MA (50, 1, 0)	0.038 (0.003)	MA (40, 20, 0.04)	0.124 (0.004)	MA (10, 2, 0.005)	0.175 (0.004)
FR (0.025, 0.025)	0.049 (0.003)	MA (75, 40, 0.01)	0.034 (0.004)	MA (75, 1, 0.001)	0.168 (0.004)	MA (5, 2, 0.015)	0.287 (0.003)
FR (0.01, 15)	0.005 (0.003)	MA (50, 1, 0.015)	0.059 (0.003)	MA (50, 40, 0.03)	0.533 (0.004)	FR (0.025, 5)	0.277 (0.004)

Panel B: Traditional fundamental factors

	BTC	ETH	XRP	DASH
3mBill	0.315 (0.004)	0.015 (0.003)	0.364 (0.004)	0.186 (0.004)
10yBill	0.326 (0.004)	0.129 (0.004)	0.271 (0.004)	0.014 (0.005)
DJIA	0.274 (0.005)	0.269 (0.007)	0.01 (0.005)	0.18 (0.007)
GLD	0.236 (0.005)	0.127 (0.005)	0.034 (0.005)	0.045 (0.005)
MAAA	0.264 (0.005)	0.105 (0.004)	0.039 (0.005)	0.109 (0.006)
MBaa	0.237 (0.004)	0.098 (0.002)	0.445 (0.003)	0.53 (0.003)
MSCI	0.208 (0.005)	0.152 (0.007)	0.049 (0.006)	0.098 (0.007)
NSQ	0.414 (0.006)	0.21 (0.006)	0.045 (0.006)	0.088 (0.006)
OIL	0.109 (0.004)	0.173 (0.007)	0.086 (0.004)	0.022 (0.005)
MER	0.458 (0.006)	0.014 (0.003)	0.145 (0.007)	0.145 (0.006)
VIX	0.387 (0.005)	0.19 (0.004)	0.104 (0.006)	0.192 (0.007)
VXN	0.385 (0.006)	0.277 (0.006)	0.165 (0.008)	0.205 (0.008)
VXD	0.416 (0.006)	0.191 (0.004)	0.131 (0.007)	0.188 (0.007)
SP500	0.318 (0.005)	0.252 (0.007)	0.059 (0.006)	0.158 (0.007)

Panel C: Multiple currency factors

BTC	ETH	XRP	DASH	BTC
AUD	0.244 (0.005)	0.045 (0.004)	0.052 (0.006)	0.018 (0.005)
EUR	0.259 (0.005)	0.001 (0.003)	0.016 (0.006)	0.069 (0.004)
YEN	0.168 (0.004)	0.165 (0.004)	0.151 (0.005)	0.025 (0.005)
CAD	0.206 (0.005)	0.05 (0.003)	0.003 (0.006)	0.008 (0.005)
BRL	0.229 (0.004)	0.01 (0.003)	0.241 (0.004)	0.184 (0.004)
RMB	0.549 (0.006)	0.193 (0.004)	0.049 (0.005)	0.021 (0.005)
CHF	0.103 (0.005)	0.042 (0.004)	0.021 (0.005)	0.014 (0.005)
IDR	0.165 (0.005)	0.039 (0.004)	0.042 (0.005)	0.011 (0.005)
KRW	0.351 (0.005)	0.028 (0.003)	0.121 (0.005)	0.173 (0.004)
VEF	0.237 (0.003)	0.33 (0.002)	0.843 (0.003)	1.082 (0.002)
GBP	0.217 (0.004)	0.041 (0.003)	0.015 (0.005)	0.01 (0.005)
RUB	0.293 (0.004)	0.088 (0.002)	0.017 (0.005)	0.151 (0.004)
TRY	0.134 (0.004)	0.081 (0.003)	0.11 (0.005)	0.079 (0.004)

Panel D: Bitcoin and blockchain trend-based factors

	BTC	ETH	XRP	DASH
NTs	0.191 (0.004)	0.169 (0.006)	0.006 (0.006)	0.177 (0.007)
NPs	0.196 (0.004)	0.149 (0.005)	0.028 (0.005)	0.052 (0.004)
NUs	0.111 (0.006)	0.168 (0.007)	0.069 (0.009)	0.12 (0.011)
PVs	0.145 (0.004)	0.238 (0.005)	0.087 (0.005)	0.139 (0.007)
Btc-W	0.301 (0.005)	0.325 (0.005)	0.102 (0.007)	0.079 (0.006)
Eth-W	0.227 (0.004)	0.463 (0.007)	0.181 (0.008)	0.192 (0.008)
Xrp-W	0.259 (0.004)	0.143 (0.004)	0.05 (0.006)	0.023 (0.005)
Doge-W	0.103 (0.005)	0.143 (0.005)	0.059 (0.007)	0.083 (0.007)
Btc-GT	0.34 (0.005)	0.353 (0.006)	0.109 (0.007)	0.16 (0.007)
Eth-GT	0.132 (0.004)	0.46 (0.007)	0.127 (0.007)	0.164 (0.008)
Xrp-GT	0.187 (0.003)	0.203 (0.004)	0.089 (0.005)	0.062 (0.006)
Doge-GT	0.129 (0.006)	0.146 (0.006)	0.088 (0.008)	0.106 (0.008)

Panel E: Blockchain technology-based factors

	BTC	ETH	XRP	DASH
BZ	0.239 (0.004)	0.005 (0.003)	0.01 (0.006)	0.227 (0.004)
BSV	0.093 (0.003)	0.108 (0.003)	0.249 (0.004)	0.143 (0.004)
HSH	**0.028 (0.003)**	**0.459 (0.006)**	**0.007 (0.006)**	**0.022 (0.005)**
MD	0.131 (0.002)	0.176 (0.004)	0.355 (0.004)	0.163 (0.004)
TBT	0.103 (0.003)	0.163 (0.003)	0.205 (0.005)	0.395 (0.004)
TBM	0.368 (0.005)	0.445 (0.005)	0.159 (0.007)	0.191 (0.007)
DOD	0.181 (0.003)	0.046 (0.003)	0.319 (0.004)	0.189 (0.004)
UBA	0.338 (0.004)	0.22 (0.004)	0.005 (0.006)	0.15 (0.004)
DBT	0.03 (0.003)	0.1 (0.003)	0.471 (0.004)	0.688 (0.003)
EPU	0.092 (0.003)	0.046 (0.003)	0.189 (0.004)	0.194 (0.004)

Panel F: Multiple stock indices

	BTC	ETH	XRP	DASH
NI225	0.216 (0.004)	0.079 (0.003)	0.145 (0.004)	0.097 (0.004)
IBVC	0.184 (0.004)	0.205 (0.004)	0.058 (0.005)	0.105 (0.006)
BRA	0.458 (0.005)	0.168 (0.004)	0.11 (0.005)	0.078 (0.005)
TSX	0.135 (0.004)	0.214 (0.006)	0.081 (0.005)	0.075 (0.006)
KOSPI	0.249 (0.004)	0.229 (0.004)	0.074 (0.005)	0.023 (0.005)
ASX	0.169 (0.005)	0.114 (0.006)	0.092 (0.004)	0.009 (0.005)
JCI	0.221 (0.004)	0.075 (0.003)	0.152 (0.004)	0.101 (0.004)
SMI	0.147 (0.004)	0.258 (0.007)	0.007 (0.006)	0.032 (0.005)
SSE	0.075 (0.004)	0.024 (0.003)	0.083 (0.004)	0.058 (0.004)
RTS	0.195 (0.004)	0.175 (0.004)	0.03 (0.006)	0 (0.005)

Note: This table reports the Sharpe 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 of the top fifteen technical rules selected in the previous step and the selected factors in Table 3 respectively. 75% IS corresponds to period 2, as explained in Table 4, keeping 25% of the total dataset out-of-sample.

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TABLE 16 Out-of-sample profitability performance results (90% IS).

Panel A: Technical rules

	BTC		ETH		XRP		DASH
CB (15, 0.1, 25, 100)	0.029 (0.001)	CB (10, 0.03, 10, 20)	0.101 (0.001)	CB (10, 0.03, 10, 20)	0.183 (0.001)	CB (10, 0.03, 10, 20)	0.165 (0.001)
FR (0.01, 5)	0.01 (0.001)	MA (200, 5, 0.04)	0.026 (0.001)	MA (10, 2, 0.005)	0.018 (0.002)	MA (10, 5, 0.01)	0.146 (0.001)
PMA1	**0.036 (0.001)**	MA (50, 5, 0.03)	0.084 (0.001)	MA (15, 1, 0.005)	0.129 (0.001)	MA (10, 2, 0.005)	0.104 (0.001)
CB (5, 0.075, 5, 0.01)	0.067 (0.001)	MA (50, 20, 0.04)	0.07 (0.001)	**PMA1**	**0.086 (0.001)**	MA (5, 1, 0.01)	0.095 (0.001)
CB (5, 0.075, 5, 0.015)	0.143 (0.001)	MA (75, 20, 0.03)	0.078 (0.001)	MA (2,1,0.02)	0.183 (0.001)	MA (10, 5, 0.04)	0.16 (0.001)
MA (200, 125, 25)	0.025 (0.001)	MA (75, 1, 0.001)	0.047 (0.001)	MA (2,1,0.015)	0.033 (0.002)	MA (5, 2, 0.015)	0.156 (0.001)
FR (0.03, 3)	0.028 (0.001)	MA (50, 2, 0.02)	0.086 (0.001)	MA (2,1,0.02)	0.126 (0.001)	FR (0.005, 3)	0.141 (0.001)
FR (0.035, 1)	0.068 (0.001)	MA (100, 30, 0.015)	0.014 (0.001)	MA (40, 20, 5)	0.139 (0.001)	FR (0.04, 15)	0.077 (0.001)
FR (0.04, 1)	0.025 (0.001)	FR (0.07, 0.15)	0.041 (0.001)	MA (40, 1, 0.05)	0.074 (0.001)	FR (0.01, 3)	0.022 (0.002)
MA (5, 1, 0.015)	0.027 (0.001)	MA (100, 30, 0.005)	0.048 (0.001)	MA (75, 1, 0.01)	0.14 (0.001)	FR (0.005, 3)	0.103 (0.001)
MA (10, 5, 0.05)	0.008 (0.001)	FR (0.035, 0.04)	0.097 (0.001)	MA (10, 5, 0.02)	0.053 (0.002)	PMA1	0.07 (0.001)
FR (0.005, 1)	0.023 (0.001)	FR (0.04, 0.025)	0.058 (0.001)	MA (40, 20, 0.02)	0.087 (0.001)	FR (0.01, 1)	0.051 (0.001)
MA (2, 1, 0.05)	0.002 (0.001)	**PMA1**	**0.07 (0.001)**	MA (15, 1, 0.03)	0.054 (0.001)	FR (0.045, 1)	0.159 (0.001)
FR (0.005, 5)	0.059 (0.001)	PMA2	0.059 (0.001)	MA (100, 25, 0.04)	0.101 (0.001)	FR (0.045, 15)	0.145 (0.001)
MA (10, 1, 0.01)	0.091 (0.001)	FR (0.4, 0.04)	0.037 (0.001)	MA (40, 15, 25)	0.146 (0.001)	FR (0.01, 5)	0.122 (0.001)

Panel B: Traditional fundamental factors

	BTC	ETH	XRP	DASH
3mBill	0.208 (0.001)	0.163 (0.001)	0.04 (0.002)	0.146 (0.002)
10yBill	0.002 (0.001)	0.199 (0.001)	0.06 (0.001)	0.092 (0.002)
DJIA	0.003 (0.001)	0.172 (0.002)	0.02 (0.002)	0.072 (0.002)
GLD	0.13 (0.002)	0.136 (0.002)	0.039 (0.002)	0.121 (0.003)
MAAA	0.147 (0.002)	0.089 (0.001)	0.023 (0.002)	0.074 (0.002)
MBaa	0.082 (0.001)	0.015 (0.001)	0.078 (0.001)	0.027 (0.002)
MSCI	0.02 (0.001)	0.153 (0.002)	0.049 (0.002)	0.062 (0.002)
NSQ	0.122 (0.002)	0.166 (0.002)	0.029 (0.002)	0.086 (0.002)
OIL	0.101 (0.001)	0.259 (0.002)	0.064 (0.002)	0.01 (0.002)
MER	0.379 (0.003)	0.119 (0.002)	0.265 (0.004)	0.28 (0.004)
VIX	0.149 (0.002)	0.185 (0.002)	0.131 (0.003)	0.169 (0.003)
VXN	0.159 (0.002)	0.197 (0.003)	0.132 (0.003)	0.158 (0.003)
VXD	0.063 (0.001)	0.143 (0.002)	0.053 (0.002)	0.078 (0.003)
SP500	0.059 (0.001)	0.122 (0.002)	0.06 (0.002)	0.072 (0.002)

Panel C: Multiple currency factors

	BTC	ETH	XRP	DASH
AUD	0.165 (0.001)	0.132 (0.002)	0.018 (0.002)	0.02 (0.002)
EUR	0.175 (0.002)	0.089 (0.002)	0.072 (0.002)	0.08 (0.002)
YEN	0.085 (0.002)	0.086 (0.002)	0.023 (0.002)	0.047 (0.002)
CAD	0.148 (0.002)	0.197 (0.002)	0.036 (0.002)	0.063 (0.002)
BRL	0.059 (0.002)	0.104 (0.002)	0.035 (0.003)	0.043 (0.002)
RMB	0.154 (0.002)	0.17 (0.002)	0.047 (0.002)	0.019 (0.002)
CHF	0.038 (0.001)	0.09 (0.002)	0.022 (0.002)	0.086 (0.002)
IDR	0.118 (0.001)	0.091 (0.002)	0.067 (0.002)	0.019 (0.002)
KRW	0.037 (0.001)	0.058 (0.001)	0.011 (0.002)	0.013 (0.002)
VEF	0.066 (0.001)	0.012 (0.001)	0.149 (0.001)	0.197 (0.001)
GBP	0.125 (0.001)	0.085 (0.001)	0.076 (0.001)	0.014 (0.002)
RUB	0.144 (0.002)	0.135 (0.002)	0.048 (0.003)	0.072 (0.002)
TRY	0.133 (0.002)	0.11 (0.002)	0.034 (0.003)	0.045 (0.002)

Panel D: Bitcoin and Blockchain Trend-based Factors

	BTC	ETH	XRP	DASH
NTs	0.066 (0.001)	0.058 (0.001)	0 (0.002)	0.117 (0.001)
NPs	0.066 (0.001)	0.044 (0.001)	0.017 (0.002)	0.013 (0.002)
NUs	0.085 (0.001)	0.069 (0.001)	0.049 (0.002)	0.021 (0.002)
PVs	0.103 (0.001)	0.073 (0.001)	0.019 (0.002)	0.097 (0.001)
Btc-W	0.088 (0.001)	0.069 (0.001)	0.013 (0.002)	0.038 (0.002)
Eth-W	0.041 (0.001)	0.116 (0.001)	0.04 (0.003)	0.096 (0.001)
Xrp-W	0.056 (0.002)	0.04 (0.003)	0.005 (0.002)	0.034 (0.003)
Doge-W	0.043 (0.001)	0.039 (0.001)	0.01 (0.002)	0.082 (0.001)
Btc-GT	0.105 (0.001)	0.072 (0.001)	0.001 (0.002)	0.088 (0.002)
Eth-GT	0.048 (0.001)	0.091 (0.001)	0.099 (0.001)	0.001 (0.002)
Xrp-GT	0.089 (0.001)	0.072 (0.001)	0.016 (0.002)	0.077 (0.001)
Doge-GT	0.095 (0.001)	0.074 (0.001)	0 (0.002)	0.013 (0.002)

Panel E: Blockchain Technology-based Factors

	BTC	ETH	XRP	DASH
BZ	0.063 (0.001)	0.101 (0.001)	0.127 (0.001)	0.231 (0.001)
BSV	0.08 (0.001)	0.027 (0.001)	0.251 (0.001)	0.116 (0.001)
HSH	**0.017 (0.001)**	**0.232 (0.002)**	**0.084 (0.002)**	**0.146 (0.001)**
MD	0.214 (0.001)	0.124 (0.002)	0.03 (0.002)	0.156 (0.001)
TBT	0.013 (0.001)	0.209 (0.002)	0.039 (0.002)	0.108 (0.001)
TBM	0.031 (0.001)	0.099 (0.002)	0.01 (0.002)	0.019 (0.002)
DOD	0.042 (0.001)	0.063 (0.002)	0.025 (0.002)	0.062 (0.002)
UBA	0.07 (0.001)	0.1 (0.001)	0.153 (0.001)	0.305 (0.001)
DBT	0.044 (0.001)	0.133 (0.001)	0.111 (0.001)	0.252 (0.001)
EPU	0.074 (0.001)	0.065 (0.001)	0.058 (0.002)	0.083 (0.001)

Panel F: Multiple Stock Indices

	BTC	ETH	XRP	DASH
NI225	0.122 (0.002)	0.151 (0.002)	0.011 (0.002)	0.121 (0.001)
IBVC	0.004 (0.001)	0.198 (0.002)	0.033 (0.002)	0.072 (0.002)
BRA	0.149 (0.001)	0.149 (0.002)	0.059 (0.002)	0.02 (0.002)
TSX	0.109 (0.001)	0.266 (0.003)	0.123 (0.001)	0.03 (0.001)
KOSPI	0.097 (0.001)	0.095 (0.002)	0.048 (0.002)	0.032 (0.002)
ASX	0 (0.001)	0.155 (0.001)	0.108 (0.001)	0.04 (0.001)
JCI	0.106 (0.002)	0.129 (0.002)	0.021 (0.002)	0.07 (0.001)
SMI	0.034 (0.003)	0.037 (0.005)	0.031 (0.005)	0.032 (0.004)
SSE	0.102 (0.001)	0.082 (0.001)	0.036 (0.002)	0.027 (0.002)
RTS	0.195 (0.002)	0.287 (0.002)	0.089 (0.002)	0.04 (0.002)

Note: This table reports the Sharpe 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 of the top fifteen technical rules selected in the previous step and the selected factors in Table 3, respectively. 90% IS corresponds to period 3, as explained in Table 4, keeping 10% of the total dataset out-of-sample.

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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 0.159 (BZ in Panel E) to 1.358 (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 0.161–1.531. Nonetheless, the FA factors fail to maintain good performance in F2 and F3. Compared to F1, the FA factors' performance sharply declines, as with the TA factors. Here, we should note that the results of the remaining eight cryptocurrencies are consistent with those presented here. These results are presented in the online Appendix OA.8 (Tables A.14–A.16 and A.23–A.25).

Although the previous studies state that the cryptocurrency market has a certain relationship with financial markets (Li & Wang, 2017; Salisu et al., 2019), our results show that this relationship is weak or nearly nonexistent. Even other classes of fundamentals, such as BCH and BTC trend-based factors, are not found to be as important as other studies suggest (Ciaian et al., 2016; Kraaijeveld & De Smedt, 2020; Matta et al., 2015). Apart from PMA1 and HSH, we are unable to identify other factors that exhibit both explanatory power and profitability on cryptocurrency returns across all forecasting exercises. Investors in cryptocurrencies mainly enjoy 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 PMA1 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 BTC or cryptocoins 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 in investors' portfolios can lead to tail losses.

5 | CONCLUSION

In this article, 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 utilise 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 59 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 and a BCH factor (HSH) are found to have significant predictive ability across different horizons. This is confirmed consistently in both in-sample and out-of-sample tests across 12 cryptocurrencies (BTC, ETH, XRP, DASH, ADA, AVAX, BNB, DOGE, DOT, LTC, LUNA and SOL) and three forecasting exercises over the period 2015–2022. This verifies that traditional momentum strategies cannot truly capture cryptocurrency movements, but novel ones, like the one presented by Detzel et al. (2021), 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 out-of-sample across all periods. Traditional economic factors 3mBill, NSQ and OIL are found to be significant for BTC and ETH in F3. This finding is particularly interesting, as HSH is a proxy 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. The significance of economic and financial factors implies that the relationship between the cryptocurrency market and conventional financial markets is gradually becoming stronger. 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 carry genuine 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 also show the need for rigorous testing of technical rules for luck and data-snooping bias.

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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 other financial (e.g., equity and exchange) markets. Although the recent boom of 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 & Shams, 2020; Grobys & Junttila, 2021) and dark-web illegal activity (Foley et al., 2019). Meanwhile, online exchanges remain the main pathway for cryptocurrency investment, but they are not able to provide full defence against hack attacks (Grobys, 2021) and spillover effects from cyber-attacks (Caporale et al., 2021). 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 investors. Large fluctuations in the transaction costs of different cryptocurrency platforms also impede extensive formal trading activity. These issues require further investigation if cryptocoins are to gain credibility as complete financial investment instruments.

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The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Research data are not shared.

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ENDNOTES

[1] The reported figures are as of 23 January 2023 and are available from https://coinmarketcap.com/.

[2] Please refer to STW for specification of the TA universe.

[3] 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 cryptocoin for financial institutions as it has the fastest transaction confirmation. As a hard fork of BTC, the average mining speed of DASH is four times faster than that of BTC. The multiple transaction modes of DASH make it flexible and feasible for daily users. Introductions for the rest of the cryptocurrencies are provided in the online Appendix OA.1.

[4] As the cryptocurrency market always runs, we use $n=7$ for PMAs and $n=5$ for other factors. For detailed mathematical proofs and the empirical design, we refer interested readers to Detzel et al. (2021). Descriptive statistics for the five PMA ratios are available in the online Appendix OA.2.

[5] For the calculation of the Sharpe ratio, we employ the one-month fund management constant expiration rate in the CRSP file (file name is TFZ_MTH_RF) based on monthly frequency, and then 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} the monthly interest rate and 30 the average number of trading days in a month. Following Bajgrowicz and Scaillet (2012), we use SR returns as our primary trading metric. We also examine the trading performance based on the Sortino ratio and mean returns. SR measure excess returns over the risk-free rate so that trading rules can earn the risk-free rate in non-trading days. Similar to SR, the Sortino ratio is also used to measure the excess returns but with better control for downside risk.

[6] The transaction costs are not unified across different exchanges. Due to the absence of regulation in the cryptocurrency market, there is no standardised trading cost across all cryptocurrency exchanges. Specifically, exchanges establish different trading fee guidelines based on payment region, method, and amount. Until 2017, for instance, the majority of cryptocurrency exchanges, such as Huobi and OKCoin, did not impose trading fees. For practical purposes, we use the average transaction costs of 0.044% as set by Binance.

[7] We also tried the same regressions based on a two-sided test. The results obtained are similar and are not presented in the text for the sake of space

[8] The mathematical details of the procedure are presented in the online Appendix OA.6.

[9] For the exact parametrization of our TA rules, we refer the readers to Appendix OA.2 and Appendix A of Sullivan et al. (1999).

[10] For further robustness, as we did for the top performing rules in-sample, we investigate the in-sample predictive performance

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under the Sortino ratio metric for all cryptocurrencies. This is presented in Appendix OA.7 (Tables A.4.1–A.4.3). The message remains the same as in the case of the Sharpe ratio.

[11] Similar results are obtained by using the Sortino ratio metric and can be found in Appendix OA.7 (Tables A.5.1–A.5.3).

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