Trend-based Forecast of Cryptocurrency Returns*

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Abstract

Cryptocurrencies are widely known for their limited publicly available information, making it challenging to predict market returns. Technical analysis has emerged as an essential tool in this context, but its effectiveness in the cryptocurrency market remains an open question. Using data from nearly 3,000 cryptocurrencies at daily, weekly, and monthly horizons from 2013 to 2022, we systematically re-examine the efficacy of trend-based technical indicators in predicting cryptocurrency market returns and find that price-based signals are more effective in predicting short-term horizons, while volume-based signals are more powerful in predicting long-term horizons. Further analysis shows that machine learning techniques can significantly improve the performance of technical indicators, and technical indicators based on different information respond differently to the COVID-19 outbreak. These results provide direct evidence that volume imparts information to technical analysis independently of price.

JEL Classification: G12, G14, G17.

Keywords: Cryptocurrency, Return predictability, Technical analysis, Investment horizon, Machine Learning, COVID-19.

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1 Introduction

Trend-based trading strategies (e.g., moving average and momentum) have been widely employed by practitioners from every financial market. However, the effectiveness of these strategies is under debate in academia. Very recently, Jiang, Kelly, and Xiu (2022) revisited the trend-based predictability in the stock market using computer vision and motivated researchers and investors to rethink technical analysis. In this paper, we systematically examine the efficacy of trend-based technical indicators in the cryptocurrency (crypto for short, hereafter) market over various horizons in the hope of shedding new light on the issue.

We performed three empirical tests to demonstrate the predictive power of trend-based technical indicators on crypto market returns. Firstly, we tested the predictability of individual technical indicators and machine learning methods using the full sample over varying horizons. Secondly, to address potential overfitting concerns by Welch and Goyal (2008), we employed an out-of-sample assessment to evaluate how effectively technical indicators can predict future performance. Lastly, we conducted an asset allocation exercise for a mean-variance investor and calculated the certainty equivalent return improvements and Sharpe ratios to assess the economic benefits of the out-of-sample forecasts.

Three novel findings emerge from these empirical analyses. Firstly, we demonstrate that volume-based technical indicators operate primarily on a monthly frequency, whereas price-based indicators are effective at daily and weekly frequencies in predicting crypto market returns. This finding provides direct evidence in support of Blume, Easley, and O'hara (1994) assertion that volume imparts information to technical analysis independently of price. Secondly, we show that machine learning methods, particularly scaled sufficient forecasting, can significantly enhance the predictive performance of technical indicators on in-sample and out-of-sample tests across various horizons. Lastly, we find that technical analysis can more effectively forecast the market behavior of cryptos with higher market capitalization. This finding is consistent with empirical evidence suggesting that positive feedback trading is prevalent in top cryptos (da Gama Silva et al., 2019;

King and Koutmos, 2021) and such trading activity can establish price patterns that technical indicators can detect (Neely et al., 2014).

Our research offers several significant contributions to the empirical understanding of the cryptocurrency market. To the best of our knowledge, this article is the first to conduct a systematic analysis of the effectiveness of technical analysis across different sample frequencies in the crypto market. Moreover, our study breaks new ground by investigating the predictive power of technical indicators using advanced machine learning methods beyond PCA, including PLS, sPCA, and sSUFF. These sophisticated techniques significantly enhance the performance of technical indicators in all scenarios, thereby strengthening our findings. Lastly, our study's subsample analysis of COVID-19 and market sub-indices complements the growing literature on the COVID-19 impact on the crypto market and deepens our knowledge of the crypto market structure.

Our work is closely linked to the burgeoning literature on predicting crypto performance. In time series analysis, scholars have demonstrated that several predictors, such as economic fundamentals, trading volume (Balcilar et al., 2017; Bouri et al., 2019), policy uncertainty (Demir et al., 2018; Colon et al., 2021), investor attention (Shen, Urquhart, and Wang, 2019; Lin, 2021), and sentiment (Anastasiou, Ballis, and Drakos, 2021; Guégan and Renault, 2021), can effectively forecast future Bitcoin or crypto market returns. In the cross-section, researchers have found that various factors, such as network effect (Liu, Tsyvinski, and Wu, 2021), downside risk (Zhang et al., 2021), and seasonality (Kaiser, 2019), can be employed to form portfolios that generate significantly positive future returns. Our paper provides evidence of time-series return predictability at the market level from a technical analysis perspective.

Our study also contributes to the research on the effectiveness of technical analysis. Previous studies have demonstrated the practicality of technical analysis across various asset types, including the stock market (Zhu and Zhou, 2009; Neely et al., 2014), futures and commodity market (Park and Irwin, 2010; Yin, Yang, and Su, 2017), currency market (Abbey and Doukas, 2012; Neely and Weller, 2012), and crypto market (Corbet et al., 2019; Gerritsen et al., 2020;

Detzel et al., 2021). Unlike prior research that focuses on a single frequency, our article evaluates the effectiveness of technical indicators at multiple frequencies and synthesizes technical analysis using the latest machine learning techniques.

The rest of the paper is structured as follows. Section 2 describes the data, variables, and forecasting techniques used in our study. Section 3 presents and discusses our empirical findings. Finally, Section 4 concludes the paper.

2 Data, Variables and Forecasting Methods

In this section, we describe how we construct the crypto market index and introduce the three types of technical indicators used in our analyses. We then briefly overview the forecasting methods employed for testing the return predictability of the crypto market.

2.1 Data and Variables

We obtained cryptocurrency data from Coinmarketcap.com and constructed a value-weighted crypto market index at a daily frequency using all available coins. Our initial data collection included 5,909 coins with their daily statistics on open, close, high, and low prices, trading volume, and market capitalization from January 1, 2013 to May 28, 2022. To ensure data quality and comprehensive market coverage, we excluded cryptos with a market capitalization smaller than US$500,000 and slightly broadened our market coverage compared to Liu, Tsyvinski, and Wu (2022), who only included coins with market capitalizations over US$1,000,000. Additionally, we limited our sample to cryptos with complete price, trading volume, and capitalization statistics, resulting in a narrower sample size of 2,963 cryptocurrencies for the entire study period, starting from the beginning of 2014.

The yearly characteristics of the coins are presented in Panel A of Table 1. It is evident that the number of coins has been steadily increasing over the sampling period, rising from 125 in 2014 to

1,951 in May 2022. However, an intriguing finding from the descriptive statistics is that the crypto market size is starting to shrink in 2022, despite 2021 being the year when the market achieved the highest number of coins satisfying our filters and the highest daily average trading volume of over 160 million dollars. This could suggest a possible slowdown or correction in the cryptocurrency market in 2022, potentially due to the market becoming over-saturated with a large number of coins or a shift in investor sentiment. However, further research and analysis would be required to confirm the underlying causes and implications for the cryptocurrency market going forward.

[*Insert Table 1 about here*]

The excess market return for cryptocurrencies is calculated by subtracting the return on the crypto market level index from the risk-free rate, as measured by the yield on 1-month T-bills. We consider crypto excess market returns at three data frequencies: daily, weekly, and monthly, where the weekly and monthly returns are cumulatively calculated using the daily returns at the respective frequency.[1] Panel B of Table 1 reports the return characteristics of the market indices and major cryptos under three data frequencies, respectively. In particular, we separately constructed two sub-indices using the top 10 largest cryptos (Mega) in the market cap and the rest of the cryptos (ExMega). It shows that the Mega index returns track the features of the market index returns very well at all frequencies, while ExMega index returns are generally higher and more volatile. In addition, the sizable annualized Sharpe ratios indicate that cryptocurrencies, therefore as an alternative asset category, could cater to the investment needs of the investors at different trading frequencies (see Brauneis and Mestel, 2019; Nagy and Benedek, 2021, for example). All the summary statistics at each frequency are consistent in magnitude with those reported in Liu and Tsyvinski (2021).

To examine the performance of technical indicators in forecasting the returns on the cryptocurrency market. we follow Neely et al. (2014); Detzel et al. (2021), among many others, to construct

[1]Since the cryptocurrency market operates 24/7, we use the Sunday-Sunday definition for identifying a trading week. In case the readers/practitioners are interested in the results on buy-and-hold returns (weekly/monthly rebalancing), we report the results in Appendix B.

24 technical indicators at each trading frequency based on three major trend-following strategies: moving average (MA), momentum (MOM), and "on-balance" volume (VOL). In particular, MA is a commonly used indicator that shows the average price of an asset over a specified period of time. Trend-following traders use moving averages to smooth out the price data, making it easier to identify trends and enter trades in the same direction as the trend. MOM is a technical indicator that shows the rate of change in the price of an asset over a given period of time. It measures the strength of the trend and can be used to identify potential trend reversals. VOL is calculated by adding the volume of trades on up days and subtracting the volume of trades on down days, which can also be used to identify the strength of the trend and potential trend reversals. In combination, MA, MOM, and VOL can provide trend-following traders with a comprehensive view of the strength and direction of the trend in an asset. By using these indicators in combination, traders can reduce the likelihood of false signals and increase the probability of identifying profitable trading opportunities.

For MA strategy, we define a buy signal if the short-term moving average exceeds or is equal to the long-term, and a sell signal vice versa:

$$S_{i,t} = \begin{cases} 1 & \text{if } \mathrm{MA}_{s,t} \geq \mathrm{MA}_{l,t}, \\ 0 & \text{if } \mathrm{MA}_{s,t} < \mathrm{MA}_{l,t}. \end{cases} \tag{1}$$

with

$$\mathrm{MA}_{j,t} = \frac{1}{j} \sum_{i=0}^{j-1} P_{t-i} \quad \text{for } j = s, l, \tag{2}$$

where P_t is the index value of the cryptocurrency market at time t, and s (l) represents short (long) MA ($s < l$). Intuitively, the short MA is at high sensitivity to recent price movement than the long MA, the MA rule intuitively recognizes shifts in price patterns for cryptocurrencies. For clarity, we denote the MA indicator with MA lengths s and l by $\mathrm{MA}(s,l)$. Following the convention of technical analysis, we choose s = 5, 10, 30 and l = 90, 180, 360 for daily frequency, s = 1, 2, 4 and l = 12, 26, 52 for weekly frequency, and s = 1, 2, 3 and l = 6, 9, 12 for monthly frequency.

The momentum strategy is based on comparing the current crypto market index level with its historical level. If the present market index is greater than its m-period-ahead price level, the market is bullish, a buy signal is generated due to "positive" momentum indicating a continuing trend of earning higher yields in the future. Mathematically, we write

$$S_{i,t} = \begin{cases} 1 & \text{if } P_t \geq P_{t-m}, \\ 0 & \text{if } P_t < \mathrm{P}_{t-m}. \end{cases} \tag{3}$$

We consider both short- and long-term momentum strategies in this study. That is, we set m = 5, 10, 30, 90, 180, 360 at daily frequency, m = 1, 2, 4, 12, 26, 52 at weekly frequency, m = 1, 2, 3, 6, 9, 12 at monthly frequency, respectively, to include momentum horizons from one day to one year.

Lastly, we consider the volume-based trading strategies complementary to the price-following strategies. Following Neely et al. (2014), we generate the trading signals using the "on-balance" volume, which is defined as

$$\mathrm{OBV}_t = \sum_{k=1}^{t} \mathrm{VOL}_k D_k, \tag{4}$$

where VOL_k is the aggregated trading volume at time k and D_k is the dummy variable, an 1 if P_k is higher or equal to P_{k-1} and if smaller a -1 otherwise. Thus the signal derived by "on-balance" volume is

$$S_{i,t} = \begin{cases} 1 & \text{if } \mathrm{MA}^{\mathrm{OBV}}_{s,t} \geq \mathrm{MA}^{\mathrm{OBV}}_{l,t}, \\ 0 & \text{if } \mathrm{MA}^{\mathrm{OBV}}_{s,t} < \mathrm{MA}^{\mathrm{OBV}}_{l,t}, \end{cases} \tag{5}$$

where

$$\mathrm{MA}^{\mathrm{OBV}}_{j,t} = \frac{1}{j} \sum_{i=0}^{j-1} \mathrm{OBV}_{t-i} \quad \text{for } j = s, l. \tag{6}$$

Similar to the moving average strategy, we denote the volume-based signals $\mathrm{VOL}(s,l)$ with MA lengths s and l and consider the same short and long horizon parameter settings as in MA strategies under each trading frequency.

2.2 Forecasting Methods

This paper examines the joint predictive power of trend-based trading signals using several cutting-edge machine learning techniques, including principal component analysis (PCA), partial least squares (PLS), scaled principal component analysis (sPCA), scaled sufficient forecasting (sSUFF), least absolute shrinkage and selection operator (Lasso), and elastic net (ENet).

The initial four machine learning methods - PCA, PLS, sPCA, and sSUFF - are considered to be techniques for reducing dimensionality. These methods aim to extract common latent factors from predictors through averaging, in order to reduce noise and enhance the signal. They also enable the decorrelation of predictors that are strongly dependent on each other. While PCA compresses data into principal components based on the covariance structure among predictors, it fails to consider the connection between predictors and future returns. This means that the ultimate goal of forecasting returns is not integrated into the dimension reduction phase.

PLS is an improvement on PCA as it considers both the influence from the predictors and the target. As shown by Kelly and Pruitt (2013, 2015), PLS is a special case of the three-pass regression. The algorithm starts by computing the univariate return prediction coefficient for each predictor using OLS, which stands for the degree to which the returns are sensitive to different predictors. By taking the average of all predictors into one component with weights corresponding to the first-stage regression coefficient, PLS put the greatest weight on the strongest predictors and the smallest weight on the weakest. This allows PLS to exploit the predictor covariation with the forecast objective directly.

To overcome the deficiencies of PCA, Huang et al. (2022b) also suggested a modified version of PCA, designated sPCA, which includes useful information from the target in the factor-extracting technique. Under the sPCA framework, each predictor is scaled according to its predictive slope or t-statistics on the target variable, resulting in a panel of scaled predictors. The common factors are then determined by using standard PCA to the scaled predictors. Notably, sPCA is typically more effective than PCA in the presence of weak components since it gives diminishing weights to irrelevant predictors.

In addition to linear factor models, Huang et al. (2022a) extends the same scaling idea to the sufficient forecasting method (SUFF) by Fan, Xue, and Yao (2017), which is designed for estimating a nonlinear predictive relationship with high-dimensional predictors. Similarly, the efficacy of sSUFF is focused on outperforming SUFF in the presence of weak factors, while the presence of strong factors is unlikely to result in adverse effects. In practice, we employ both linear and nonlinear sSUFF in our predictive model. The linear sSUFF (sSUFF_l) is conducted by directly regressing algorithm-generated predictive indices on future returns, while the nonlinear sSUFF employs a fitted nonlinear combination of predictive indices using local linear regression and then regresses the fitted value on the target.

Apart from the dimension reduction methods, we also consider the two most commonly used variable selection methods: Lasso by Tibshirani (1996), and ENet by Zou and Hastie (2005). Both models can be classified as penalized linear regression models, where a penalty term (or regularization) is introduced to the OLS objective function to avoid over-fitting issues. In particular, the Lasso imposes an L_1 parameter penalization while the ENet imposes both L_1 and L_2 penalization to the linear regression model. Mechanically, the penalization can produce suboptimal forecasts and stabilize the model's out-of-sample performance when predictors are highly correlated.

3 Empirical Results

In this section, we investigate the predictive power of technical indicators for crypto market returns. Initially, we test the baseline in-sample forecasting performance of the individual indicators and the common components derived by different machine learning algorithms at varying frequencies. After that, we look at how well the prediction worked during out-of-sample periods. Lastly, we look at the economic value of the out-of-sample performance from an asset allocation standpoint and investigate the profitability from investing in a smaller basket of cryptocurrencies using sub-indices.

3.1 In-sample Forecasts

We begin by evaluating the in-sample performance of crypto market return prediction. Firstly, we examine the usual univariate predictive regression model at three distinct time frequencies:

$$R_{t+1} = \alpha_i + \beta_i S_{i,t} + \varepsilon_{i,t+1}, \tag{7}$$

where R_{t+1} is the excess return of the crypto market index over the risk-free rate at time $t+1$; $S_{i,t}$ is one of the 24 trading signals at the respective trading frequency. The regression uses data from January 1, 2015 to May 28, 2022, and adopts Newey and West (1987)'s robust variance-covariance estimator to adjust the standard error.

[*Insert Table 2 about here*]

The Panel A of Table 2 reports the in-sample regression slopes, Newey-West t-statistics, and R^2s in predicting the market excess returns with individual technical indicators under each trading frequency. Evidently, all the technical indicators positively predict the market returns, and the in-sample R^2s increase as the trading frequency decreases from daily to monthly. This finding accords with the graphical evidence shown in Figure 1, showing that index price trajectories are rougher at higher frequencies as high-frequency tradings are more likely to inject the market microstructure noise into the crypto prices.

[*Insert Figure 1 about here*]

We then test the joint return predictability of technical indicators. To avoid overfitting, we employ several state-of-the-art machine learning methods, namely, PCA, PLS, sPCA, and sSUFF, to reduce the predictors' dimensionality while preserving the predictive signals. Following Neely et al. (2014), with each forecasting method, we construct a single factor to predict the crypto market returns. We also evaluate Lasso and elastic net to see how effectively they forecast market excess returns.

Panel B of Table 2 summarizes the F-statistics and the R^2s of each forecasting method.[2] Three findings are in order. First, the F-statistics are all significant at 5% significance level, indicating that all machine learning approaches have solid prediction ability for the whole data period of 2015 to 2022. Second, the single factor models all achieve sizable R^2s, especially the nonlinear sSUFF method gains the highest in-sample R^2, which is several times more than the largest one that an individual technical indicator can achieve. For example, the sSUFF method in daily predictive regression achieves an in-sample R^2 of 3.4%, which is almost 8 times more than MOM(30). At monthly frequency, the R^2 exhibited from the in-sample test of sSUFF can be to the size of 24.54%, which is also more than 2 times the R^2 generated by VOL(3,9). Lastly, the variable selection methods also achieve impressive results in predicting market returns. Specifically, the Lasso gains an in-sample R^2 of 0.72%, 4.28%, and 12.89% at daily, weekly, and monthly frequency, respectively. These numbers are substantially larger than the largest R^2 that an individual predictor or a single factor[3] can achieve, indicating that technical forecasting using multiple indicators could be much more effective than relying on a single one.

3.2 Out-of-sample Forecasts

In-sample analysis has been shown to be susceptible to over-fitting and sample-size biases, such as the Stambaugh bias and the look-ahead problem (see Welch and Goyal, 2008, among others). Therefore, to address these issues, we also evaluate the out-of-sample forecasting performance of the technical indicators. Following the approach of Welch and Goyal (2008), Kelly and Pruitt (2013), and others, we implement a recursive predictive regression model based on various

[2] We report the F-statistics to reflect the joint significance of the predictor because the Lasso and ENet include more than one variable after shrinkage and selection.

[3] Note that sSUFF is a multi-factor model while sSUFF_l is a single-factor model.

technical indicators. Specifically, we estimate the model as:

$$\widehat{R}_{t+1} = \widehat{\alpha}_t + \widehat{\beta}_t S_{1:t;t} \tag{8}$$

where $\widehat{\alpha}_t$ and $\widehat{\beta}_t$ are derived by regressing $\{R_{s+1}\}_{s=1}^{t-1}$ on a constant and a technical indicator via OLS, using $\{S_{1:t;s}\}_{s=1}^{t-1}$ as the regressors. We also test the out-of-sample forecasting ability of the previously described machine learning algorithms, using the period from January 1, 2018 to May 28, 2022 as the out-of-sample assessment period. To ensure economic rationality, we follow the concept of Campbell and Thompson (2008) and set the predicted return to zero whenever a negative return forecast is made.

To evaluate the performance of the predictions in out-of-sample periods, we use two statistics: the R^2_{OS} statistic from Campbell and Thompson (2008) and the MSFE-adjusted statistic from Clark and West (2007). The R^2_{OS} measures the proportionate decrease in mean squared forecast error (MSFE) for the predictive regression prediction compared to the average historical baseline:

$$R^2_{OS} = 1 - \frac{\sum_{t=p}^{T-1} \left(R_{t+1} - \widehat{R}_{t+1}\right)^2}{\sum_{t=p}^{T-1} \left(R_{t+1} - \bar{R}_{t+1}\right)^2}. \tag{9}$$

Here, $\widehat{R}_t$ is the forecast based on each technical indicator, and $\bar{R}_t$ represents the historical average baseline based on the constant expected return model ($R_{t+1} = \alpha + \varepsilon_{t+1}$).[4]

[*Insert Table 3 about here.*]

The out-of-sample predictive regression results using individual technical indicators are summarized in Panel A of Table 3. Interestingly, the results reveal a striking pattern in the relationship between the strategy type, formation horizons, and trading frequencies. First of

[4] It could also be of interest to apply the in-sample and out-of-sample Sharpe ratios (see, e.g., Barillas et al., 2020; Kan, Wang, and Zheng, 2022) as the evaluation criteria which take into account the fat-tailed feature of financial data, estimation risk, and the transaction cost. However, it is beyond the current scope of the paper and will be left for future studies.

all, it shows that the price-following strategies (MA and MOM) are more effective at daily and weekly frequencies than at monthly frequencies, especially when the strategies are formed using a relatively short-horizon signal. For example, at daily frequency, the R^2_{OS}s are only positive for MA indicators with long leg horizon of fewer than 360 days, and MA(5,90) achieves the largest out-of-sample R^2 of 0.21% is significant at 5% significance level. Similarly, the momentum strategies that gain positive R^2_{OS} are all with a formation period of less than one year. These results reinforce the findings in the cryptos literature where strong return predictability is mostly found at high frequency, i.e., 5-minute, hourly, and daily, using the price-based predictors (e.g., Aslan and Sensoy, 2020; Akyildirim, Goncu, and Sensoy, 2021; Wen et al., 2022, etc.).

In contrast to price-following indicators, volume-based trading signals demonstrate an excellent out-of-sample predictive ability for market-level returns at monthly frequencies. However, at daily and weekly frequencies, they are inadequate. This finding is consistent with Gerritsen et al. (2020), where the authors found that on-balance volume trading strategies could not beat buy-and-hold benchmarks at the daily frequency. Additionally, our novel finding on the dichotomy between price- and volume-following strategies supports Blume, Easley, and O'hara (1994), where they constructed a theoretical model showing that volume provides information separately from price. The authors claim that in early times, traders may acquire information indicating a significant price discrepancy relative to the genuine value but take conservative positions due to uncertainty about the underlying value. In later times, as prices approach their true values, traders become more confident and take larger positions to capitalize on even minor price differences. Therefore, the theory suggests that volume delays in reflecting the timely information carried by the price. Our empirical results confirm this theory by demonstrating that volume-based indicators perform much better in forecasting monthly returns than daily returns.

Following in-sample analysis, we also check the out-of-sample return predictability using machine learning methods that aggregate all the information provided by the technical indicators. The results are presented in Panel B of Table 3. Similar to the in-sample results, the common predictors extracted by PCA, PLS, sPCA, and sSUFF all perform well in terms of generating positive and sizable out-of-sample R^2s. Particularly, the nonlinear sSUFF method preserves its outstanding in-sample performance in the out-of-sample analysis. It generates the largest R^2_{OS} at all three sample frequencies with daily 0.30%, weekly 2.70%, and monthly 9.19%. We also checked the performance of Lasso and elastic net. However, their performances are not as impressive as in the in-sample analysis and are unstable across different sample frequencies. This is reasonable because, as mentioned in Gu, Kelly, and Xiu (2020), penalized linear regressions may only provide inferior predictions when predictors are strongly correlated, and so may not perform as capably as predictor-averaging-based machine learning approaches, such as PCA and PLS.

Knowing that the COVID-19 outbreak may substantially impact cryptos' price volatility, we separately evaluate the out-of-sample performance of each machine learning method under pre- and post-COVID subsamples using March 2020 when WHO proclaimed COVID-19 a worldwide pandemic as the cutoff. It shows that the predictability for daily and weekly returns is primarily concentrated in the post-COVID period (i.e., $R^2_{OS,Post}$ is larger than $R^2_{OS,Pre}$). By contrast, the predictability is concentrated in the pre-COVID period for monthly returns (see, e.g., sSUFF and Lasso). Mechanically, price-based indicators drive the daily return predictability, and volume-based indicators drive the monthly return predictability. Therefore, the pre- and post-COVID R^2_{OS}s result from the fact that when the market becomes more unstable, the timely information in price becomes more valuable and elevates the predictive power of price-based indicators, while information delay in volume will depreciate the forecasting ability of volume-based indicators.

We are also aware that the level of market efficiency, specifically in its weak form, can fluctuate over time and can impact the predictability of returns. Cui et al. (2023) asserted that the portfolio construction in cryptos market should explicitly take in account the substantial tail risk that investors confront. Therefore, we conducted further analysis to assess the out-of-sample R^2 ($R^2_{OS,down}$) during market downturns, defined as the period when returns fall in the bottom decile (i.e., left tail). Our findings show that $R^2_{OS,down}$ values are significantly positive and large, indicating that return predictability is substantial during market downturns. It is important to note that this predictability may differ from that observed solely in the post-COVID period.

[*Insert Table 4 about here.*]

To further investigate how market size affects return predictability, we reconduct the out-of-sample analysis on the two market sub-indices, where the first index is constructed using the top 10 largest cryptos (Mega) and the latter index excludes the 10 largest cryptocurrencies from its calculations (ExMega), and report the results in Table 4. Evidently, the R^2_{OS}s for the Mega index are all greater than those for the ExMega index, indicating the cryptos with large market capitalization are more predictable using technical analysis. This finding is in line with the empirical discovery that positive feedback trading is prevalent among top cryptocurrencies. (see da Gama Silva et al., 2019; King and Koutmos, 2021) and such trades may establish price patterns that can be captured by technical indicators (Neely et al., 2014).

3.3 Asset Allocation Analysis

Having observed the substantial predictive power of technical indicators on cryptocurrency returns, we now seek to measure the economic value that risk-averse investors could realize by incorporating this knowledge into their asset allocation decisions. To this end, we follow Campbell and Thompson (2008) and Ferreira and Santa-Clara (2011) to compute the certainty equivalent return (CER) gain and the Sharpe ratio, assuming a mean-variance investor who employs out-of-sample return forecasts to allocate between the crypto market index and risk-free bills. At the end of each period t, the investor determines the optimal proportion of the portfolio to allocate to cryptocurrency for the next period as

$$w_t = \frac{1}{\gamma} \frac{\widehat{r}_{t+1}}{\widehat{\sigma}^2_{t+1}}, \tag{10}$$

where γ represents the degree of risk aversion, $\widehat{r}_{t+1}$ is a forecast of the crypto market excess return, and $\widehat{\sigma}^2_{t+1}$ is a forecast of its variance. The investor then allocates share $1 - w_t$ to risk-free bills, and the realized portfolio return in period $t+1$ is

$$R^p_{t+1} = w_t r_{t+1} + r^f_{t+1}, \tag{11}$$

where r^f_{t+1} is the risk-free return. We estimate the variance of the crypto market return using a rolling window of past returns covering the preceding five years, as recommended by Campbell and Thompson (2008), Neely et al. (2014), and Guo et al. (2022), among others. We also restrict $w_t \in [0,1]$ to exclude short sales and leverage.

The portfolio's CER for such investors can be expressed as:

$$\text{CER}p = \widehat{\mu}_p - \frac{1}{2}\gamma\widehat{\sigma}^2_p, \tag{12}$$

where $\widehat{\mu}_p$ is the mean of the investor's portfolio throughout the out-of-sample period, and $\widehat{\sigma}^2_p$ is the variance. We calculate the CER gain as the difference in CER between the return forecasts derived by each ML technique and the historical average. We also investigate whether the portfolio's annualized Sharpe ratios based on predictive regression are significantly higher than those of the investment portfolio that uses the historical average. To further examine the robustness of the asset allocation exercise, we adjust the risk aversion parameter (γ) to 5 and consider the cases when the bid-ask spread is counted in trading or not.[5] Since we do not have access to the quote data, we adopt the efficient estimator proposed by Ardia, Guidotti, and Kroencke (2022) to estimate the bid-ask spread using daily open, high, low, and close price data.[6]

[*Insert Table 5 about here.*]

[5] Recent Forbes news mentioned that many US crypto exchanges are embracing zero-fee trading. Binance. US's fees were already among the smallest, at 10 bps, matching that of FTX (10 bps for makers and 20 for takers) before the zero-cost policy was implemented. https://www.forbes.com/sites/javierpaz/2022/07/21/binance-out-on-a-no-fee-bitcoin-limb-limits-volume-decline-but-muddies-its-profit-prospects/?sh=50ae987563ff

[6] There are many alternative methods for estimating bid-ask spreads using low-frequency information, e.g., Roll (1984); Hasbrouck (2009); Corwin and Schultz (2012); Abdi and Ranaldo (2017), to name a few. However, most of the methods are designed for stocks only Hasbrouck (2009); Corwin and Schultz (2012); Abdi and Ranaldo (2017).

Consistent with the out-of-sample analysis, the Panel A of Table 5 shows that all machine learning techniques achieve significant and positive CER gains for market index when their R^2_{OS} values are statistically significant, as reported in Table 3. Specifically, the sSUFF algorithm leads to a monthly CER gain of 7.27%, indicating that investors with a risk aversion of 5 may accept a yearly portfolio management fee of 7.27% as an opportunity cost for adopting sSUFF's monthly predictive regression forecast instead of using the historical average, assuming a transaction cost of half effective spreads. Furthermore, investment portfolios with positive CER gains all exhibit significant Sharpe ratios.[7]

Considering that the market index has included many illiquid small-cap cryptos, it would be more practically relevant to check the asset allocation results by only using liquid cryptos. Therefore, we reconduct the analysis with the Mega index and report the results in the Panel B of Table 5. It shows that our main findings in Panel A are preserved. Specifically, the sSUFF algorithm leads to a post-transaction-cost monthly CER gain of 7.18% which is of a similar magnitude to that in Panel A.

Overall, the asset allocation exercise reinforces the in-sample and out-of-sample test results, indicating that technical indicators can offer considerable economic value for risk-averse investors.

4 Conclusion

This article provides empirical evidence on the predictability of crypto market returns using trend-based technical indicators at daily, weekly, and monthly frequencies. Our results show that price-based indicators have statistically and economically significant predictive power for daily and weekly returns, while volume-based indicators have strong predictive power for monthly returns. Additionally, we employ several machine learning methods for market return prediction and find that sSUFF consistently outperforms individual technical indicators and other methods both in

[7] As one of the referees has suggested, it would be of interest to compare the machine learning methods with the $1/N$ simple averaging strategy (Naïve), we report the corresponding asset allocation result in Appendix A. It shows that the machine learning methods consistently beat the Naïve strategy in the out-of-sample test and asset allocation exercise.

and out of sample across all trading frequencies. Finally, we conduct a sub-index analysis and conclude that the predictability of crypto market returns is mainly attributable to the leading cryptocurrencies. Overall, our findings suggest that technical indicators can provide valuable information for investors in the crypto market, and machine learning methods can further enhance their predictive power.

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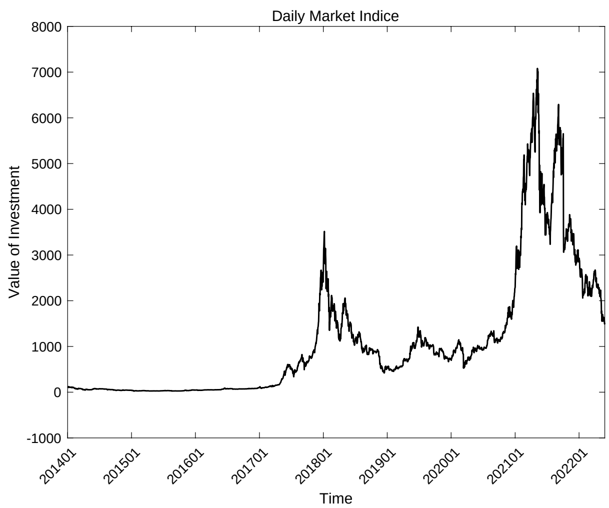
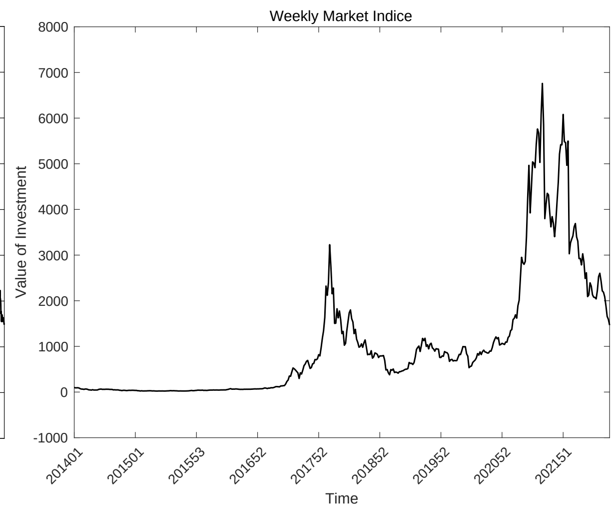
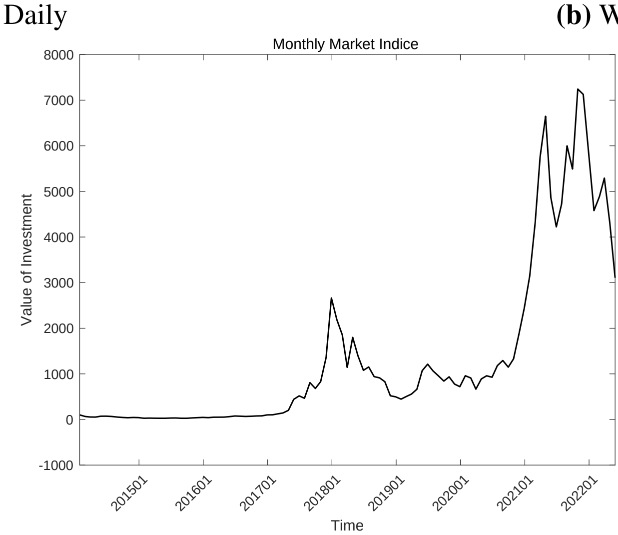


(a) Daily



(b) Weekly



(c) Monthly

Figure 1. Market Indices at Various Frequencies. From January 1, 2014 through May 28, 2022, three market indices for cryptocurrencies are rebalanced on a daily, weekly, and monthly basis, respectively, using all cryptocurrencies available on the market with market capitalizations exceeding $500,000. Index return is a value-weighted series based on the coin's last period market capitalization, set the same initial value of 100 to facilitate comparison.

Table 1 Summary Statistics

This table reports the summary statistics of the cryptocurrencies. Panel A summarizes the number of cryptocurrencies, mean and median of market capitalization and trading volumes on yearly basis from 2014 to 2022. The trading volumes are reported at three frequencies, i.e., daily, weekly, and monthly, where the weekly and monthly trading volumes are the cumulative trading volumes of the daily volumes within that week and month, respectively. Panel B reports the return characteristics (i.e., mean, standard deviation, Sharpe ratio) of three crypto indices and three major crypto coins at various frequencies. The market index is the value-weighted average price of the cryptos that satisfies our filters. The (ExMega) Mega index is constructed using the (cryptos excluding) top 10 cryptos in market capitalization. The crypto indices, Bitcoin, and Ripple data range from January 1, 2014 to May 28, 2022. The Ethereum data ranges from August 8, 2015 to May 28, 2022.

Panel A: Characteristics by Year

		Market Capitalization (in millions)		Trading Volume (in thousands)					
				Daily		Weekly		Monthly	
Year	Number	Mean	Median	Mean	Median	Mean	Median	Mean	Median
2014	125	214.26	2.49	1,021.16	21.22	7,148.18	160.22	30,918.06	688.82
2015	85	117.16	1.79	1,031.81	7.42	7,168.48	58.36	31,704.77	262.30
2016	170	136.94	1.97	1,547.03	10.02	10,845.55	82.45	47,218.73	406.89
2017	639	470.41	7.64	20,839.31	88.79	147,501.21	783.40	669,635.82	4,657.34
2018	1,253	402.80	7.98	23,583.89	96.81	165,145.09	739.02	721,196.58	3,372.51
2019	1,268	252.19	4.19	64,525.27	97.96	450,466.92	759.33	1,970,449.03	3,478.90
2020	1,532	335.89	5.18	122,334.99	172.71	863,851.92	1,361.77	3,780,990.27	6,494.10
2021	2,261	1,247.71	13.21	167,330.72	506.08	1,169,166.09	3,945.81	5,148,487.36	18,857.40
2022	1,951	1,092.57	12.13	102,477.33	441.39	709,718.32	3,273.96	2,977,134.74	14,561.13
Full	2,963	702.72	7.43	101,015.29	203.07	707,409.32	1,581.51	3,084,395.06	7,584.37

Panel B: Market Indices and Major Cryptocurrency Returns

	Daily			Weekly			Monthly		
Index/Coin	Mean	Stdev.	SR	Mean	Stdev.	SR	Mean	Stdev.	SR
Market Index	0.002	0.039	0.815	0.013	0.109	0.835	0.065	0.267	0.842
Mega Index	0.002	0.039	0.786	0.012	0.108	0.807	0.064	0.259	0.858
ExMega Index	0.002	0.048	0.762	0.017	0.141	0.875	0.089	0.403	0.768
Bitcoin	0.002	0.042	1.131	0.014	0.105	0.950	0.061	0.230	0.916
Ethereum	0.005	0.062	1.408	0.035	0.194	1.315	0.167	0.505	1.147
XRP	0.004	0.079	0.952	0.040	0.373	0.775	0.233	1.122	0.719

Table 2 In-sample Forecast of Cryptocurrency Market Returns

This table provides in-sample estimation results for the predictive regression

$$R_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1},$$

where R_{t+1} denotes the excess market return (in %) at various frequencies and X_t is one of the return predictors at the respective data frequency. In Panel A, the return predictors are 24 technical indicators from three categories: moving average (MA), momentum (MOM), and volume (VOL), each of which generates a dummy trading signal, with a 1 representing buying and a 0 representing selling. The names of the indicators included in brackets indicate the short and long horizons for respective trading frequencies. In Panel B, the return predictors are the common factors extracted from the 24 technical indicators using various machine learning methods, namely, the PCA, PLS, sPCA by Huang et al. (2022b), the scaled sufficient forecasting (sSUFF) by Huang et al. (2022a) with sSUFF$_l$ being the linear forecast and sSUFF being the nonlinear forecast using local linear regression, the least absolute shrinkage and selection operator (Lasso), and the elastic net (ENet). The sample ranges from January 1, 2015 to May 28, 2022. The t-statistics reported are based on the Newey-West standard errors with 4 lags and R^2s are in percentages (%). ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Individual Technical Indicators

	Daily				Weekly				Monthly		
Predictor	β	t-stat	R^2	Predictor	β	t-stat	R^2	Predictor	β	t-stat	R^2
MA(5,90)	0.19***	2.57	0.23	MA(1,12)	1.33**	2.16	1.46	MA(1,6)	4.97**	1.68	3.35
MA(5,180)	0.18***	2.47	0.22	MA(1,26)	1.36***	2.36	1.54	MA(1,9)	4.53	1.61	2.79
MA(5,360)	0.16**	2.26	0.17	MA(1,52)	1.29***	2.35	1.38	MA(1,12)	3.51	1.14	1.67
MA(10,90)	0.15**	2.04	0.15	MA(2,12)	1.17**	1.90	1.13	MA(2,6)	4.74	1.64	3.05
MA(10,180)	0.17**	2.30	0.18	MA(2,26)	1.33**	2.31	1.47	MA(2,9)	3.88	1.29	2.05
MA(10,360)	0.15**	2.13	0.15	MA(2,52)	1.27**	2.31	1.34	MA(2,12)	3.21	1.04	1.40
MA(30,90)	0.16**	2.14	0.16	MA(4,12)	0.98**	1.65	0.80	MA(3,6)	7.29***	2.92	7.20
MA(30,180)	0.18***	2.49	0.21	MA(4,26)	1.21**	2.01	1.20	MA(3,9)	5.70**	2.02	4.41
MA(30,360)	0.13**	1.84	0.11	MA(4,52)	0.92*	1.56	0.69	MA(3,12)	4.12	1.37	2.31
MOM(5)	0.12*	1.57	0.09	MOM(1)	0.87**	1.81	0.63	MOM(1)	4.16	1.60	2.34
MOM(10)	0.23***	3.08	0.33	MOM(2)	1.70***	3.16	2.38	MOM(2)	5.93**	2.15	4.78
MOM(30)	0.26***	3.37	0.43	MOM(4)	1.54***	3.06	1.95	MOM(3)	4.78	1.58	3.09
MOM(90)	0.13**	1.72	0.11	MOM(12)	1.39***	2.34	1.59	MOM(6)	3.39	1.13	1.56
MOM(180)	0.22***	3.00	0.31	MOM(26)	1.17**	2.05	1.13	MOM(9)	3.41	1.25	1.58
MOM(360)	0.07	0.98	0.03	MOM(52)	0.36	0.66	0.11	MOM(12)	2.69	0.98	0.98
VOL(5,90)	0.14**	1.86	0.13	VOL(1,12)	1.75***	3.03	2.52	VOL(1,6)	8.47***	3.23	9.74
VOL(5,180)	0.16**	2.00	0.17	VOL(1,26)	1.31**	2.09	1.43	VOL(1,9)	8.38***	2.95	9.52
VOL(5,360)	0.14**	1.82	0.13	VOL(1,52)	1.49***	2.54	1.85	VOL(1,12)	7.97***	2.76	8.62
VOL(10,90)	0.19**	2.30	0.22	VOL(2,12)	1.40***	2.53	1.62	VOL(2,6)	6.99***	2.54	6.63
VOL(10,180)	0.17**	2.11	0.18	VOL(2,26)	0.92*	1.44	0.71	VOL(2,9)	8.55***	3.06	9.91
VOL(10,360)	0.12*	1.48	0.09	VOL(2,52)	1.56***	2.72	2.01	VOL(2,12)	7.93***	2.65	8.52
VOL(30,90)	0.04	0.50	0.01	VOL(4,12)	1.13**	1.86	1.05	VOL(3,6)	8.85***	3.37	10.62
VOL(30,180)	0.10	1.26	0.06	VOL(4,26)	1.06**	1.76	0.92	VOL(3,9)	9.29***	3.40	11.71
VOL(30,360)	0.05	0.65	0.02	VOL(4,52)	1.06**	1.74	0.94	VOL(3,12)	7.86***	2.57	8.37

Table 2 (Cont'd) In-sample Forecast of Cryptocurrency Market Returns

This table provides in-sample estimation results for the predictive regression

$$R_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1},$$

where R_{t+1} denotes the excess market return (in %) at various frequencies and X_t is one of the return predictors at the respective data frequency. In Panel A, the return predictors are 24 technical indicators from three categories: moving average (MA), momentum (MOM), and volume (VOL), each of which generates a dummy trading signal, with a 1 representing buying and a 0 representing selling. The names of the indicators included in brackets indicate the short and long horizons for respective trading frequencies. In Panel B, the return predictors are the common factors extracted from the 24 technical indicators using various machine learning methods, namely, the simple averages (Naïve), PCA, PLS, sPCA by Huang et al. (2022b), the scaled sufficient forecasting (sSUFF) by Huang et al. (2022a) with sSUFF_l being the linear forecast and sSUFF being the nonlinear forecast using local linear regression, the least absolute shrinkage and selection operator (Lasso), and the elastic net (ENet). The sample ranges from January 1, 2015 to May 28, 2022. The R^2s are reported in percentages (%). ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel B: Machine Learning Methods

	Daily		Weekly		Monthly	
Predictor	F-statistic	R^2	F-statistic	R^2	F-statistic	R^2
Naïve	8.12***	0.30	9.81***	2.49	6.89**	7.42
PCA	7.06***	0.26	9.17***	2.33	6.75**	7.28
PLS	9.80***	0.36	10.70***	2.71	8.37***	8.87
sPCA	8.03***	0.30	9.47***	2.41	7.70***	8.22
sSUFF_l	7.06***	0.26	9.17***	2.33	6.76**	7.29
sSUFF	95.02***	3.40	156.72***	28.53	30.45***	24.54
Lasso	19.55***	0.72	17.16***	4.28	12.72***	12.89
ENet	18.23***	0.67	17.03***	4.25	11.81***	12.07

Table 3 Out-of-sample Forecast of Cryptocurrency Market Returns

This table provides out-of-sample estimation results by recursively estimating the predictive regression. In Panel A, the return predictors are 24 technical indicators from three categories: moving average (MA), momentum (MOM), and volume (VOL), each of which generates a dummy trading signal, with a 1 representing buying and a 0 representing selling. The names of the indicators included in brackets indicate the short and long horizons for respective trading frequencies. In Panel B, the return predictors are the common factors extracted from the 24 technical indicators using principal component analysis (PCA), partial least squares (PLS), scaled PCA (sPCA) by Huang et al. (2022b), and scaled sufficient forecasting (sSUFF) by Huang et al. (2022a) with sSUFF_l being the linear forecast and sSUFF being the nonlinear forecast using local linear regression, respective. Two shrinkage and variable selection methods, i.e., the least absolute shrinkage and selection operator (Lasso) and the elastic net (ENet), are also considered for comparison. All R^2s are in percentages (%) and CW denotes the Clark and West (2007) test statistic. $R^2_{OS,Pre}$ and $R^2_{OS,Post}$ denote the out-of-sample R^2 with the pre- and post-COVID samples, respectively. The sample is split in March 2020 when WHO declared COVID-19 a global pandemic. $R^2_{OS,down}$ is the out-of-sample R^2 evaluated using the sample when the returns are in the bottom decile. The full sample ranges from January 1, 2015 to May 28, 2022. The out-of-sample period is from January 1, 2018 to May 28, 2022. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Individual Technical Indicators

	Daily			Weekly			Monthly	
Predictors	R^2_{OS}	CW	Predictors	R^2_{OS}	CW	Predictors	R^2_{OS}	CW
MA(5,90)	0.21**	1.98	MA(1,12)	1.34**	1.92	MA(1,6)	−1.35	0.51
MA(5,180)	0.09*	1.40	MA(1,26)	0.52*	1.30	MA(1,9)	−2.88	0.13
MA(5,360)	−0.06	0.61	MA(1,52)	0.06	1.00	MA(1,12)	−7.27	−0.29
MA(10,90)	0.04	1.06	MA(2,12)	0.71*	1.39	MA(2,6)	−1.15	0.57
MA(10,180)	0.01	1.03	MA(2,26)	0.46	1.26	MA(2,9)	−3.32	0.18
MA(10,360)	−0.08	0.50	MA(2,52)	−0.03	0.86	MA(2,12)	−7.59	−0.43
MA(30,90)	0.13*	1.57	MA(4,12)	0.17	0.86	MA(3,6)	7.64**	1.81
MA(30,180)	0.11*	1.52	MA(4,26)	0.46	1.16	MA(3,9)	−1.17	0.61
MA(30,360)	−0.11	0.19	MA(4,52)	−0.85	0.05	MA(3,12)	−5.84	−0.15
MOM(5)	−0.02	0.78	MOM(1)	−0.18	0.43	MOM(1)	−0.22	0.58
MOM(10)	0.32***	2.38	MOM(2)	1.86**	2.21	MOM(2)	2.15	1.25
MOM(30)	0.35**	2.24	MOM(4)	1.59***	2.36	MOM(3)	−1.02	0.58
MOM(90)	0.05	1.07	MOM(12)	1.16*	1.63	MOM(6)	−4.67	−0.11
MOM(180)	0.24**	2.07	MOM(26)	0.36	1.08	MOM(9)	−7.65	−0.52
MOM(360)	−0.20	−0.98	MOM(52)	−1.77	−1.87	MOM(12)	−8.63	−1.24
VOL(5,90)	0.10*	1.31	VOL(1,12)	2.86***	2.80	VOL(1,6)	12.13***	2.99
VOL(5,180)	0.04	0.92	VOL(1,26)	1.37**	1.85	VOL(1,9)	8.85**	1.96
VOL(5,360)	0.00	0.62	VOL(1,52)	1.39**	1.73	VOL(1,12)	6.89**	1.82
VOL(10,90)	0.17*	1.53	VOL(2,12)	1.58**	2.27	VOL(2,6)	5.38**	1.82
VOL(10,180)	0.06	1.04	VOL(2,26)	0.29	0.80	VOL(2,9)	10.79***	2.37
VOL(10,360)	−0.10	0.04	VOL(2,52)	1.17*	1.52	VOL(2,12)	6.52**	1.71
VOL(30,90)	−0.21	−0.79	VOL(4,12)	0.89*	1.48	VOL(3,6)	11.43***	2.51
VOL(30,180)	−0.18	−0.25	VOL(4,26)	0.33	0.87	VOL(3,9)	12.14***	2.38
VOL(30,360)	−0.25	−1.75	VOL(4,52)	−0.71	0.15	VOL(3,12)	6.20**	1.68

Table 3 (Cont'd) Out-of-sample Forecast of Cryptocurrency Market Returns

This table provides out-of-sample estimation results for recursively estimating the predictive regression. In Panel A, the return predictors are 24 technical indicators from three categories: moving average (MA), momentum (MOM), and volume (VOL), each of which generates a dummy trading signal, with a 1 representing buying and a 0 representing selling. The names of the indicators included in brackets indicate the short and long horizons for respective trading frequencies. In Panel B, the return predictors are the common factors extracted from the 24 technical indicators using simple averages (Naïve), principal component analysis (PCA), partial least squares (PLS), scaled PCA (sPCA) by Huang et al. (2022b), and scaled sufficient forecasting (sSUFF) by Huang et al. (2022a) with sSUFF$_l$ being the linear forecast and sSUFF being the nonlinear forecast using local linear regression, respective. Two shrinkage and variable selection methods, i.e., the least absolute shrinkage and selection operator (Lasso) and the elastic net (ENet), are also considered for comparison. All R^2s are in percentages (%) and CW denotes the Clark and West (2007) test statistic. $R^2_{OS,Pre}$ and $R^2_{OS,Post}$ denote the out-of-sample R^2 with the pre- and post-COVID samples, respectively. The sample is split in March 2020 when WHO declared COVID-19 a global pandemic. $R^2_{OS,down}$ is the out-of-sample R^2 evaluated using the sample when the returns are in the bottom decile. The full sample ranges from January 1, 2015 to May 28, 2022. The out-of-sample period is from January 1, 2018 to May 28, 2022. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel B: Machine Learning Methods

	Daily					Weekly					Monthly				
Predictor	R^2_{OS}	CW	$R^2_{OS,Pre}$	$R^2_{OS,Post}$	$R^2_{OS,down}$	R^2_{OS}	CW	$R^2_{OS,Pre}$	$R^2_{OS,Post}$	$R^2_{OS,down}$	R^2_{OS}	CW	$R^2_{OS,Pre}$	$R^2_{OS,Post}$	$R^2_{OS,down}$
Naïve	0.13*	1.59	0.12	0.15*	0.66**	1.32**	2.10	0.79	2.06**	1.53*	5.24*	1.37	4.62	6.18	11.46**
PCA	0.20**	1.91	0.06	0.33**	0.99**	1.93***	2.33	1.10	3.08**	2.56*	4.66*	1.34	3.34	6.66	13.53***
PLS	0.25**	2.11	0.10	0.39**	1.04**	1.94***	2.38	1.22*	2.94**	3.13**	5.66*	1.54	4.05	8.10*	15.13***
sPCA	0.19**	1.87	0.02	0.34**	0.86**	1.66**	2.16	0.85	2.79**	2.69*	5.61*	1.52	4.01	8.02	15.54***
sSUFF$_l$	0.19**	1.85	0.06	0.31**	0.98**	1.89**	2.30	1.05	3.07**	2.67*	5.45*	1.49	4.23	7.28	12.78***
sSUFF	0.30**	2.12	0.25*	0.35**	1.40***	2.70***	2.46	1.24	4.72***	4.04**	9.19**	1.88	9.89*	8.14	16.59**
Lasso	0.24**	2.06	0.20	0.27*	1.14***	1.23**	1.71	0.96	1.62*	2.28*	8.83**	2.10	9.57*	7.71*	17.26*
ENet	0.02	0.95	−0.15	0.18	1.01***	0.69*	1.43	−0.01	1.68*	1.85*	6.08**	1.74	6.34*	5.69	12.22*

Table 4 Out-of-sample Forecast of Sub-Indices

This table provides out-of-sample estimation results on crypto market sub-indices by recursively estimating the predictive regression. Mega Index is a value-weighted index based on the top 10 coins ranked by the previous period's market capitalization, ExMega Index uses all the cryptos in the market excluding the top 10 largest cryptos. The return predictors are the common factors extracted from the 24 technical indicators using simple averages (Naïve), principal component analysis (PCA), partial least squares (PLS), scaled PCA (sPCA) by Huang et al. (2022b) and scaled sufficient forecasting (sSUFF) by Huang et al. (2022a) with sSUFF$_l$ being the linear forecast and sSUFF being the nonlinear forecast using local linear regression, respectively. Two shrinkage and variable selection methods, i.e., least absolute shrinkage and selection operator (Lasso) and elastic net (ENet) are also considered for comparison. All R^2_{OS}s are in percentages (%) and CW denotes the Clark and West (2007) test statistic. The in-sample estimation period is from January 1, 2015 to December 31, 2017 and the out-of-sample evaluation period is January 1, 2018 through May 28, 2022. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Mega Index						ExMega Index					
	Daily		Weekly		Monthly		Daily		Weekly		Monthly	
Predictors	R^2_{OS}	CW	R^2_{OS}	CW	R^2_{OS}	CW	R^2_{OS}	CW	R^2_{OS}	CW	R^2_{OS}	CW
Naïve	0.19**	1.94	0.76*	1.35	4.16	1.24	0.08	1.22	0.89	1.27	3.53	1.05
PCA	0.20**	1.86	0.88*	1.47	3.14	1.21	0.11*	1.49	0.65*	1.33	2.44	1.17
PLS	0.26**	2.08	0.88*	1.48	4.02*	1.40	0.06*	1.48	0.39*	1.35	−1.19	0.92
sPCA	0.18**	1.80	0.77*	1.40	4.06*	1.39	0.05*	1.31	0.17	1.23	−0.69	0.95
sSUFF$_l$	0.18**	1.81	1.39**	1.76	5.82*	1.60	0.12*	1.50	0.61*	1.32	0.41	1.03
sSUFF	0.14*	1.60	2.66***	2.64	11.56*	1.64	−0.04**	1.79	0.44*	1.39	5.22**	1.65
Lasso	0.36***	2.67	0.75	1.23	10.84***	2.56	−0.10	0.45	1.30**	1.78	−8.24	0.25
ENet	0.23**	2.07	0.08	0.83	2.84*	1.39	−0.02	0.71	0.14	1.07	−6.63	0.38

Table 5 Asset Allocation Performance

This table reports the annualized CER gains (in %) and annualized Sharpe ratios for a mean-variance investor, who allocates assets between the cryptocurrency market and risk-free bills using the out-of-sample forecasts in daily, weekly, and monthly frequency. The investor's risk aversion is set to five. We consider two scenarios: zero transaction cost and a dynamic transaction cost of half-spread per transaction. The daily bid-ask spread is estimated using Ardia, Guidotti, and Kroencke (2022), and the weekly and monthly bid-ask spread is the daily average of the corresponding week and month, respectively. Panel A reports the results using the market index and Panel B presents the results using the Mega index. The in-sample estimation period is from January 1, 2015 to December 31, 2017, and the out-of-sample evaluation period is from January 1, 2018 through May 28, 2022.

Panel A: Market Index

	Daily				Weekly				Monthly			
Predictors	CER_0	SR_0	CER_{bas}	SR_{bas}	CER_0	SR_0	CER_{bas}	SR_{bas}	CER_0	SR_0	CER_{bas}	SR_{bas}
Naïve	4.12	0.21	3.43	0.17	5.14	0.36	4.91	0.34	4.21	0.52	4.14	0.51
PCA	5.21	0.33	4.81	0.31	8.19	0.53	7.81	0.51	4.82	0.58	4.69	0.57
PLS	7.97	0.45	6.52	0.40	8.10	0.56	7.42	0.53	5.77	0.64	5.60	0.62
sPCA	4.46	0.35	3.97	0.33	6.29	0.49	5.86	0.47	5.78	0.63	5.62	0.62
sSUFF_l	4.80	0.32	4.29	0.29	8.27	0.53	7.84	0.51	4.82	0.62	4.67	0.60
sSUFF	14.50	0.62	4.08	0.29	9.28	0.65	6.84	0.57	7.47	0.74	7.27	0.73
Lasso	10.87	0.44	3.41	0.19	6.72	0.48	4.88	0.41	6.14	0.66	5.91	0.64
ENet	1.40	0.13	−5.65	−0.11	3.17	0.37	1.51	0.31	4.26	0.56	4.08	0.55

Panel B: Mega Index

	Daily				Weekly				Monthly			
Predictors	CER_0	SR_0	CER_{bas}	SR_{bas}	CER_0	SR_0	CER_{bas}	SR_{bas}	CER_0	SR_0	CER_{bas}	SR_{bas}
Naïve	5.56	0.27	5.32	0.26	1.82	0.26	1.62	0.25	3.93	0.53	3.87	0.52
PCA	3.09	0.35	2.94	0.34	1.71	0.37	1.35	0.35	4.21	0.58	4.11	0.57
PLS	6.36	0.48	5.98	0.46	1.01	0.39	0.44	0.37	5.22	0.64	5.09	0.63
sPCA	2.43	0.36	2.25	0.35	−0.05	0.36	−0.43	0.34	5.30	0.63	5.18	0.62
sSUFF_l	2.51	0.33	2.34	0.33	5.23	0.47	4.72	0.45	6.56	0.67	6.43	0.66
sSUFF	8.76	0.57	5.52	0.48	12.06	0.57	10.24	0.51	7.40	0.74	7.18	0.73
Lasso	16.02	0.64	13.76	0.57	2.49	0.41	1.06	0.37	8.92	0.80	8.67	0.79
ENet	10.90	0.48	8.75	0.41	−0.48	0.28	−1.71	0.23	3.37	0.56	3.16	0.54

Appendices

A Additional Asset Allocation Results

Table A1 Asset Allocation Performance with Naïve Strategy as Benchmark

This table reports the annualized CER gains (in %) and annualized Sharpe ratios for a mean-variance investor, who allocates assets between the crypto market index and risk-free bills using the out-of-sample forecasts in daily, weekly, and monthly frequency. The investor's risk aversion is set to five. We consider two scenarios: zero transaction cost and a dynamic transaction cost of half-spread per transaction. The daily bid-ask spread is estimated using Ardia, Guidotti, and Kroencke (2022), and the weekly and monthly bid-ask spread is the daily average of the corresponding week and month, respectively. The in-sample estimation period is from January 1, 2015 to December 31, 2017, and the out-of-sample evaluation period is from January 1, 2018 through May 28, 2022.

	Daily				Weekly				Monthly			
Predictors	CER_0	SR_0	CER_{bas}	SR_{bas}	CER_0	SR_0	CER_{bas}	SR_{bas}	CER_0	SR_0	CER_{bas}	SR_{bas}
PCA	1.10	0.33	1.22	0.32	3.06	0.53	2.91	0.51	0.60	0.58	0.55	0.57
PLS	3.85	0.45	3.51	0.43	2.96	0.56	2.51	0.53	1.56	0.64	1.46	0.62
sPCA	0.34	0.35	0.43	0.34	1.15	0.49	0.95	0.47	1.57	0.63	1.48	0.62
sSUFF_l	0.68	0.32	0.76	0.30	3.13	0.53	2.93	0.51	0.60	0.62	0.53	0.60
sSUFF	10.38	0.62	5.82	0.47	4.14	0.65	1.94	0.57	3.26	0.74	3.13	0.73
Lasso	6.75	0.44	3.56	0.32	1.58	0.48	−0.03	0.41	1.93	0.66	1.77	0.64
ENet	−2.72	0.13	−5.71	0.01	−1.97	0.37	−3.40	0.31	0.05	0.56	−0.06	0.55

B Results on Buy-and-hold Returns

Table B1 Summary Statistics

This table reports the summary statistics of the cryptocurrencies. Panel A summarizes the number of cryptocurrencies, mean and median of market capitalization, and trading volumes on yearly basis from 2014 to 2022. The trading volumes are reported at three frequencies, i.e., daily, weekly, and monthly, where the weekly and monthly trading volumes are the cumulative trading volumes of the daily volumes within that week and month, respectively. Panel B reports the return characteristics (i.e., mean, standard deviation, Sharpe ratio) of three crypto indices and three major crypto coins at various frequencies. The market index is the value-weighted average price of the cryptos that satisfies our filters. The (ExMega) Mega index is constructed using the (cryptos excluding) top 10 cryptos in market capitalization. The crypto indices, Bitcoin, and Ripple data range from January 1, 2014 to May 28, 2022. The Ethereum data ranges from August 8, 2015 to May 28, 2022.

Panel A: Characteristics by Year

		Market Capitalization (in millions)		Trading Volume (in thousands)					
				Daily		Weekly		Monthly	
Year	Number	Mean	Median	Mean	Median	Mean	Median	Mean	Median
2014	125	214.26	2.49	1,021.16	21.22	7,010.81	146.21	29,046.53	456.32
2015	85	117.16	1.79	1,031.81	7.42	7,198.66	56.44	31,464.03	222.47
2016	170	136.94	1.97	1,547.03	10.02	10,944.64	80.60	49,019.65	373.79
2017	639	470.41	7.64	20,839.31	88.79	150,390.66	805.56	732,329.80	5,087.00
2018	1,253	402.80	7.98	23,583.89	96.81	166,267.74	721.97	741,680.21	2,940.46
2019	1,268	252.19	4.19	64,525.27	97.96	450,091.76	737.69	1,979,036.33	3,107.67
2020	1,532	335.89	5.18	122,334.99	172.71	867,795.31	1,351.90	3,873,111.79	6,005.66
2021	2,261	1,247.71	13.21	167,330.72	506.08	1,173,810.60	3,888.18	5,283,453.15	17,876.90
2022	1,951	1,092.57	12.13	102,477.33	441.39	706,541.02	3,191.42	2,928,584.63	12,797.64
Full	2,963	702.72	7.43	101,015.29	203.07	709,828.50	1,555.71	3,147,280.94	6,938.25

Panel B: Market Indices and Major Cryptocurrency Returns

	Daily			Weekly			Monthly		
Index/Coin	Mean	Stdev.	SR	Mean	Stdev.	SR	Mean	Stdev.	SR
Market Index	0.002	0.039	0.815	0.014	0.107	0.934	0.062	0.272	0.795
Mega Index	0.002	0.039	0.786	0.013	0.105	0.892	0.060	0.263	0.795
ExMega Index	0.002	0.048	0.762	0.019	0.151	0.908	0.095	0.415	0.797
Bitcoin	0.002	0.042	1.131	0.014	0.106	0.963	0.063	0.238	0.911
Ethereum	0.005	0.062	1.408	0.035	0.182	1.376	0.178	0.524	1.177
Ripple	0.004	0.079	0.952	0.032	0.276	0.844	0.266	1.270	0.725

Table B2 In-sample Forecast of Cryptocurrency Market Returns

This table provides in-sample estimation results for the predictive regression

$$R_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1},$$

where R_{t+1} denotes the excess market return (in %) at various frequencies and X_t is one of the return predictors at the respective data frequency. In Panel A, the return predictors are 24 technical indicators from three categories: moving average (MA), momentum (MOM), and volume (VOL), each of which generates a dummy trading signal, with a 1 representing buying and a 0 representing selling. The names of the indicators included in brackets indicate the short and long horizons for respective trading frequencies. In Panel B, the return predictors are the common factors extracted from the 24 technical indicators using various machine learning methods, namely, the PCA, PLS, sPCA by Huang et al. (2022b), the scaled sufficient forecasting (sSUFF) by Huang et al. (2022a) with sSUFF$_l$ being the linear forecast and sSUFF being the nonlinear forecast using local linear regression, the least absolute shrinkage and selection operator (Lasso), and the elastic net (ENet). The sample ranges from January 1, 2015 to May 28, 2022. The t-statistics reported are based on the Newey-West standard errors with 4 lags and R^2s are in percentages (%). ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Individual Technical Indicators

	Daily				Weekly				Monthly		
Predictor	β	t-stat	R^2	Predictor	β	t-stat	R^2	Predictor	β	t-stat	R^2
MA(5,90)	0.19***	2.57	0.23	MA(1,12)	1.46***	2.45	1.85	MA(1,6)	5.41**	1.75	3.77
MA(5,180)	0.18***	2.47	0.22	MA(1,26)	1.16**	1.92	1.18	MA(1,9)	4.54*	1.51	2.65
MA(5,360)	0.16**	2.26	0.17	MA(1,52)	1.16**	2.11	1.17	MA(1,12)	4.89**	1.70	3.08
MA(10,90)	0.15**	2.04	0.15	MA(2,12)	1.47***	2.46	1.87	MA(2,6)	5.28**	1.75	3.59
MA(10,180)	0.17**	2.30	0.18	MA(2,26)	1.24**	2.22	1.34	MA(2,9)	4.79*	1.62	2.95
MA(10,360)	0.15**	2.13	0.15	MA(2,52)	1.07**	1.96	1.01	MA(2,12)	4.55*	1.57	2.67
MA(30,90)	0.16**	2.14	0.16	MA(4,12)	1.05**	1.76	0.97	MA(3,6)	8.00***	3.09	8.24
MA(30,180)	0.18***	2.49	0.21	MA(4,26)	1.00*	1.63	0.87	MA(3,9)	5.57**	1.92	3.99
MA(30,360)	0.13**	1.84	0.11	MA(4,52)	0.94**	1.67	0.77	MA(3,12)	4.36*	1.47	2.45
MOM(5)	0.12*	1.57	0.09	MOM(1)	0.81*	1.49	0.57	MOM(1)	3.87*	1.43	1.93
MOM(10)	0.23***	3.08	0.33	MOM(2)	1.32***	2.61	1.52	MOM(2)	3.71*	1.47	1.77
MOM(30)	0.26***	3.37	0.43	MOM(4)	1.33***	2.44	1.53	MOM(3)	5.84**	1.93	4.39
MOM(90)	0.13**	1.72	0.11	MOM(12)	1.06**	1.87	0.98	MOM(6)	4.26*	1.45	2.33
MOM(180)	0.22***	3.00	0.31	MOM(26)	1.07**	1.87	1.00	MOM(9)	2.90	1.01	1.08
MOM(360)	0.07	0.98	0.03	MOM(52)	0.14	0.24	0.02	MOM(12)	1.08	0.39	0.15
VOL(5,90)	0.14**	1.86	0.13	VOL(1,12)	0.55	0.84	0.27	VOL(1,6)	6.10**	2.25	4.79
VOL(5,180)	0.16**	2.00	0.17	VOL(1,26)	1.08**	1.80	1.01	VOL(1,9)	6.82***	2.36	5.99
VOL(5,360)	0.14**	1.82	0.13	VOL(1,52)	0.63	1.07	0.34	VOL(1,12)	6.68**	2.27	5.74
VOL(10,90)	0.19**	2.30	0.22	VOL(2,12)	0.85*	1.47	0.63	VOL(2,6)	6.18**	2.09	4.91
VOL(10,180)	0.17**	2.11	0.18	VOL(2,26)	1.08**	1.93	1.01	VOL(2,9)	8.55***	3.01	9.42
VOL(10,360)	0.12*	1.48	0.09	VOL(2,52)	0.34	0.54	0.10	VOL(2,12)	8.08***	3.01	8.41
VOL(30,90)	0.04	0.50	0.01	VOL(4,12)	0.37	0.58	0.12	VOL(3,6)	6.36**	2.13	5.21
VOL(30,180)	0.10	1.26	0.06	VOL(4,26)	1.16**	2.07	1.18	VOL(3,9)	7.72***	3.00	7.68
VOL(30,360)	0.05	0.65	0.02	VOL(4,52)	0.71*	1.32	0.45	VOL(3,12)	7.37***	2.77	6.99

Table B2 (Cont'd) In-sample Forecast of Cryptocurrency Market Returns

This table provides in-sample estimation results for the predictive regression

$$R_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1},$$

where R_{t+1} denotes the excess market return (in %) at various frequencies and X_t is one of the return predictors at the respective data frequency. In Panel A, the return predictors are 24 technical indicators from three categories: moving average (MA), momentum (MOM), and volume (VOL), each of which generates a dummy trading signal, with a 1 representing buying and a 0 representing selling. The names of the indicators included in brackets indicate the short and long horizons for respective trading frequencies. In Panel B, the return predictors are the common factors extracted from the 24 technical indicators using various machine learning methods, namely, the simple averages (Naïve), PCA, PLS, sPCA by Huang et al. (2022b), the scaled sufficient forecasting (sSUFF) by Huang et al. (2022a) with sSUFF_l being the linear forecast and sSUFF being the nonlinear forecast using local linear regression, the least absolute shrinkage and selection operator (Lasso), and the elastic net (ENet). The sample ranges from January 1, 2015 to May 28, 2022. The R^2s are reported in percentages (%). ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel B: Machine Learning Methods

	Daily		Weekly		Monthly	
Predictor	F-statistic	R^2	F-statistic	R^2	F-statistic	R^2
Naïve	8.12***	0.30	6.95***	1.78	5.57**	6.08
PCA	7.06***	0.26	6.54**	1.68	5.57**	6.08
PLS	9.80***	0.36	8.09***	2.06	6.32**	6.85
sPCA	8.03***	0.30	7.49***	1.91	6.03**	6.55
sSUFF_l	7.06***	0.26	6.73***	1.72	5.58**	6.09
sSUFF	95.02***	3.40	75.08***	16.22	38.20***	30.20
Lasso	19.55***	0.72	11.52***	2.91	10.11***	10.52
ENet	18.23***	0.67	11.15***	2.82	9.31***	9.76

Table B3 Out-of-sample Forecast of Cryptocurrency Market Returns

This table provides out-of-sample estimation results by recursively estimating the predictive regression. In Panel A, the return predictors are 24 technical indicators from three categories: moving average (MA), momentum (MOM), and volume (VOL), each of which generates a dummy trading signal, with a 1 representing buying and a 0 representing selling. The names of the indicators included in brackets indicate the short and long horizons for respective trading frequencies. In Panel B, the return predictors are the common factors extracted from the 24 technical indicators using simple averages (Naïve), principal component analysis (PCA), partial least squares (PLS), scaled PCA (sPCA) by Huang et al. (2022b), and scaled sufficient forecasting (sSUFF) by Huang et al. (2022a) with sSUFF_l being the linear forecast and sSUFF being the nonlinear forecast using local linear regression, respective. Two shrinkage and variable selection methods, i.e., the least absolute shrinkage and selection operator (Lasso) and the elastic net (ENet), are also considered for comparison. All R^2s are in percentages (%) and CW denotes the Clark and West (2007) test statistic. $R^2_{OS,Pre}$ and $R^2_{OS,Post}$ denote the out-of-sample R^2 with the pre- and post-COVID samples, respectively. The sample is split in March 2020 when WHO declared COVID-19 a global pandemic. $R^2_{OS,down}$ is the out-of-sample R^2 evaluated using the sample when the returns are in the bottom decile. The full sample ranges from January 1, 2015 to May 28, 2022. The out-of-sample period is from January 1, 2018 to May 28, 2022. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Individual Technical Indicators

	Daily			Weekly			Monthly	
Predictors	R^2_{OS}	CW	Predictors	R^2_{OS}	CW	Predictors	R^2_{OS}	CW
MA(5,90)	0.21**	1.98	MA(1,12)	1.13*	1.58	MA(1,6)	0.35	0.80
MA(5,180)	0.09*	1.40	MA(1,26)	−0.45	0.69	MA(1,9)	−1.97	0.41
MA(5,360)	−0.06	0.61	MA(1,52)	−0.10	0.86	MA(1,12)	−2.65	0.45
MA(10,90)	0.04	1.06	MA(2,12)	1.01*	1.50	MA(2,6)	0.54	0.91
MA(10,180)	0.01	1.03	MA(2,26)	0.53*	1.31	MA(2,9)	−2.90	0.43
MA(10,360)	−0.08	0.50	MA(2,52)	−0.41	0.60	MA(2,12)	−3.80	0.27
MA(30,90)	0.13*	1.57	MA(4,12)	0.78*	1.33	MA(3,6)	8.23**	1.96
MA(30,180)	0.11*	1.52	MA(4,26)	0.14	0.88	MA(3,9)	−1.03	0.72
MA(30,360)	−0.11	0.19	MA(4,52)	−0.74	0.32	MA(3,12)	−4.17	0.18
MOM(5)	0.02	0.78	MOM(1)	−0.70	0.28	MOM(1)	0.93	0.92
MOM(10)	0.32***	2.38	MOM(2)	0.08	1.25	MOM(2)	0.90	1.00
MOM(30)	0.35**	2.24	MOM(4)	0.52	1.26	MOM(3)	2.61	1.19
MOM(90)	0.05	1.07	MOM(12)	0.40	1.18	MOM(6)	−1.52	0.46
MOM(180)	0.24**	2.07	MOM(26)	−0.01	0.87	MOM(9)	−6.51	−0.32
MOM(360)	−0.20	−0.98	MOM(52)	−1.87	−1.41	MOM(12)	−8.24	−1.76
VOL(5,90)	0.10*	1.31	VOL(1,12)	−0.57	−0.28	VOL(1,6)	4.80**	1.81
VOL(5,180)	0.04	0.92	VOL(1,26)	−0.33	0.45	VOL(1,9)	0.89	0.96
VOL(5,360)	0.00	0.62	VOL(1,52)	−1.47	−0.51	VOL(1,12)	1.19	0.97
VOL(10,90)	0.17*	1.53	VOL(2,12)	−0.28	0.41	VOL(2,6)	3.64*	1.35
VOL(10,180)	0.06	1.04	VOL(2,26)	−0.19	0.76	VOL(2,9)	9.16**	1.99
VOL(10,360)	−0.10	0.04	VOL(2,52)	−1.97	−1.35	VOL(2,12)	7.28**	1.81
VOL(30,90)	−0.21	−0.79	VOL(4,12)	−0.92	−0.56	VOL(3,6)	3.43*	1.32
VOL(30,180)	−0.18	−0.25	VOL(4,26)	−0.12	0.84	VOL(3,9)	5.91**	1.79
VOL(30,360)	−0.25	−1.75	VOL(4,52)	−0.98	−0.08	VOL(3,12)	4.34*	1.56

Table B3 (Cont'd) Out-of-sample Forecast of Cryptocurrency Market Returns

This table provides out-of-sample estimation results for recursively estimating the predictive regression. In Panel A, the return predictors are 24 technical indicators from three categories: moving average (MA), momentum (MOM), and volume (VOL), each of which generates a dummy trading signal, with a 1 representing buying and a 0 representing selling. The names of the indicators included in brackets indicate the short and long horizons for respective trading frequencies. In Panel B, the return predictors are the common factors extracted from the 24 technical indicators using simple averages (Naïve), principal component analysis (PCA), partial least squares (PLS), scaled PCA (sPCA) by Huang et al. (2022b), and scaled sufficient forecasting (sSUFF) by Huang et al. (2022a) with sSUFF_l being the linear forecast and sSUFF being the nonlinear forecast using local linear regression, respective. Two shrinkage and variable selection methods, i.e., the least absolute shrinkage and selection operator (Lasso) and the elastic net (ENet), are also considered for comparison. All R^2s are in percentages (%) and CW denotes the Clark and West (2007) test statistic. $R^2_{OS,Pre}$ and $R^2_{OS,Post}$ denote the out-of-sample R^2 with the pre- and post-COVID samples, respectively. The sample is split in March 2020 when WHO declared COVID-19 a global pandemic. $R^2_{OS,down}$ is the out-of-sample R^2 evaluated using the sample when the returns are in the bottom decile. The full sample ranges from January 1, 2015 to May 28, 2022. The out-of-sample period is from January 1, 2018 to May 28, 2022. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel B: Machine Learning Methods

	Daily				Weekly				Monthly			
Predictor	R^2_{OS}	CW	$R^2_{OS,Pre}$	$R^2_{OS,Post}$	R^2_{OS}	CW	$R^2_{OS,Pre}$	$R^2_{OS,Post}$	R^2_{OS}	CW	$R^2_{OS,Pre}$	$R^2_{OS,Post}$
Naïve	0.13*	1.59	0.12	0.15*	0.43	0.93	0.39	0.47	3.44	1.16	3.82	2.70
PCA	0.20**	1.91	0.06	0.33**	0.41	1.10	0.02	0.88	3.25	1.20	4.01	1.76
PLS	0.25**	2.11	0.10	0.39**	0.27	1.08	−0.07	0.68	2.86	1.17	3.40	1.80
sPCA	0.19**	1.87	0.02	0.34**	0.30	1.09	−0.11	0.81	2.82	1.17	3.26	1.95
sSUFF_l	0.19**	1.85	0.06	0.31**	0.33	1.07	−0.04	0.79	3.40	1.20	3.90	2.43
sSUFF	0.30**	2.12	0.25*	0.35**	1.55**	1.79	1.89	1.14*	4.70*	1.37	4.77	4.57
Lasso	0.24**	2.06	0.20	0.27*	−1.50	−0.72	−2.29	−0.54	3.71*	1.33	7.38*	−3.47
ENet	0.02	0.95	−0.15	0.18	−0.49	0.29	−0.12	−0.93	3.03	1.17	3.60	1.90

Table B4 Out-of-sample Forecast of Sub-Indices

This table provides out-of-sample estimation results on crypto market sub-indices by recursively estimating the predictive regression. Mega Index is a value-weighted index based on the top 10 coins ranked by the previous period's market capitalization, ExMega Index uses all the cryptos in the market excluding the top 10 largest cryptos. The return predictors are the common factors extracted from the 24 technical indicators using simple averages (Naïve), principal component analysis (PCA), partial least squares (PLS), scaled PCA (sPCA) by Huang et al. (2022b) and scaled sufficient forecasting (sSUFF) by Huang et al. (2022a) with sSUFF_l being the linear forecast and sSUFF being the nonlinear forecast using local linear regression, respectively. Two shrinkage and variable selection methods, i.e., least absolute shrinkage and selection operator (Lasso) and elastic net (ENet) are also considered for comparison. All R^2_{OS}s are in percentages (%) and CW denotes the Clark and West (2007) test statistic. The in-sample estimation period is from January 1, 2015 to December 31, 2017 and the out-of-sample evaluation period is from January 1, 2018 through May 28, 2022. ***, ** and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Mega Index						ExMega Index					
	Daily		Weekly		Monthly		Daily		Weekly		Monthly	
Predictors	R^2_{OS}	CW	R^2_{OS}	CW	R^2_{OS}	CW	R^2_{OS}	CW	R^2_{OS}	CW	R^2_{OS}	CW
Naïve	0.19**	1.94	0.77	1.25	3.51	1.18	0.08	1.22	0.31	0.94	3.13	1.26
PCA	0.20**	1.86	0.75*	1.29	3.63	1.27	0.11*	1.49	−0.53	0.78	3.48*	1.42
PLS	0.26**	2.08	0.60	1.22	2.99	1.19	0.06*	1.48	−0.97	0.69	2.57*	1.28
sPCA	0.18**	1.80	0.54	1.18	2.92	1.18	0.05*	1.31	−0.81	0.68	2.37	1.27
sSUFF_l	0.18**	1.81	0.87*	1.41	4.22*	1.36	0.12*	1.50	−0.41	0.86	3.05*	1.37
sSUFF	0.14*	1.60	1.00*	1.61	4.46*	1.40	−0.04**	1.79	0.51*	1.44	−5.82	0.33
Lasso	0.36***	2.67	−0.70	0.25	1.16	0.73	−0.10	0.45	−0.41	0.81	1.03	1.01
ENet	0.23**	2.07	−0.79	0.19	2.98	1.12	−0.02	0.71	−0.94	0.50	1.16	0.91

Table B5 Asset Allocation Performance

This table reports the annualized CER gains (in %) and annualized Sharpe ratios for a mean-variance investor, who allocates assets between the cryptocurrency market and risk-free bills using the out-of-sample forecasts in daily, weekly, and monthly frequency. The investor's risk aversion is set to five. We consider two scenarios: zero transaction cost and a dynamic transaction cost of half-spread per transaction. The daily bid-ask spread is estimated using Ardia, Guidotti, and Kroencke (2022), and the weekly and monthly bid-ask spread is the daily average of the corresponding week and month, respectively. The in-sample estimation period is from January 1, 2015 to December 31, 2017, and the out-of-sample evaluation period is from January 1, 2018 through May 28, 2022.

	Daily				Weekly				Monthly			
Predictors	CER_0	SR_0	CER_{bas}	SR_{bas}	CER_0	SR_0	CER_{bas}	SR_{bas}	CER_0	SR_0	CER_{bas}	SR_{bas}
Naïve	4.12	0.21	3.43	0.17	1.80	0.31	1.50	0.29	−0.53	0.57	−1.04	0.51
PCA	5.21	0.33	4.81	0.31	1.09	0.40	0.53	0.37	−0.84	0.60	−1.81	0.53
PLS	7.97	0.45	6.52	0.40	1.39	0.41	0.53	0.38	−1.35	0.60	−2.43	0.52
sPCA	4.46	0.35	3.97	0.33	0.31	0.40	−0.27	0.37	−1.26	0.60	−2.29	0.53
sSUFF_l	4.80	0.32	4.29	0.29	0.47	0.38	−0.15	0.36	−0.59	0.60	−1.54	0.52
sSUFF	14.50	0.62	4.08	0.29	12.60	0.69	10.16	0.60	2.29	0.63	0.97	0.53
Lasso	10.87	0.44	3.41	0.19	−7.48	0.09	−8.97	0.03	1.35	0.64	−0.50	0.53
ENet	1.40	0.13	−5.65	−0.11	−2.33	0.23	−3.66	0.18	−1.15	0.56	−2.10	0.48