A Trend Factor for the Cross-Section of Cryptocurrency Returns

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Abstract

We propose CTREND, a new trend factor for cryptocurrency returns, which aggregates price and volume information across different time horizons. Using data on more than 3,000 coins, we employ machine learning methods to exploit information from various technical indicators. The resulting signal reliably predicts cryptocurrency returns. The effect cannot be subsumed by known factors and remains robust across different subperiods, market states, and alternative research designs. Moreover, it survives the impact of transaction costs and persists in big and liquid coins. Finally, an asset pricing model that incorporates CTREND outperforms competing factor models—providing a superior explanation of cryptocurrency returns.

Keywords: cryptocurrency markets, asset pricing, anomalies, return predictability, technical analysis, the cross-section of returns

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I. Introduction

Investing in cryptocurrencies is not a walk in the park. Traders lack a single widely accepted valuation model, and voices claiming that crypto assets are worthless are not uncommon (Christopher, 2014; Taleb, 2021). The lack of fundamental data forces investors to rely largely on market prices and infer information about cryptocurrency adoption and valuation from their movements (Cong et al., 2021; Sockin and Xiong, 2023). This, in turn, can link price fluctuations to investor demand—leading to the emergence of the trend-like behavior of cryptocurrency markets (Hackethal et al., 2022; Kogan et al., 2023; Weber et al., 2023).

Cross-sectional studies of the cryptocurrency market generally agree that past returns help predict future performance (e.g., Liu and Tsyvinski, 2021; Cong et al., 2022; Liu et al., 2022; Borri et al., 2022). However, the information content of past prices can be much richer. Numerous studies of stocks, bonds, commodities, and exchange rates document the predictive abilities of technical signals (e.g., Park and Irwin, 2007; Neely et al., 2014; Han et al., 2016b; Avramov et al., 2021). Techniques using oscillators, moving averages, or even past volume or volatility effectively predict future payoffs (Sweeney, 1986; Shynkevich, 2016; Han and Kong, 2022). Given the dearth of fundamental data, their information content may be essential for explaining the cross-section of cryptocurrency returns. Ignoring them can lead to an incomplete understanding of the mechanisms that drive price dynamics in cryptocurrency markets.

In this study, we propose CTREND, a new cryptocurrency trend factor, which captures information on past prices and volume over different time horizons. Using data on more than 3,000 coins over the period from 2015 to 2022, we compute 28 popular technical signals, including momentum oscillators, moving averages, volume-based indicators, and volatility measures. Next, we employ machine learning methods to extract an aggregate signal that captures the unique information from different indicators. Rather than arbitrarily selecting specific predictors, our agnostic approach lets the data speak and automatically extracts information from multiple features. The resulting signal is a reliable predictor of the cross-section of cryptocurrency returns.

Figure 1 illustrates the key findings. A long-short strategy that buys a value-weighted quintile of coins with the highest expected returns and sells those with the lowest returns earns 3.87% per week, clearly beating other prominent cryptocurrency factors. The abnormal returns cannot be subsumed by popular asset pricing models, such as the cryptocurrency capital asset pricing model (CCAPM) or the Liu et al. (2022) (LTW hereafter) three-factor model. Furthermore, the relationship between CTREND and future returns is confirmed by bivariate portfolio sorts and cross-sectional regressions, and other popular return predictors fail to explain it. Finally, it does not derive from a single technical indicator, but rather aggregates information across multiple technical signals.

[Insert Figure 1 about here]

The CTREND effect is remarkably robust. It holds across various subperiods and remains largely unaffected by different market states. Moreover, it survives several changes in research designs. In a separate experiment, we examine 53,920 implementations, considering alternative sample preparation methods, data cleaning procedures, forecast estimations, and portfolio designs. The CTREND delivers robust performance under most of them, consistently generating impressive risk-return profiles that dwarf other factors.

Notably, the significance of the CTREND signal goes beyond simply delivering impressive portfolio returns. A cross-sectional CTREND factor proves effective in pricing cryptocurrency returns. It renders the momentum effect insignificant while at the same time not being subsumed by any other factors. Furthermore, it explains the abnormal returns of well-known anomalies and trading strategies far better than other prevailing models. In particular, a three-factor model that includes the CMKT, CSMB, and CTREND factors significantly outperforms the distinctive model proposed by LTW; it produces lower pricing errors, explains anomalies more accurately, and reduces abnormal returns more effectively. Its superiority is also confirmed by the well-known Gibbons et al. (1989) test. As a result, the CTREND factor emerges as a strong contender for a new benchmark in asset pricing that is specifically tailored for cryptocurrency research.

Finally, we explore the practical implications of the CTREND effect from an investment perspective. The predictive power of this technical signal is not limited to some obscure segments of the cryptocurrency market; on the contrary, it is ubiquitous in even the largest and most liquid coins. Despite the short-term nature of the CTREND trading signal and significant portfolio turnover, the profits generated are resilient to transaction costs. Moreover, abnormal returns remain significant over longer holding periods—up to four weeks. Consequently, the CTREND effect can be translated into an effective trading strategy.

Our study contributes to three main strands of asset pricing research. First, we add to the rapidly growing body of evidence on the cross-sectional predictability of cryptocurrency returns (Liu et al., 2021; Liu and Tsyvinski, 2021; Borri and Shakhnov, 2022; Liu et al., 2022; Zhang et al., 2021; Babiak and Erdis, 2022; Bianchi et al., 2022; Borri et al., 2022). In particular, our paper closely connects with studies proposing sparse factor pricing models to explain the cross-section of cryptocurrency returns (e.g., Liu et al., 2022; Bianchi and Babiak, 2021; Cong et al., 2022). In the context of cryptocurrency pricing, our findings are consistent with models suggesting that crypto investors infer information about adoption and valuation from price behavior. Kogan et al. (2023) offer a model in which past price movements contain information about future adoption, consistent with the perspectives in Cong et al. (2021) and Sockin and Xiong (2023). With this in mind, we offer a new signal called CTREND that effectively captures the cross-sectional return variation in cryptocurrency markets and outperforms established cryptocurrency factor pricing models.

Second, we extend the long-standing debate on the effectiveness of technical analysis and its implications for market efficiency. Schwager (1993, 2012) and Menkhoff (2010) show that technical indicators are frequently exploited by investors and hedge fund managers, and Avramov et al. (2018) argue that analysts' recommendations based on technical analysis typically beat those that rely on fundamental information. The extant literature confirms the profitability of technical signals (Lo et al., 2000; Park and Irwin, 2007; Zhu and Zhou, 2009; Hung and Lai, 2022; Brogaard and Zareei, 2023). For example, Brock et al. (1992) demonstrate the effectiveness of moving averages, and Kwon and Kish (2002) broaden the evidence to volume-based indicators. Neely et al. (2014) show that technical indicators successfully predict the market risk premium. Further analyses in Shynkevich (2016) and Sweeney (1986) document similar patterns in bond and foreign exchange markets. Although most studies consider technical analysis in a time-series context, its signals also help explain cross-sectional returns. As shown by Han et al. (2013), moving averages predict characteristic-sorted portfolios, and later Han et al. (2016a) and Han and Kong (2022) confirm their findings for an extended sample period and commodity markets. Avramov et al. (2021) find that the moving average distance is priced in the cross-section of stock returns. Finally, our paper is most closely related to Han et al. (2016b) and Liu et al. (2024), who aggregate information from various moving averages to predict the cross-section of stock returns in the United States and China. To our knowledge, none of the studies have scrutinized the cross-section of cryptocurrency returns.

Lastly, we add to the emerging literature on technical analysis applications in the cryptocurrency market. In contrast to the efficient market hypothesis (Fama, 1970), previous studies show that technical indicators effectively predict the returns of major cryptocurrencies (Corbet et al., 2019; Hudson and Urquhart, 2021; Ahmed et al., 2020; Gerritsen et al., 2020; Goutte et al., 2023; Grobys et al., 2020; Anghel, 2021; Detzel et al., 2021; Svogun and Bazán-Palomino, 2022; Bazán-Palomino and Svogun, 2023; Tan and Tao, 2023; Wei et al., 2023). Nevertheless, those studies explore the time-series predictability of a handful of cryptocurrencies, typically with several pre-selected indicators. On the contrary, our study concentrates on cross-sectional returns and aggregates information from various trading signals; thus, our study provides a test of the efficient market hypothesis in the cross-section of cryptocurrency returns.

The remainder of the paper proceeds as follows. Section II outlines our theoretical framework. Section III discusses the data and methods. Section IV presents the baseline findings. Section V provides additional insights and robustness checks. Section VI focuses on asset pricing tests. Section VII considers the practical investor perspective. Finally, Section VIII concludes.

II. Theoretical Framework

The asset pricing literature offers multiple theories linking past price and volume data to future price movements. Many of them consider links between momentum effects and investor behavior. De Long et al. (1990) state that noise traders who participate in positive feedback trading contribute to return continuations. Barberis et al. (1998) argue that prices may trend slowly when investors underestimate the importance of new information in making decisions. The seminal work of Hong and Stein (1999) investigates the effects of information-based trading and suggests that the delayed adjustment of stock prices to private information creates momentum effects. Price trends may arise from a range of behavioral biases, although several models can justify expected trends in rational equilibriums; Chan et al. (1996), Grinblatt and Han (2005), and Daniel et al. (2023) are examples of studies that examine behavioral biases. For instance, Cespa and Vives (2012) demonstrate that the existence of liquidity traders and uncertain asset payoff leads to logical price trends in the markets.

Building on Wang (1993), Han et al. (2016b) and Liu et al. (2024) present theoretical models that link signals derived from past price and volume information to future stock returns. They distinguish between two classes of market participants: informed investors and uninformed traders. While the first group has access to fundamental information about the dividend process and economic conditions, uninformed traders do not. Therefore, they infer the long-term dividend growth rate from past price changes. In short, rising price trends suggest a solid dividend growth rate and, conversely, falling prices signal a poor financial outlook. Based on this reasoning, uninformed investors may rationally follow the trend, thus promoting predictable price patterns in the stock market.

The proposed model considers the availability of fundamental information. If fundamental information were scarce, investors would naturally be driven to technical signals as the only source of rational inference. Notably, the cryptocurrency market can be considered unique in this context. To begin with, access to relevant fundamental information is more limited than in the equity universe. While some fundamental valuation approaches have been proposed (Hayes, 2017; Biais et al., 2023; Pagnotta and Buraschi, 2018; Sockin and Xiong, 2023), they are not yet as widespread or broadly accepted as equity dividend or cash flow-based models. Some voices from both academia and the industry even argue that cryptocurrencies may have no fundamental value at all (Christopher, 2014; Taleb, 2021). In addition, the nature of cryptocurrency valuation models tends to be structurally different from their stock market counterparts—relying on mining costs or currency characteristics rather than discounting future earnings. Moreover, unlike equities, crypto investors lack periodic cash flow information (Kogan et al., 2023), which allows them to reassess their beliefs about the asset's value (Luo et al., 2020). As a result, cryptocurrency traders are likely to base their investment decisions on past prices and technical indicators. In line with this view, this asset class is commonly referred to as "speculative investments" (Yermack, 2015), prone to speculative bubbles (Cheah and Fry, 2015; Cagli, 2019) and characterized by a high degree of herding behavior (Bouri et al., 2019; Almeida and Gonçalves, 2023).

Notably, a growing body of evidence suggests that the scarcity of fundamental information and, consequently, the reliance on price data is reflected in the behavior of cryptocurrency traders. Investor characteristics in this asset class have been studied by Pursiainen and Toczynski (2022), Di Maggio et al. (2022), and Auer et al. (2023), to name a few. Hackethal et al. (2022), who examine data from a German online bank that caters to crypto traders, find that they are more risk-taking and even more biased than stock traders. Kogan et al. (2023), who examine a dataset of 200,000 retail traders from eToro, show that crypto investors are more prone to momentum-like strategies than their stock market counterparts. They explain this with a model where past price changes contain information about future adoption, which indirectly affects intrinsic value—consistent with Cong et al. (2021), and Sockin and Xiong (2023). The uniqueness of cryptocurrency traders and their reliance on past prices is reflected in numerous studies. For example, Weber et al. (2023) show that information about historical returns leads individuals to increase their desired crypto holdings and makes them more likely to subsequently purchase cryptocurrencies. Hackethal et al. (2022) show that cryptocurrency investors are much more likely to buy stocks with strong performance and lottery-like characteristics than investors in the stock market, consistent with naive trend following (Kumar and Dhar, 2001; Sapp and Tiwari, 2004; Barber and Odean, 2008) and certain forms of gambling in financial markets (Kumar, 2009). In summary, due to the lack of easily accessible fundamental information, investors use different models when forming beliefs about cryptocurrencies compared to stocks.

In conclusion, the limited availability of fundamental data highlights the role of past price and volume information in determining expected returns. As a result, the trend-based factors—such as those of Han et al. (2016b) and Liu et al. (2024), which aggregate past price information—may prove crucial in predicting and explaining the cross-section of returns. Moreover, not only moving averages but also other technical indicators—such as momentum oscillators and volatility indicators—suggest trend-following behavior in the cross-section of cryptocurrencies. We test these hypotheses in the empirical sections of this paper.

III. Data and Methods

In this section, we introduce our data and methodology, starting with the presentation of our data sample. Next, we continue with a discussion of the technical indicators considered in the study and an exploratory examination of their information content for future cryptocurrency returns. Finally, we describe how we calculate the aggregate CTREND signal.

A. Data Sources and Preparation

We collect price, volume, and market capitalization data from Coinmarketcap.com, where price information contains high, open, low, and closing prices. Following Liu et al. (2022), for an observation to be valid, we require non-missing observations for the closing price, volume, and market capitalization. We remove all the cases for which the market capitalization exceeds that of Bitcoin, as this indicates erroneous observations.[1] As is common in the literature, we limit our sample to cryptocurrencies with a minimum market capitalization of USD 1 million (Liu and Tsyvinski, 2021; Liu et al., 2022; Garfinkel et al., 2023). We further control for extreme outliers in returns by removing the 1% most extreme observations by truncating the returns at the 0.5% and 99.5% percentiles. Our sample period starts in April 2015 and ends in May 2022, yielding a total 423 weekly observations.

[1] Note that this filter eliminates a total of ten daily observations across the entire study period and cross-section.

Table 1 illustrates our filtered sample over time. The number of available cryptocurrencies varies from below 100 in 2015 to over 2,000 in 2021, with the overall number of unique coins being 3,244. The mean market capitalization ranges from USD 135 million (2015) to USD 1,38 billion (2021), markedly surpassing the median values. This demonstrates the strongly concentrated cryptocurrency market with few names accounting for most of the market capitalization. Liquidity, measured by the aggregate trading volume, exhibits similar patterns.

[Insert Table 1 about here]

B. Technical Indicators

While the stock market literature shows that investors commonly employ moving average-based strategies beyond fundamental analysis (Schwager, 1993; Lo et al., 2000), no fundamental data are available to cryptocurrency investors. As a result, they are likely to employ a diverse set of technical indicators beyond moving averages. Therefore, we consider a vast list of a) momentum oscillators, b) moving averages, c) volume, and d) volatility indicators, previously studied in the literature and popular among market practitioners. In total, we calculate 28 signals that we use as inputs to construct an aggregate trend characteristic. Notably, we make two assumptions regarding the selection of technical indicators. First, we only consider indicators that allow the formation of a straightforward cross-sectional signal. Second, we calculate the indicators using the common estimation horizons suggested in the literature to avoid a data-snooping bias. Although the calculation of all technical indicators is comprehensively described in Online Appendix A, we briefly characterize them here.

2. Sample Selection

The first group of indicators contains momentum oscillators, widely embraced by market practitioners (see, e.g., Ciana, 2011). To begin with, the relative strength index (*rsi*) quantifies the ratio of average gains to average losses over the preceding fourteen days. Next, the fast and slow stochastic oscillators *stochK* and *stochD* compare the price of an asset to a range of prices over a 14-day period, with *stochD* being a three-day moving average of *stochK*. The *stochRSI* is defined as the difference between an asset's current *rsi* and its lowest *rsi* over a 14-day period, scaled by the range of *rsi* values. Lastly, the commodity channel index (*cci*) compares the average deviation of the current price to a moving average.

The second category includes signals based on price moving averages. Han et al. (2013) and Han et al. (2016b) provide theoretical and empirical support for using simple moving averages (SMAs). We account for seven SMAs of different lengths (denoted by *sma_∗d*, where ∗ denotes the number of days). Specifically, we consider the 3-, 5-, 10-, 20-, 50-, 100-, and 200-day SMAs (Brock et al., 1992; Han et al., 2016b; Liu et al., 2024).[2] Following Han et al. (2016b), we scale the SMAs by the cryptocurrencies' closing prices at the end of each week to ensure their stationarity and mitigate the impact of high-priced cryptocurrencies. We augment the set of moving average indicators by including the average convergence/divergence (*macd*) indicator and the difference of *macd* to a signal line (*macd_diff_signal*), both widely used by practitioners and discussed in the literature (see, e.g., Ciana, 2011; Neely et al., 2014). The *macd* measures the difference between a

[2]Note that we omit longer SMAs such as the 400-, 600-, 800-, or 1,000-day SMAs studied in Han et al. (2016b) because the time-series of cryptocurrency data is relatively short.

slow (26-day) and a fast (12-day) exponential moving average (EMA) of daily closing prices. To mitigate the influence of size effects, we express the difference in the slow and fast EMAs as a percentage of the fast EMA.[3] The *macd_diff_signal* is the difference of *macd* and a nine-day EMA of the *macd*.

The third class comprises volume indicators. Liu et al. (2024) show that SMAs of past trading volume help to predict stock returns in China. We include the 3-, 5-, 10-, 20-, 50-, 100-, and 200-day SMAs of dollar trading volume ($volsma\_*d$) and normalize them by the current trading volume (Liu et al., 2024). Analogous to the *macd* defined above, we define *volmacd* as the difference between two EMAs of the past dollar trading volume. We again express this difference as the percentage of the fast EMA.[4] We also include the difference of *volmacd* to the signal line (*volmacd_diff_signal*). Another popular volume indicator is the Chaikin money flow (*chaikin*) indicator, which measures the money flow volume over time. A high positive value of *chaikin* indicates buying pressure, while a high negative value indicates selling pressure.

The last group of technical signals consists of volatility-based indicators. This category comprises the lower (*boll_low*), middle (*boll_mid*), and upper (*boll_high*) Bollinger band. The lower and upper Bollinger bands are calculated by adding (subtracting) two standard deviations of the previous closing prices to (from) the middle Bollinger band, defined as the 20-day moving average of past closing prices. Again, we scale the Bollinger bands by the current closing price to control for the impact of high-priced cryptocurrencies. Finally, we include the Bollinger bandwidth (*boll_width*), which is the difference between

[3]This normalization makes the *macd* equivalent to the percentage price oscillator (PPO).
[4]This indicator is also known as the percentage volume oscillator (PVO).

the upper and lower bands, scaled by the middle Bollinger band. A small bandwidth indicates low volatility, while a high spread indicates high volatility.

2. Performance of Technical Indicators

Table 2 briefly overviews the information content of our technical indicators. Following the common practice in the cryptocurrency literature, we sort cryptocurrencies into quintiles based on the cross-sectional rank of the respective technical indicator and form value-weighted weekly-rebalanced portfolios (Liu et al., 2022). Furthermore, we report the performance of long-short strategies buying (selling) the quintile of cryptocurrencies with the highest (lowest) technical indicator ranks, which offer an acid test for a monotonic relationship in the cross-section of returns.

[Insert Table 2 about here]

To disentangle the exposure to common risk factors, we supplement the average returns with multifactor alphas. Specifically, we calculate them using the one-factor CCAPM:

$$r_{p,t} = \alpha + \beta_{CMKT} CMKT_t + \epsilon_t \tag{1}$$

and the LTW three-factor model:[5]

$$r_{p,t} = \alpha + \beta_{CMKT} CMKT_t + \beta_{CSMB} CSMB_t + \beta_{CMOM} CMOM_t + \epsilon_t \tag{2}$$

$r_{p,t}$ in the equations above is the excess return on an examined portfolio p at time t and $CMKT_t$, $CSMB_t$, and $CMOM_t$ denote the returns on market, size, and momentum

[5]The factors are available from Yukun Liu's dropbox: https://www.dropbox.com/s/ziyh9pjooroxali/LTW_3factor.xlsx?dl=0

factors of LTW at time t. The regression coefficients β_{CMKT}, β_{CSMB}, and β_{CMOM} measure the factor exposures, α is the intercept (alpha), and ϵ_t is the residual return. For details on factor properties, see Table B.2 in the Online Appendix.

As seen in Table 2, more than a half of the indicators generates reliable mean returns on the long-short portfolios, which are significant at the 5% level. Furthermore, in fourteen cases, these profits cannot be fully captured by the CCAPM; in eight of them, even the three-factor model cannot explain their performance. In other words, the return predictability by technical indicators is not simply the cryptocurrency size or momentum effect in disguise.

Significant alphas are concentrated mainly in the momentum oscillator group, where four indicators generate significant abnormal returns. Significant average returns and CCAPM alphas are also visible for the moving average indicators. Still, in this case, most of them are subsumed by the three-factor model, which incorporates the momentum factor. Finally, abnormal returns in the volume and volatility categories are less prevalent.[6]

[6]Interestingly, the sign of abnormal returns on long-short cryptocurrency portfolios do not always align with the patterns known from the time-series literature in the equity universe. For example, the long-short strategy based on the *rsi*, which is supposed to be a reversal indicator, generates a significant positive abnormal return. That is, coins that are considered "overbought", following classical technical analysis, continue to generate large positive returns. Thus, the *rsi*—as well as all other oscillators—indicate a trend continuation rather than a reversal. Similarly, price moving averages also signal trend-following behavior. Note that Han et al. (2016b) show that moving averages indicate a trend-following or reversal depending on the fraction of technicians in the markets: a large fraction of technical analysts leads to the occurrence of trend-following patterns, while a low presence results in reversals. Because cryptocurrencies are a relatively new asset class commonly referred to as "speculative investments" (Yermack, 2015), they may be prone to speculative bubbles (Cheah and Fry, 2015; Cagli, 2019) and characterized by a high degree of herding behavior (Bouri et al., 2019; Almeida and Gonçalves, 2023). Consequently, cryptocurrency investors are likely to follow strong trends so that the trends will be further fueled, and technical indicators are associated with trend continuation.

C. The CTREND Factor

A single technical indicator may represent a noisy predictor of future market movements; because of this, technical analysts frequently enhance the quality of their forecasts by combining multiple signals. The construction of our trend factor follows the same philosophy: We integrate all variables seen in Table 2 into a single trend measure, regardless of whether an indicator significantly predicts future cryptocurrency returns. Therefore, instead of sorting cryptocurrencies into portfolios based on a single technical indicator—which may be a noisy predictor of cryptocurrency returns—we follow the approach in Han et al. (2016b) and generate an aggregate measure of future returns using cross-sectional regressions. Specifically, the authors use cross-sectional regressions to summarize the information in moving averages of various lengths and create a trend factor based on their aggregate trend measure.

Although the approach of Han et al. (2016b) generates impressive results in the U.S. market, two problems may arise. First, it may be subject to data snooping issues as the forecasts are based on an arbitrary pre-selection of technical indicators. Even though moving averages are common indicators used by practitioners, the information content of past market data may be much richer, and other indicators are used complementarily (Ciana, 2011; Neely et al., 2014). Second, some signals may be uninformative or highly correlated with other signals, leading to inefficient forecasts from multivariate regressions. To overcome these problems and formulate predictions in a data-driven way, we build on the combined elastic net (C-ENet) as proposed in Dong et al. (2022), which combines the benefits of shrinkage and forecast combination. Specifically, we employ the cross-sectional combined elastic net estimator (CS-C-ENet) of Han et al. (2023).

Let $r_{i,t}$ denote the excess return of cryptocurrency i at time t and $z_{i,j,t-1}$ the j-th technical indicator, with $j = 1, \ldots, J$ being the number of technical indicators available. Han et al. (2016b) propose estimating the following cross-sectional multivariate regression over a sequence of M periods:

$$r_{i,t} = \alpha_t + \sum_{j=1}^{J} z_{i,j,t-1}\beta_{j,t} + u_{i,t} \quad \forall t \tag{3}$$

Using the Fama and MacBeth (1973) technique, the coefficients are smoothed over M periods, i.e.:

$$\bar{\alpha}_t = \frac{1}{M}\sum_{m=0}^{M-1} \hat{\alpha}_{t-m} \tag{4}$$

$$\bar{\beta}_{j,t} = \frac{1}{M}\sum_{m=0}^{M-1} \hat{\beta}_{j,t-m} \tag{5}$$

Smoothing the coefficients over time increases the efficiency of the estimation by stabilizing the coefficients, which yields more accurate estimates in noisy datasets. The $t+1$ out-of-sample forecast is obtained as follows:

$$\hat{r}_{i,t+1} = \bar{\alpha}_t + \sum_{j=1}^{J} \bar{\beta}_{j,t} z_{i,j,t} \tag{6}$$

The predictive regression in equation (3) may be inefficient in noisy and high-dimensional data sets, such as cryptocurrency returns. Based on insights from time-series analyses (see, e.g., Rapach et al., 2010), Han et al. (2023) argue that the simple forecast combination of univariate return estimates often outperforms its multivariate counterpart because the forecast combination approach has a strong shrinkage effect (i.e., it shrinks the magnitude of each slope by $1/J$) and improves the estimation efficiency. As a result, the forecast combination approach is less likely to be subject to overfitting, resulting in improved out-of-sample performance.

The combined Fama-MacBeth approach begins with estimating J univariate Fama-MacBeth regressions over a sequence of M periods as described in equation (7):

$$r_{i,t} = \alpha_{j,t} + z_{i,j,t-1}\beta_{j,t} + u_{i,t} \quad \forall j, t \tag{7}$$

For each technical indicator j, a $t+1$ return forecast is computed as

$$\hat{r}^{j}_{i,t+1} = \bar{\alpha}_{j,t} + \bar{\beta}_{j,t} z_{i,j,t} \tag{8}$$

with $\bar{\alpha}_{j,t}$ and $\bar{\beta}_{j,t}$ being the average coefficients from univariate Fama-MacBeth regressions analogous to equations (4) and (5), respectively. Note that in Han et al. (2023), the coefficients are not smoothed over time to adapt more quickly to changing characteristic rewards. However, as mentioned above, the Fama-MacBeth technique works particularly well in noisy datasets. Because cryptocurrency returns are extremely noisy, we smooth the coefficients over time to stabilize the coefficient estimates (Haugen and Baker, 1996; Lewellen, 2015; Han et al., 2023).

A naive combined forecast for the $t+1$ return is computed as the equally weighted average of the J forecasts:

$$\hat{r}_{i,t+1} = \frac{1}{J}\sum_{j=1}^{J} \hat{r}^{j}_{i,t+1} \tag{9}$$

Although the equally weighted combined forecast in equation (9) is theoretically suboptimal—because not all technical indicators provide relevant and independent information for cryptocurrency returns—empirical studies report good performance of the equally weighted forecast combination (Clemen, 1989; Diebold, 1989; Rapach and Zhou, 2013). However, by simply averaging over J forecasts as in equation (9), noisy forecasts receive the same weight as informative forecasts. We follow Dong et al. (2022) and Han et al. (2023) and refine the simple forecast combination approach by using a machine learning technique—the elastic net—to select the most informative forecasts. Specifically, we run the following pooled multivariate regression (Granger and Ramanathan, 1984):

$$r_{i,t} = \xi + \sum_{j=1}^{J} \theta_j \hat{r}_{i,t}^{j} + \eta_t \tag{10}$$

using the elastic net estimator that employs L^1 and L^2 shrinkage.[7] In equation (10), ξ denotes an intercept and θ_j denotes the optimal weight of forecast j. Estimating equation (10) through the use of the elastic net results in coefficient estimates for which $\theta_j \neq 0$ or $\theta_j = 0$, allowing to "select" the most informative forecasts, while shrinking the contribution of others to zero. Diebold and Shin (2019) show that selecting the relevant forecasts as described in equation (10) and simply averaging over the surviving forecasts significantly improves the out-of-sample accuracy of the combined forecast. Dong et al. (2022) and Han et al. (2023) build on this insight and obtain the return forecast by averaging all univariate forecasts with $\theta_j > 0$, instead of weighting the forecasts with θ_j to an aggregate forecast. Note that the economic restriction $\theta_j > 0$ implies that a return forecast should be positively correlated with the actual return. Thus, the $t+1$ forecast of the cross-sectional combined elastic net (CS-C-ENet) is obtained by calculating

$$: r_{i,t+1} = \frac{1}{\jmath} \sum_{j \in \jmath} \hat{r}_{i,t+1}^{j} \tag{11}$$

with $\jmath$ denoting the set of forecasts obtained from univariate Fama-MacBeth regressions as

[7] Following Dong et al. (2022) and Han et al. (2023), we set the parameter that controls the trade off between L^1 and L^2 regularization to 0.5 and optimize the regularization strength λ according to the corrected akaike information criterion (AIC).

in equation (8) with $\theta_j > 0$ (equation (10)). In the remainder of this paper, we refer to the predictions from equation (11) as the cryptocurrency trend signal, called CTREND. However, in Section B, we also report the results when using alternative estimation methods, such as multivariate Fama-MacBeth or pooled regressions.

Before estimating the model, we mitigate the influence of potential outliers in technical indicators by transforming them into their cross-sectional ranks and mapping the ranks into the interval [-0.5, 0.5] (Kelly et al., 2019; Gu et al., 2020). All regressions are estimated by minimizing the value-weighted sum of squared residuals to mitigate the influence of micro-cap coins with minor economic significance (Hou et al., 2020; Han et al., 2023). The model parameters are estimated using a fixed rolling window of 52 weeks, and these parameters are then used to predict returns for the following week. We test the robustness of the results regarding these settings in Section B.

IV. Baseline Findings

We begin our empirical analysis by evaluating the return predictability of the CTREND signal using portfolio sorts. Next, we continue with cross-sectional regressions.

A. Univariate Portfolio Sorts

To assess the predictability of the aggregate CTREND signal, we employ quintile portfolios similar to those in Table 2. At the beginning of each week, we rank cryptocurrencies on the CTREND signal and group cryptocurrencies into five portfolios. The portfolios are value-weighted and rebalanced weekly. We construct the CTREND factor as a long-short strategy buying (selling) the baskets with the highest (lowest) expected return. Table 3 reports the results of this exercise.

[Insert Table 3 about here]

Sorting cryptocurrencies on CTREND reveals a clear pattern in portfolio payoffs: the high-CTREND quintiles markedly outperform the low ones. The return increases monotonically from the bottom to the top portfolio, and the spread between the extreme quintiles equals 3.87% (t-stat = 5.19). Furthermore, the annualized Sharpe ratio on the long-short strategy reaches 1.94, suggesting a remarkable risk-return profile.

The subsequent columns illustrate the risk exposures of the quintile portfolios. The spread portfolio does not exhibit major market or size exposure, and the respective betas are close to zero. However, the momentum beta is sizeable and significant, equaling 0.79; this indicates that the CTREND effect correlates closely with momentum. Nevertheless, despite its substantial exposure to CMOM, the long-short portfolio exhibits an impressive weekly alpha of 2.62% (t-stat = 4.22) against the LTW three-factor model. In other words, while the momentum effect matters, it is far from fully capturing the CTREND alphas.[8]

Whilst CTREND relates to certain cryptocurrency characteristics, such as momentum, it extracts information beyond. To illustrate this further, we perform an additional variable importance analysis, reported in Online Appendix C. The CTREND factor does not rely on a sparse set of features, but rather extracts predictability from a wide range of different technical indicators, with the *boll_mid*, *cci*, and *macd* scoring highest.

The rightmost section of Table 3 displays additional portfolio characteristics such as

[8]While we use factor data obtained directly from LTW to ensure the comparability of our study, our results remain consistent for factors constructed using our dataset. As seen in Online Appendix B, Table B.7, in this convention, the CTREND factor earns a weekly LTW alpha of 2.61%, remaining statistically significant at the 1% level.

the average market capitalization (*mcap*), the Amihud (2002) illiquidity measure (*illiq*), or idiosyncratic risk (*idiovol*). Table B.1 in Online Appendix B provides a detailed explanation of these characteristics. These characteristics signal that abnormal returns do not simply stem from some dusty corner of the cryptocurrency market, populated by small and illiquid coins. On the contrary, the CTREND premium may be effectively harvested via portfolio sorts, even in liquid and large coins. Section A takes a closer look at this potential concern.

To sum up, the trend pattern in the returns is evident. However, its source is yet uncertain. Theoretically, rather than representing an independent asset pricing phenomenon, the CTREND effect could be another anomaly in disguise, such as momentum. Hence, in an additional robustness check, we supplement our analyses with bivariate portfolio sorts. Specifically, we sort the cryptocurrencies into halves based on different control variables and terciles of the CTREND signal. The selection of control variables includes popular predictors from the cryptocurrency literature, including market beta (*beta*), market capitalization (*mcap*), Amihud (2002) illiquidity ratio (*illiq*), idiosyncratic risk (*idiovol*), and momentum measures calculated over various horizons, ranging from one to four weeks of trailing data (*ret_*_0*).[9,10] Then, we calculate the average returns of portfolios with a consistent level of the control characteristics and different levels of the CTREND variable. The resulting portfolios capture the incremental effect of

[9]Table B.1 in Online Appendix B provides a detailed explanation of all these control variables.

[10]Notably, certain cryptocurrency studies also advocate other return predictors, which could potentially be used as control variables. These include, e.g., trading volume (Bianchi et al., 2022), downside risk (Zhang et al., 2021), volatility (Bouri et al., 2022), and lottery demand (Grobys and Junttila, 2021). However, these variables prove insignificant within our sample, demonstrating no return predictability over cryptocurrency returns (see Table B.5 in the Online Appendix).

CTREND after controlling for other predictors. For the sake of conciseness, we report the results in Table B.3 in Online Appendix B.

The results confirm our initial findings. The mean returns on the long-short CTREND portfolios remain positive and significant in all cases, ranging from 1.42% to 3.10%. In other words, while other predictors capture between 20% and 63% of the abnormal returns, they cannot subsume them further. Importantly, this also applies to the double-sorts on momentum, which could be an ostensibly similar phenomenon. The abnormal returns on long-short bivariate portfolios also endure after accounting for factor exposure with the CCAPM and LTW factors.

Noteworthily, the largest drop in raw and abnormal returns is observed for the Amihud (2002) ratio. The mean return of the long-short portfolio and α^{CCAPM} are still significant, exceeding 1.4%, but α^{LTW} shrinks to 0.62%, remaining significant only at the 10% level. This suggests a certain relationship between liquidity and CTREND profits, which we will examine further in Sections B and A.

B. Cross-Sectional Regressions

While bivariate portfolios are powerful in disentangling the impact of two features without imposing a linear functional form, they also face two shortcomings. First, they can only accommodate controlling for up to two or three variables since finer triple or quadruple sorts are typically infeasible. Second, grouping coins into portfolios may lead to information loss. Therefore, we supplement our analyses with cross-sectional predictive regressions in the spirit of Fama and MacBeth (1973). Specifically, we examine whether the aggregate trend indicator predicts the cross-section of next week's cryptocurrency returns after controlling for other variables. Importantly, following Hou et al. (2020), we estimate the regressions using weighted least squares (WLS), with weights tied to cryptocurrency market capitalizations, rather than ordinary least squares (OLS). This framework allows us to reduce the impact of tiny and illiquid cryptocurrencies whose economic importance is negligible, and thus aligns more closely with trading practice.

Table 4 presents the results of this analysis. Essentially, the cross-sectional regressions confirm the robust predictive ability of technical analysis. Observe first the univariate regressions seem in column 1. The average CTREND coefficient equals 2.36 and is strongly significant, with a t-statistic of five. The subsequent regressions incorporate different control variables from the same set as in the bivariate portfolio sorts. Specifications 2 to 7 also account for various combinations of the impacts of beta, market size, illiquidity, and idiosyncratic volatility. In all these cases, the CTREND effect remains strong and significant. Notably, despite the earlier evidence from Section B, even the Amihud ratio cannot capture the CTREND effect. In columns 8 to 11, we report regressions with CTREND and various momentum measures. None of these variables subsumes the CTREND signal; on the contrary, the CTREND variable typically renders most momentum signals insignificant—except two-week momentum, which remains significant at the 1% level. Finally, specification 12 pursues a "kitchen-sink" approach, jointly controlling for all individual control variables. The CTREND effect remains robust, asserting that even a combination of commonly known factors does not suffice to subsume it.

[Insert Table 4 about here]

To conclude, cross-sectional regressions corroborate the predictive abilities of the

CTREND variable. The aggregated technical signal provides reliable and incremental information about future cryptocurrency returns, which is not contained in other popular return predictors for the cryptocurrency market.

V. Further Insights and Robustness Checks

This section provides additional insights and robustness checks. First, we examine the CTREND performance in different subperiods and market states. Second, we investigate the role of non-standard errors in our findings.[11]

A. Subperiod Analysis

In the equity universe, numerous studies suggest that return predictability is not time-invariant. Notably, this also applies to technical analysis and momentum signals. For example, whether due to investor learning or improving market efficiency (Schwert, 2003; Chordia et al., 2014; Hanson and Sunderam, 2014; McLean and Pontiff, 2016; Zaremba et al., 2020), the return predictability has been found to decline over time in certain markets.[12] Fieberg et al. (2024) notice that a similar trend also haunts many cryptocurrency anomalies. Furthermore, the magnitude of mispricing fluctuates along with market sentiment and uncertainty and increases in times of high illiquidity or idiosyncratic risk, strengthening limits to arbitrage (Nagel, 2012; Stambaugh et al., 2012; Jacobs, 2015;

[11] Lastly, we also differentiate between cryptocurrency types by dividing them into coins and tokens. For example, Ma et al. (2023) shows that coins and tokens differ in their characteristics and, in particular, in their probability of default. Cong and Xiao (2021) propose an even more refined distinction between cryptocurrency types (i.e., general payment, platform tokens, product tokens, and security tokens), but this reduces the cross section for some groups excessively, making portfolio sorting no longer feasible. We report the results for the coin/token split in Table B.4 in Appendix B and note that the results are qualitatively unchanged from our main results in Table 3.

[12] Notably, Jacobs (2016) and Jacobs and Müller (2020) observe no similar tendency of profitability decrease driven by investor learning in international markets.

Avramov et al., 2019). Do similar patterns also hold for the cryptocurrency CTREND factor?

Overall, the performance of the long-short CTREND portfolio is remarkably stable, even over periods when classical momentum strategies disappoint, such as post-2017 (see Figure B.2 in Online Appendix B). However, for a more formal look at return dynamics over time, Table 5 reports the performance of the CTREND factor in subperiods. Specifically, we first divide the sample into two roughly equal subperiods: from April 2015 to the first week of November 2018 and November 2018 to May 2022. Second, we categorize the sample into periods of high and low market volatility and uncertainty, where market volatility is measured via the value-weighted average of the standard deviation of daily returns over the previous week, and uncertainty is proxied by the cryptocurrency uncertainty index (Lucey et al., 2022). In both cases, we use the time-series median to differentiate between "high" and "low" market states (Avramov et al., 2023; Fieberg et al., 2024). Lastly, we assess the returns in bear and bull markets, defined as the weeks in which the 12-month trailing return on the cryptocurrency market portfolio is below or above the sample median.

[Insert Table 5 about here]

The CTREND anomaly generally does not depend on any particular market state, remaining significant during high and low volatility and uncertainty periods (Panels B and C). In particular, abnormal returns do not originate solely from risky market phases. In fact, the returns are noticeably higher during stable market periods (5.46%) rather than volatile ones (2.27%). Furthermore, unlike the momentum effect in—for example—stocks, CTREND does not originate only from bullish markets. Although CTREND generates higher returns in bullish markets (4.49%), it also generates a high average weekly return of 3.25% in bearish markets. Lastly, although an inevitable decline in profitability over time is visible (Panel A), this trend is not critical. Even in recent years, the average long-short portfolio return remains sizeable and significant, amounting to 3.26% per week. Though the raw returns are lower in the second half, the alphas against the LTW three-factor model are almost unchanged.

B. Accounting for Non-Standard Errors

The construction of trend factor portfolios in the previous analyses relies on certain assumptions regarding data and methodology, closely following the proposed design in LTW. However, no research design is carved in stone, and various studies may resort to alternative approaches. Even seemingly irrelevant methodological choices may lead to vastly differing conclusions—in the stock (Menkveld et al., 2024; Walter et al., 2023; Soebhag et al., 2024) and cryptocurrency (Fieberg et al., 2023) markets alike. Menkveld et al. (2024) christen this problem *non-standard errors*.

To analyze the role of non-standard errors, we compute long-short CTREND portfolios using a variety of alternative research designs. First, we consider different algorithms for deriving the predictive signal of CTREND. While the CS-C-ENet approach used in our main analyses combines both forecast combination and forecast selection, we now test the multivariate Fama-MacBeth (FM) approach as described in equation (6) and used in Han et al. (2016b), and the combined Fama-MacBeth (CFM) approach as described in equation (9). In addition, we test equivalents that use pooled instead of cross-sectional regressions, i.e., we test the pooled ordinary least squares regression

(POLS), the combined pooled ordinary least squares regression (CPOLS), and the combined elastic net (C-ENet) as proposed in Dong et al. (2022).[13,14]

In addition to the above, we examine a number of other methodological choices that can be grouped into three broad categories, all of which are listed in the two leftmost columns of Table 6. These include dataset preparation (Panel A), trend factor construction (Panel B), and CS-C-ENet estimation (Panel C). All standard settings used in the primary analyses are shown in bold. In total, our experiment includes 53,920 combinations.

The design choices in the first category—dataset preparation (Panel A)—include the treatment of outliers (truncation or winsorization and the threshold for each), the exclusion of stablecoins, and the size and price filters. Trend factor-specific design choices (Panel B) include portfolio construction issues, i.e., the choice of weighting scheme and breakpoints for selecting the upper and lower quantiles. We also consider the type of estimation window (rolling or expanding) and, in the latter case, the number of in-sample estimates required (26, 52, 78, 104). Moreover, Le Pennec et al. (2021) and Cong et al. (2023) raise awareness about the use of volume data from cryptocurrency platforms. The data may be biased due to wash volume; therefore, we additionally consider a research design that excludes all volume-based indicators from our analyses.

Lastly, we account for an implementation lag between the calculation of the CTREND signal and portfolio construction. Typical cryptocurrency research assumes that the portfolio is created immediately after the signal is calculated. As a result, data from

[13] See Dong et al. (2022) for a detailed description of these estimators.

[14] Note that we subtract the cross-sectional mean from the returns to ensure that the aggregate measure of expected returns best extracts the cross-sectional information from technical indicators. This is equivalent to controlling for time-invariant effects (Bali and Cakici, 2010). This step is essential when pooling time series and cross-sectional observations.

days up to $t-1$ are used to predict returns on day t. In practice, such an immediate implementation is not always feasible. To mitigate this problem, certain studies assume a one-day implementation lag, meaning that they compute the trading signal on day $t-1$, construct the portfolio on day t, and measure its performance starting on day $t+1$ (Bianchi and Babiak, 2021; Bianchi et al., 2022; Fieberg et al., 2023). Accordingly, we compute the CTREND returns with and without the one-day implementation lag.

Finally, Panel C reports two design choices specific to the CS-C-ENet. When creating the aggregate forecast described in Section C, we perform parameter estimation and forecast selection using in-sample data. However, the forecast selection may not hold out-of-sample; therefore, we consider a research design in which we split the in-sample observations into a training and validation set. While the training data is used for estimating the parameters, the validation set covering the most recent 12 weeks of data is only used for forecast selection, as described in equation 10. Our second design choice regarding the estimation of the CS-C-ENet addresses the weighting of the individual forecasts. While we follow the recommended approach in the literature and use the equally weighted average of all selected forecasts (Clemen, 1989; Diebold, 1989; Rapach and Zhou, 2013; Dong et al., 2022; Han et al., 2023), we could alternatively use the θ parameters as weights.

[Insert Table 6 about here]

Panel A of Figure 2 presents the distribution of Sharpe ratios of the CTREND factor across all 53,920 possible research design choices. Most of the specifications generate remarkably high risk-return profiles, with most Sharpe ratios varying between 0.5 and 2.5.

The Sharpe ratio of the CTREND factor in the baseline setting, marked as the dashed vertical line, is at the upper edge of the distribution, but there are settings that produce much higher Sharpe ratios. Interestingly, we observe a long right tail of exceptionally high Sharpe ratios, originating from certain research designs emphasizing small and volatile coins, where return outliers—both positive and negative alike—are more common. To mitigate their impact—and for robustness—Figure B.1 in Online Appendix B reports analogous results for value-weighted portfolios only. This approach allows us to minimize the influence of the tiniest cryptocurrencies. The results remain consistent and most of the specifications are in the Sharpe ratio range of 0.5 to 2. Although many design choices introduce stress into the CTREND construction, for example, by reducing the cross-section or using inefficient methods, we find that using the Lo (2002) Sharpe ratio test, the CTREND factor achieves a significant positive Sharpe ratio (5% level) in 79% of all combinations. In other words, the CTREND performance is robust to various modifications in portfolio implementation.

[Insert Figure 2 about here]

Panels B and C show the respective probability density plots for the CSMB and CMOM factors. The Sharpe ratios for both CSMB and CMOM are also located on the right side of the distribution. However, CMOM has a long left tail, which results in high negative Sharpe ratios. Furthermore, CMOM rarely reaches Sharpe ratios of 2, confirming the superiority of CTREND. Using the Lo (2002) Sharpe ratio test, the Sharpe ratio of CSMB is positive and significant in 56% of all research designs—meanwhile, CMOM is only significant in 49% of all combinations.

Panel D of Figure 2 zooms into the question of non-standard errors by displaying the plots for different CTREND estimation methods. In general, the results seem similar across different models. However, the performance of the simple FM approach appears noticeably worse, showing a higher dispersion of potential outcomes. This highlights the risk of overfitting in the estimation process and the benefits of applying more advanced methods. Variable selection and penalized regressions prove superior in this regard.

The annualized Sharpe ratios for our baseline methodology—CS-C-ENet—range from -1.45 to 10.92—with the median Sharpe ratio being 1.34. Notably, again, the distributions encompass a certain number of extreme Sharpe ratios resulting from certain combinations that emphasize small and illiquid cryptocurrencies. In particular, the combination of equal-weighting and turning off the market capitalization filter of 1 million USD yields extreme Sharpe ratios as high as 10.92.

Although both CSMB and CMOM typically exhibit worse risk-adjusted performance, they also show a lower spread of the results. The CSMB factor attains a maximum Sharpe ratio of 4.60, and the median is 0.94. The maximum Sharpe ratio of the CMOM factor is 2.30, and the minimum is -4.47. The median Sharpe ratio of CMOM is only 0.83—thus considerably lower than that of CTREND.

How do specific design choices affect the performance of cryptocurrency factors? Table 6 reports the median annualized Sharpe ratios of the CTREND, CSMB, and CMOM factors under alternative research designs. For the CTREND factor estimated using the CS-C-ENet as in our primary analyses, the Sharpe ratio increases on average for higher levels of truncation or winsorization; however, the actual choice of whether to use truncation or winsorization does not substantially affect the performance. Including or excluding stablecoins does not change the results. Similarly, the research design choices that do not affect the results are the type of estimation window (i.e., rolling or expanding window), the number of in-sample observations, and the breakpoints used to create the factor. Likewise, excluding all volume-based indicators from our analysis does not considerably affect the CTREND performance. Applying a price filter of 1 USD decreases the median Sharpe ratio of the CTREND factor from 1.64 to 1.13, while the performance of the CSMB and CMOM factors also decreases. However, this filter drastically reduces the size of the cross-section. Lastly, adding an implementation lag of one trading day also decreases the profitability of the CTREND factor, but not for the CSMB and CMOM factors. However, regardless of the specific design choice considered, the median Sharpe ratio of CTREND is higher than that of the CMOM factor. Looking at the design choices for estimating the CS-C-ENet, we find that adding a validation sample reduces the median Sharpe ratio from 1.47 to 1.19. In contrast, the forecast weights play a minor role in this regard, although the equally weighted forecast aggregation has slightly higher Sharpe ratios—supporting the findings in the previous literature (Clemen, 1989; Diebold, 1989; Rapach and Zhou, 2013).

To conclude, our analysis reveals that the relative performance of the CTREND factor, compared to other cryptocurrency factors, is robust across various research design choices.

VI. Asset Pricing Tests

In this section, we explore the ability of the CTREND factor to price other anomalies and factors in the cryptocurrency market. First, we embark on spanning tests, comparing the CTREND factor with other prominent cryptocurrency factors. Next, we extend our examinations to other anomalies.

A. CTREND Versus Other Factors

To begin with, we juxtapose the CTREND factor with the most established factors from the cryptocurrency literature, i.e., CMKT, CSMB, and CMOM. We aim to find out to what extent different factors (and models) span the efficient frontier, rendering each other redundant.

Following the argument in Barillas and Shanken (2018), an asset pricing model can be considered as mean-variance efficient—and thus as having the best asset pricing capabilities—if the Sharpe ratio of its tangency portfolio is larger than that of competing asset pricing models. Building on this, we perform a mean-variance frontier expansion test, which evaluates the pricing ability of a model without relying on specific test assets. As outlined in Novy-Marx and Velikov (2016) and Soebhag et al. (2024), if a factor captures incremental information about average returns, it will improve the efficient frontier's span when added to the model. Denote $MVP_{M_0,t}$ as the return of the tangency portfolio obtained from the factor set M_0 and $MVP_{M_1 \cup M_0,t}$ as the return of the tangency portfolio holding both factor sets M_1 and M_0. If the factor set M_1 adds information to M_0, $MVP_{M_1 \cup M_0,t}$ will outperform $MVP_{M_0,t}$; therefore the factor set M_0 is not mean-variance efficient and thus the additional factors M_1 are relevant. Statistically, we run the following time-series regression:

$$MVP_{M_1 \cup M_0,t} = \alpha + \beta MVP_{M_0,t} + \epsilon_t \tag{12}$$

with α and β being regression coefficients and ϵ_t being regression residuals.[15] If the alpha of this regression is positive and statistically significant, the factors M_1 improve the span of the efficient frontier of factor set M_0. We focus on out-of-sample mean-variance portfolios to mitigate potential overfitting. Specifically, we estimate the portfolio weights using data over the previous 52 weeks, calculate the realized portfolio return, and re-estimate the weights. To ensure comparability, we rescale the portfolio weights to target weekly volatility of 10%, which approximately equals the volatility of the cryptocurrency market over the sample period.

Table 7 reports the results of this experiment. In general, they emphasize the superiority of the asset pricing models incorporating the CTREND factor. To begin with, consider the first column, which shows the alphas of an MVP that includes CTREND and one of the LTW factors against the CTREND factor alone. Adding the market factor to CTREND significantly boosts the return of the mean-variance portfolio by 0.91% (t-stat = 2.07), suggesting that both the market and the CTREND factor are relevant for spanning the mean-variance frontier. When adding the CSMB factor to the CMKT and CTREND model, the alpha is 1.50% and statistically significant at the 1% level (t-stat = 2.93). However, the CMOM factor is never significant. When added to the three-factor model consisting of CMKT, CSMB, and CTREND, the alpha is only 0.37% and insignificant (t-stat = 1.02), suggesting that the CMOM does not improve the model further. In the last

[15]Specifically, we estimate unrestricted maximum Sharpe ratio portfolios with weights $\boldsymbol{w}$ obtained by solving

$$\boldsymbol{w} = \frac{\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}}{\mathbf{1}'\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}}$$

with $\boldsymbol{w}$ denoting the $K \times 1$ vector of factor weights, $\boldsymbol{\Sigma}$ being the $K \times K$ variance-covariance matrix of factor returns, and $\boldsymbol{\mu}$ being the $K \times 1$ vector of factor means. $\mathbf{1}$ is a $K \times 1$ vector of ones.

column, we test whether adding the CTREND factor to the three-factor LTW model improves its performance. The alpha is 2.77% (t-stat = 3.80), suggesting that the CTREND factor does indeed contain information not captured by the LTW factors. To conclude, we find that CTREND expands the efficient frontier, while the CMOM factor does not. This suggests that CMOM should be replaced by CTREND in the model.

[Insert Table 7 about here]

B. Pricing Cryptocurrency Anomalies

Having concluded that the CMOM factor is redundant and should be replaced by CTREND, we now extend the examinations to other patterns in cryptocurrency returns. Specifically, we verify the ability of CTREND-augmented models to price known cryptocurrency anomalies. To this end, in the first step, we form a sample of cryptocurrency characteristic-sorted portfolios. To be precise, we form two separate sets. The first group contains well-known anomalies in the cross-section of cryptocurrency returns that were studied in LTW. Specifically, we create long-short quintile portfolios from one-way sorts on market capitalization (*mcap*), price (*prc*), maximum daily price over the past week (*maxdprc*), one-week (*ret_1_0*), two-week (*ret_2_0*), three-week (*ret_3_0*), four-week (*ret_4_0*) momentum, four-week momentum skipping the most recent week (*ret_4_1*), price volume (*prcvol*), volume scaled by market capitalization (*volscaled*), and volatility of price volume (*stdprcvol*).[16] The portfolios are value weighted, held for one week, and then rebalanced. Table B.8 in the Online Appendix summarizes the performance

[16]LTW test further anomalies and the cryptocurrency literature provides a battery of additional patterns in the cross-section of cryptocurrency returns. However, we do not find that other strategies generate a significant spread in cryptocurrency returns. The results can be found in Table B.5 in Online Appendix B.

of anomaly portfolios. Consistent with LTW, all portfolios generate significant return spreads.

The second group comprises all long-short portfolios based on individual technical indicators that are outlined in Table 2. Finally, we analyze the strategies in both groups pooled together. With these anomalies at hand, we examine their average returns with three different asset pricing models: the CCAPM, the three-factor model of LTW, and the three-factor model that replaces the LTW momentum factor with the CTREND factor:

$$r_{p,t} = \alpha + \beta_{CMKT} CMKT_t + \beta_{CSMB} CSMB_t + \beta_{CTREND} CTREND_t + \epsilon_t \tag{13}$$

For simplicity, we name the last model the TREND model.

Figure 3 presents the results of this analysis. While the upper sections offer a bird's-eye overview of the model performance, comparing the average rates of returns on all characteristic-sorted portfolios with the alphas from different asset pricing models, the bottom part offers a more formal analysis. Specifically, it reports several simple statistics that capture the performance of the model: average absolute alphas and t-statistics, weighted pricing errors Δ,[17] and p-values from the GRS tests of Gibbons et al. (1989). The GRS test verifies the hypothesis that all alphas of a set of portfolios are equal to zero.

In general, all tests point to the superiority of the TREND model. To begin with, the CCAPM clearly fails to cope well with abnormal returns (Panel A). The anomaly alphas are close to the 45-degree line, indicating that the abnormal returns increase consistently with the average raw returns and that the model can hardly explain their

[17] Following Shanken (1992) and Liu et al. (2024), weighted pricing errors are defined as $\Delta = \boldsymbol{\alpha}' \boldsymbol{\Sigma}^{-1} \boldsymbol{\alpha}$, with $\boldsymbol{\Sigma}$ denoting the covariance matrix of regression residuals.

payoffs. Furthermore, many alphas remain statistically significant. The alphas are significant for as many as 20 anomalies (in the full set), and the average absolute alpha is 2.69%. The hypotheses of the GRS tests are clearly rejected—not only for the full sample of all characteristics, but also for its subsamples of LTW anomalies and technical indicators.

[Insert Figure 3 about here]

The three-factor model of LTW (Panel B) seems to do a better job, but its performance is far from perfect. Overall, the alphas rise steadily with average returns, and many are still significantly different from zero. Yet, we still observe 11 unexplained significant alphas, and the average absolute abnormal return is 1.44%. The GRS tests continue to reject the hypothesis of zero alphas. The model struggles particularly with technical indicators, where the average absolute alpha is 1.51%.

Finally, Panel C shows the application of the TREND model, which seems to be the most effective. The abnormal returns, if any, are scattered almost randomly around the horizontal axis. There is no longer any relationship between the average returns and the alphas. This suggests that the model does a good job of explaining the known patterns in the cross-section of cryptocurrency returns. Finally, only two portfolios continue to generate abnormal returns that are still significantly different from zero. Table B.9 in Online Appendix B, which provides an insight into the alphas of individual portfolios, helps to identify these two exceptions: *mcap* and *stockK*, where *stochK* is borderline significant with a t-statistic of 1.98. Apart from these two portfolios, no other portfolios have significant alphas after taking the TREND model factors into account. Interestingly, although the TREND model does not include a momentum factor, it successfully explains all the returns of the momentum-sorted portfolios. Meanwhile, as can be seen in Table B.8 in the Online Appendix and Table 2, the LTW model fails to explain the size effect and the two- and three-week momentum returns, as well as that of eight technical indicators.

Further details in the lower part of Panel C show that the average absolute alpha shrinks to only 0.68%, and the associated t-statistic is 1.13. More importantly, the average price error Δ decreases significantly when the CTREND factor is added, falling to 0.112. Finally, the p-values from the GRS test indicate that only the TREND model can explain the abnormal returns of the characteristic-sorted portfolios. The p-values for both the CCAPM and the LTW models are below 1%, indicating that the abnormal returns are significantly different from zero. Meanwhile, the p-value for the TREND model is 8.02%, indicating that it captures the known patterns in the cross-section of coin returns relatively well.

Finally, it is also worth noting that no model passes the GRS test for the LTW anomalies. This finding is due to the CSMB factor—constructed from tercile portfolios—which fails to capture the returns of the *mcap* quintile portfolios, which produce a larger return spread than tercile portfolios. However, the explanatory power of the CTREND factor beats other approaches by producing lower pricing errors and absolute alphas.

To sum up, a three-factor model that incorporates the CMKT, CSMB, and CTREND factors captures the cross-section of cryptocurrency returns well and significantly outperforms other prominent approaches in the literature.

VII. Practical Investment Considerations

Our analyses so far document a robust cross-sectional pattern in cryptocurrency returns. However, to what extent can it be harvested in practice? To shed light on the real-life implementability of a CTREND investment strategy, we explore three questions. First, we verify that the strategy does not originate solely from difficult-to-trade coins. Second, we consider the impact of transaction costs. Third, we look at more extended holding periods.

A. Controlling for Difficult-to-Arbitrage Cryptocurrencies

Numerous stock market anomalies derive predictability from illiquid micro caps, which are hardly tradeable in practice (Hou et al., 2020). Likewise, certain prominent cryptocurrency patterns, such as size or liquidity, tend to concentrate in the smallest cryptocurrencies with marginal economic significance (Fieberg et al., 2024). Should the CTREND factor stem from a similar environment, its practical implication would be limited.

To scrutinize this issue, we examine the performance of the CTREND strategy within the subsets of the largest and most liquid assets. Specifically, each week, we remove between 50% and 90% of the cryptocurrencies with the lowest market capitalization or liquidity, as measured by the Amihud (2002) ratio. Additionally, based on these measures, we create two subsets—including the 100 largest and most liquid cryptocurrencies, respectively. Next, within each of these subsets, we apply the standard quintile sorts on CTREND to examine the magnitude of return predictability associated with this phenomenon. Table 8 summarizes the findings.

[Insert Table 8 about here]

The CTREND effect does not come from some shady corner of the cryptocurrency market. On the contrary, the return predictability remains robust in more liquid and larger assets. For example, the average weekly hedge portfolio return in the sample encompassing 50% of the biggest cryptocurrencies (Panel A) equals 3.84%, resembling the result for the total sample (see Table 3). Similarly, considering only the 10% largest cryptocurrencies each week, the average return is 2.51%, the alphas against the CCAPM and LTW model exceed 2%, and are statistically significant at the 1% level. Panel B reveals a similar pattern for the most liquid cryptocurrencies. The mean long-short portfolio return in the top 50% of the sample reaches 4.36%, and in the 10% most liquid coins, the mean return is still large and statistically significant. To sum up, the CTREND effect originates mainly from the biggest and most liquid cryptocurrencies. In consequence, the premium remains strong in tradeable cryptocurrencies, making it a good candidate for practical portfolio implementation.

B. Transaction Costs

Novy-Marx and Velikov (2016) show that many equity anomalies are associated with substantial portfolio turnover, which prevents them from being forged into profitable investment strategies. In particular, momentum and technical analysis signals typically lead the ranking of trade-intensive signals. Not surprisingly, our aggregate measure, which combines many technical indicators, may also require a high level of portfolio turnover. In order to scrutinize the practical consequences, we assess the CTREND profits net of trading costs. To this end, we first calculate the turnover of each portfolio p following the definition of Gu et al. (2020):

$$TO_{p,t} = \frac{1}{2}\sum_{i \in L} |w_{i,t} - \frac{w_{i,t-1}\,(1 + r_{i,t})}{\sum_i w_{i,t-1}\,(1 + r_{i,t})}| + \frac{1}{2}\sum_{j \in S} |w_{j,t} - \frac{w_{j,t-1}\,(1 + r_{j,t})}{\sum_j w_{j,t-1}\,(1 + r_{j,t})}| \tag{14}$$

where $i \in L$ and $j \in S$ indicate that a coin belongs to the long or short legs, respectively. We report the turnover for the long-short portfolios as the average of the long and short legs, thus representing the proportion of the portfolio that needs to be replaced each week. To estimate profits adjusted for the trading costs, we follow Bianchi et al. (2022) and use a conservative transaction cost rate of 30 basis points (bpts) for the long and 40bpts for the short leg. We calculate the net anomaly return $r^{net}_{p,t}$ of strategy p at time t as:

$$r^{net}_{p,t} = \left(\sum_{i \in L} w_{i,t} r_{i,t} - \sum_{j \in S} w_{j,t} r_{j,t}\right) - \left(tc^l \sum_{i \in L} |w_{i,t} - w_{i,t-1}| + tc^s \sum_{j \in S} |w_{j,t} - w_{j,t-1}|\right) \tag{15}$$

with tc^l and tc^s denoting the transaction cost rate for trading a long and short positions, respectively. However, the assumed transaction cost rates of 30 and 40bpts may be conservative. Bianchi et al. (2022) use data from CryptoCompare, which tends to cover larger cryptocurrencies, while our sample additionally includes many small coins. As a robustness check, we adopt two additional transaction cost rates, each of which is 10bpts higher. We also report two types of breakeven transaction cost (BETC) rates, i.e., a BETC rate that sets the return to exactly zero and a BETC rate for which the net return is no longer statistically significant at the 5% level (BETC 5%) (Grundy and Martin, 2001; Han et al., 2016b).

Panel A of Table 9 summarizes the impact of trading costs on the CTREND strategies. Overall, their performance seems relatively robust. Admittedly, the portfolio turnover is substantial, reaching 68% per week, indicating that an investor must replace a considerable fraction weekly. However, the gross portfolio returns exceed these implementation costs, and the net payoffs on the long-short CTREND strategy range between 2.90% (t-stat = 3.89) and 2.35% (t-stat = 3.16)—depending on the assumed transaction cost rate. Furthermore, the BETC rate, at which the mean net return is erased to zero, equals 1.41%. Even if the fee was as high as 0.88%, the strategy's profit would remain significant at the 5% level. The results shown in Panel B once more support the finding that the CTREND effect is not driven by small hard-to-trade cryptocurrencies. A CTREND factor based on the largest 100 cryptocurrencies earns between 2.45% and 1.90% per week—all statistically significant. Although the CTREND strategy requires intense trading and frequent portfolio rebalancing, it remains resilient despite high transaction costs.

[Insert Table 9 about here]

One common way to mitigate trading costs is to extend the portfolio holding period, thereby reducing portfolio turnover and transaction costs through less frequent rebalancing. Table B.10 in the Online Appendix sheds light on how longer holding periods affect the CTREND portfolios. Overall, reducing the rebalancing frequency markedly affects performance. Even with two-week rebalancing, the average weekly returns drop by 1.5 percentage points to reach 2.34%. The mean returns remain significant at the 5% level as long as the holding periods do not exceed four weeks. In other words, while the CTREND strategy requires high turnover, it continues to generate high payoffs if it is rebalanced no more than roughly once a month.

Interestingly, while the CTREND signal may seem short-lived, it is more persistent than most momentum signals in the market, as seen in Table B.10. Most cryptocurrency momentum strategies no longer produce significant profits at a three- or even two-week horizon. Moreover, the CTREND strategy beats all other momentum strategies within up to two-week horizons. Consequently, while seemingly trading-intensive, CTREND still fares favorably against the background of comparable trading signals in the cryptocurrency world.

VIII. Conclusion

Our study comprehensively examines the cross-sectional return predictability in cryptocurrency markets using technical analysis signals. Using data on more than 3,000 coins from 2015 to 2022, we show that many signals capture information for future cryptocurrency returns that cannot be captured by prevailing cryptocurrency asset pricing models. By utilizing machine learning techniques, we extract the incremental information content of the signals and aggregate them into CTREND, an overall measure of trends in the cross-section of cryptocurrencies. CTREND turns out to be an effective predictor of cryptocurrency returns.

A long-short strategy that buys the quintile of cryptocurrencies with the highest predicted return and shorts those with the lowest earns 3.87% per week. These returns cannot be captured by common factor models, such as the CCAPM or the three-factor model, nor subsumed by popular predictors of cryptocurrency returns. The impact of CTREND is notably stable. The phenomenon holds across various subperiods and remains robust to fluctuations in market conditions. Additionally, its resilience is confirmed through a multitude of research design modifications. We examine 53,920 distinct implementations that consider alternative methods for sample preparation, data preprocessing, forecasting models, and portfolio configurations. CTREND delivers excellent performance in most scenarios and offers a remarkable risk/return profile.

Lastly, we explore the practical implications of the CTREND effect. The outcomes are promising from an investor perspective. The return predictability of the aggregate technical signal does not come from difficult-to-arbitrage coins but remains strong in the market's biggest and most liquid coins. Furthermore, despite the short-term nature of the trading signal and substantial portfolio turnover, portfolio profits withstand the impact of transaction costs. Finally, they remain significant for longer holding periods of up to four weeks. In a nutshell, the CTREND effect could be potentially forged into an effective trading strategy.

One limitation of our study is the reliance on a number of preselected technical features. Jiang et al. (2023) and Kaczmarek and Pukthuanthong (2023) take an alternative approach and extract information directly from past prices and their graphical representations. Subsequent research could extend our analysis in this direction. Furthermore, future studies of the topics discussed in this paper should focus on exploring the nature and sources of the CTREND effect. While the asset pricing literature offers several mechanisms contributing to the development of various price patterns, their examination in the cryptocurrency universe has been limited thus far. Scrutinizing them would assist in better understanding the origins of return patterns in this novel asset class.

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Figure 1: Comparison of Cryptocurrency Factors

The figure shows average returns (a) and annualized Sharpe ratios (b) for cryptocurrency factors, encompassing the cryptocurrency market factor (CMKT), size factor (CSMB), momentum factor (CMOM), and trend factor (CTREND). The sample spans the period from April 2015 to May 2022.

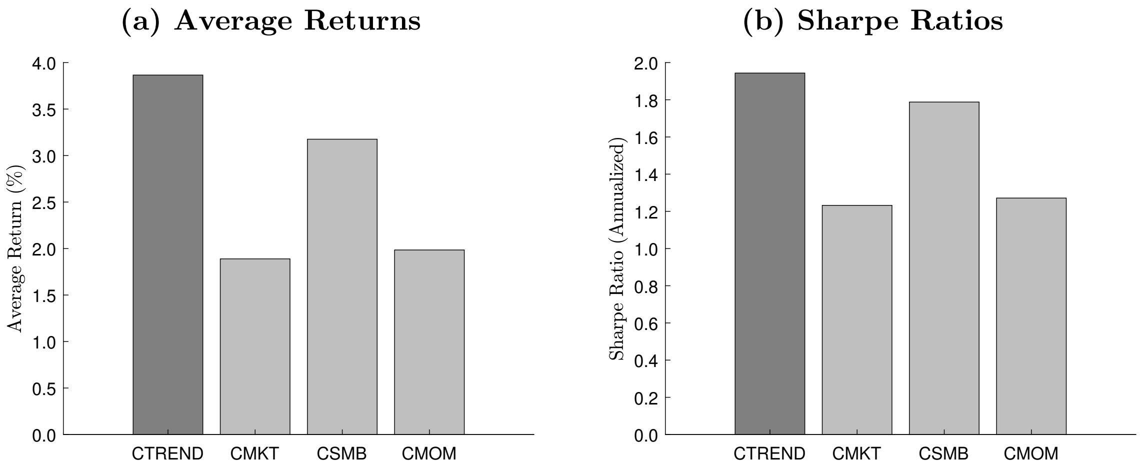
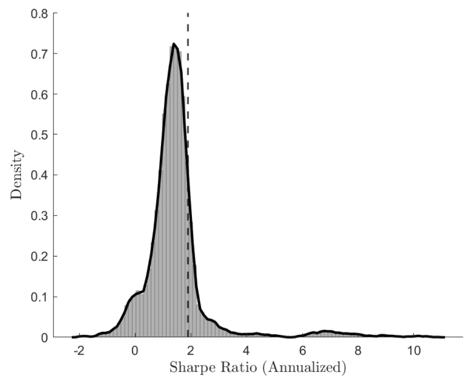


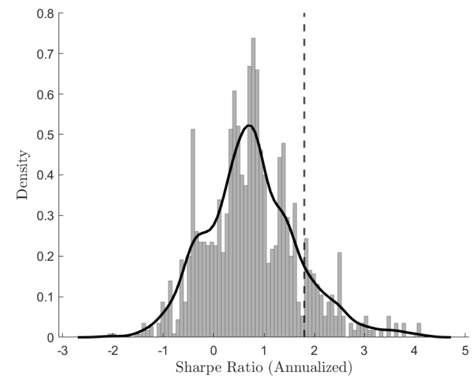
Figure 2: Distribution of Sharpe Ratios under Alternative Research Designs

The figure shows the distribution of Sharpe ratios under alternative research designs. Specifically, Panel (a) shows the density plot of the Sharpe ratios for the CTREND factor for all 53,920 combinations, (b) shows the density plot of the CSMB factor, (c) shows the density plot of the CMOM factor, and (d) compares the performance of the CTREND factor estimated with CS-C-ENet with alternative estimation methods and the CSMB and CMOM factors under 6,144 alternative research designs. The CSMB and CMOM factors are constructed as suggested in Liu et al. (2022).

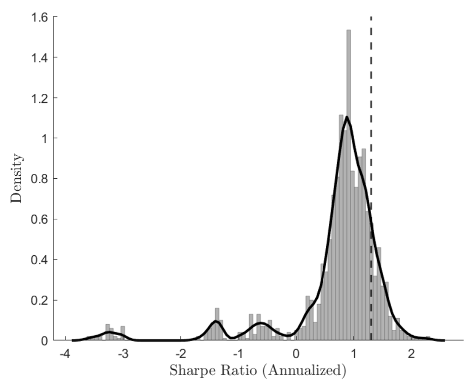
(a) Density Function CTREND



(b) Density Function CSMB



(c) Density Function CMOM



(d) Comparison With Other Factors

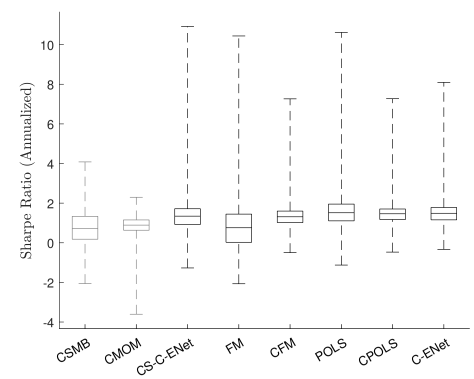
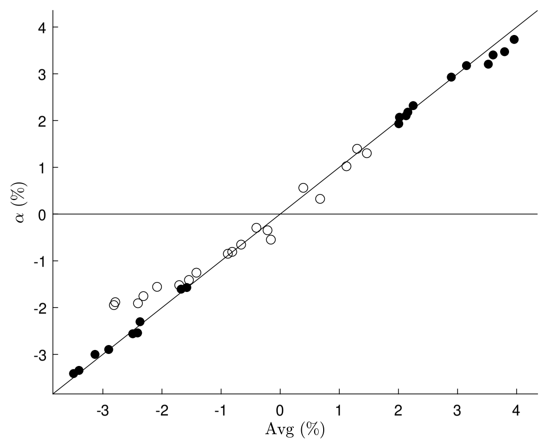


Figure 3: Anomaly Alphas

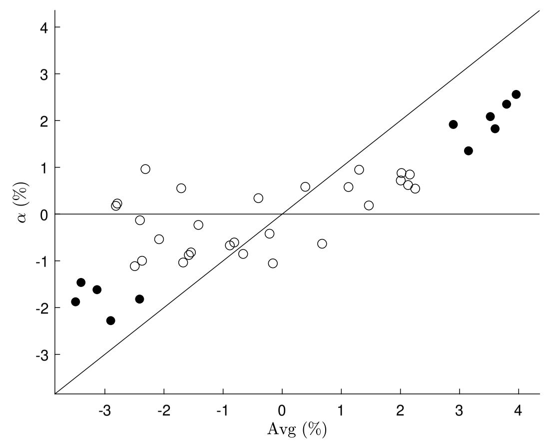
The figure shows the alphas (α) from a time-series regression of anomaly and technical indicator returns on the (a) CMKT factor, (b) CMKT, CSMB, and CMOM factors, and (c) the CMKT, CSMB, and CTREND factors. The alphas on the vertical axis are compared with their average returns (*Avg.*) on the horizontal axis. All values are in percentage terms. The black dots represent alphas that are significantly different from zero at the 5% level. The tables below the respective figures show the average absolute alphas (Avg $|\alpha|$), average absolute t-statistics (Avg $|t|$), the number of abnormal returns significant at the 5% level (N_{sig}), the weighted pricing error (Δ), defined as $\Delta = \alpha' \Sigma^{-1} \alpha$ (Shanken, 1992; Liu et al., 2024), with Σ denoting the variance-covariance matrix of the residuals from regressing hedge portfolio returns on risk factors, and the p-value of the Gibbons et al. (1989) (GRS) test of the null hypothesis that all alphas are mutually zero. Statistics are reported for the LTW anomalies (LTW), technical indicators (TI), and both (All) that have a statistically significant alpha with respect to the CCAPM. All numbers are presented in percentage terms. The study period is from April 2015 to May 2022.

(a) CCAPM



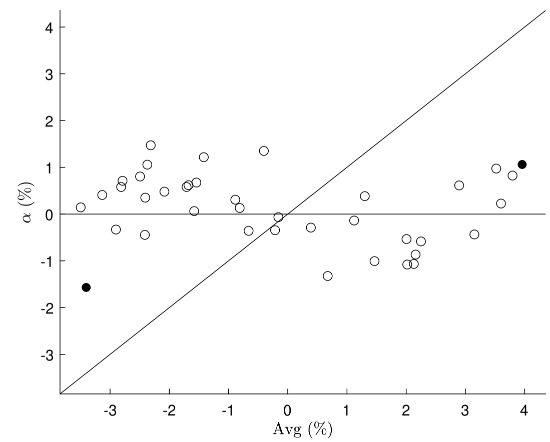
	LTW	TI	All
Avg $\|\alpha\|$	2.82	2.64	2.69
Avg $\|t\|$	3.59	3.33	3.40
N_{sig}	5	15	20
Δ	0.132	0.123	0.221
GRS (p)	0.00%	0.19%	0.00%

(b) LTW



	LTW	TI	All
Avg $\|\alpha\|$	1.23	1.51	1.44
Avg $\|t\|$	1.94	2.17	2.11
N_{sig}	3	8	11
Δ	0.061	0.106	0.159
GRS (p)	0.19%	0.86%	0.38%

(c) TREND



	LTW	TI	All
Avg $\|\alpha\|$	0.87	0.62	0.68
Avg $\|t\|$	1.53	1.00	1.13
N_{sig}	1	1	2
Δ	0.061	0.061	0.112
GRS (p)	0.19%	25.6%	8.02%

Table 1: Research Sample

The table reports the number of cryptocurrencies in the sample, as well as their mean and median market capitalization and dollar trading volume by year. The number of cryptocurrencies refers to the total number of cryptocurrencies that have at least one weekly observation available within a given year. The statistics for the market capitalization and volume are pooled averages or medians within a year. The study period runs from April 2015 to May 2022.

		Market Cap ($ mil.)		Volume ($ thous.)	
Year	Number	Mean	Median	Mean	Median
2015	74	135.12	2.53	1,197.87	9.75
2016	147	161.76	3.09	1,834.47	21.68
2017	773	437.21	9.10	18,770.45	126.91
2018	1,479	371.43	9.03	21,726.40	120.83
2019	1,236	268.98	5.31	69,181.28	143.07
2020	1,385	397.35	6.23	143,615.44	232.83
2021	2,214	1,381.08	13.74	187,405.60	570.81
2022	1,685	1,214.06	12.95	113,429.29	539.74
Full	3,244	746.21	8.49	107,310.18	245.17

Table 2: Technical Indicator Strategy Returns

The table reports the average weekly portfolio returns (in %) and t-statistics of quintile portfolios based on cryptocurrency technical indicators. Quintile portfolios are constructed by ranking cryptocurrencies by their technical indicators (from low to high) and assigning them into portfolios based on the quintile distribution. The portfolios are value-weighted and re-balanced weekly. A zero-investment portfolio takes a short position in cryptocurrencies in the low and a long position in cryptocurrencies in the high portfolio. The table also reports the risk-adjusted return against the CCAPM and the three-factor model proposed in Liu et al. (2022). Statistical significance at the 5% level is indicated by bold numbers. The study period is from April 2015 to May 2022.

	L	2	3	4	H	H - L	α^{CCAPM}	α^{LTW}
Momentum Oscillators								
rsi	0.00	0.75	**1.75**	**2.42**	**3.52**	**3.52**	**3.16**	**2.09**
	(0.00)	(1.16)	(2.38)	(3.45)	(4.76)	(5.41)	(4.85)	(3.87)
stochRSI	0.17	1.52	**1.85**	**2.11**	1.47	1.30	1.40	0.95
	(0.22)	(1.67)	(2.02)	(2.55)	(1.77)	(1.78)	(1.91)	(1.25)
stochK	-0.24	1.25	**1.37**	**2.45**	**3.72**	**3.96**	**3.71**	**2.56**
	(-0.39)	(1.70)	(2.08)	(3.37)	(4.77)	(5.73)	(5.32)	(4.13)
stochD	0.39	0.85	**1.29**	**2.18**	**3.29**	**2.89**	**2.90**	**1.92**
	(0.53)	(1.21)	(1.99)	(3.06)	(4.46)	(4.06)	(4.00)	(2.99)
cci	-0.09	1.10	**1.58**	**2.68**	**3.70**	**3.80**	**3.48**	**2.35**
	(-0.15)	(1.46)	(2.25)	(3.65)	(4.49)	(5.03)	(4.57)	(3.40)
Moving Average Indicators								
sma_3d	**1.68**	**3.06**	**2.33**	0.73	0.80	-0.89	-0.85	-0.67
	(2.07)	(3.72)	(3.48)	(1.09)	(1.00)	(-1.11)	(-1.04)	(-0.80)
sma_5d	**3.25**	**3.26**	**1.98**	0.79	0.35	**-2.90**	**-2.93**	**-2.28**
	(3.57)	(3.85)	(2.88)	(1.24)	(0.47)	(-3.35)	(-3.34)	(-2.59)
sma_10d	**2.83**	**3.02**	**2.09**	0.67	0.46	**-2.37**	**-2.31**	-1.00
	(3.13)	(4.26)	(2.97)	(0.99)	(0.62)	(-2.90)	(-2.78)	(-1.32)
sma_20d	**3.18**	**3.14**	**1.78**	0.65	0.05	**-3.13**	**-2.99**	**-1.62**
	(3.61)	(4.12)	(2.59)	(0.86)	(0.06)	(-3.80)	(-3.58)	(-2.26)
sma_50d	**3.64**	**2.69**	**1.38**	1.30	1.15	**-2.49**	**-2.46**	-1.11
	(4.00)	(3.50)	(2.10)	(1.67)	(1.56)	(-2.88)	(-2.80)	(-1.55)
sma_100d	**3.00**	**2.48**	**2.14**	1.32	**2.04**	-0.96	-0.84	0.23
	(3.34)	(3.50)	(3.07)	(1.74)	(2.68)	(-1.12)	(-0.97)	(0.31)
sma_200d	**2.48**	**2.54**	**1.92**	**1.74**	**2.52**	0.04	0.09	0.82
	(2.97)	(3.26)	(2.84)	(2.19)	(3.02)	(0.05)	(0.11)	(1.07)
macd	1.02	1.42	**1.53**	**3.01**	**3.18**	**2.16**	**2.12**	0.85
	(1.39)	(1.79)	(2.28)	(3.78)	(3.56)	(2.50)	(2.42)	(1.17)
macd_diff_signal	0.56	1.07	**2.71**	**2.89**	**2.81**	**2.25**	**2.41**	0.54
	(0.68)	(1.43)	(3.69)	(4.11)	(3.03)	(2.46)	(2.60)	(0.63)

Table 2: Technical Indicator Strategy Returns (Continued)

	L	2	3	4	H	H - L	α^{CCAPM}	α^{LTW}
Volume Indicators								
volsma_3d	**1.72**	**2.24**	**1.79**	**2.91**	**1.50**	-0.21	-0.34	-0.42
	(2.25)	(3.00)	(2.77)	(3.46)	(1.96)	(-0.34)	(-0.52)	(-0.63)
volsma_5d	**1.99**	**2.01**	**2.49**	**2.40**	1.33	-0.66	-0.68	-0.85
	(2.61)	(2.89)	(3.40)	(2.99)	(1.80)	(-1.09)	(-1.10)	(-1.33)
volsma_10d	**2.00**	**2.44**	**2.38**	**1.40**	**1.84**	-0.16	-0.54	-1.05
	(2.62)	(3.30)	(3.23)	(2.00)	(2.14)	(-0.21)	(-0.72)	(-1.37)
volsma_20d	**2.42**	**2.45**	**1.96**	**1.57**	**1.61**	-0.81	-0.84	-0.61
	(2.85)	(3.44)	(2.72)	(2.12)	(2.03)	(-1.03)	(-1.04)	(-0.74)
volsma_50d	**2.65**	**2.04**	**2.21**	**1.91**	1.07	**-1.58**	**-1.49**	-0.88
	(3.14)	(2.98)	(2.93)	(2.55)	(1.49)	(-2.20)	(-2.05)	(-1.26)
volsma_100d	**2.76**	**2.46**	**1.86**	**1.69**	1.09	**-1.68**	-1.52	-1.04
	(3.02)	(3.68)	(2.61)	(2.28)	(1.62)	(-2.12)	(-1.90)	(-1.35)
volsma_200d	**2.76**	**2.66**	**1.79**	**2.19**	1.21	**-1.54**	-1.30	-0.82
	(3.07)	(3.74)	(2.56)	(2.99)	(1.83)	(-2.03)	(-1.70)	(-1.13)
volmacd	1.37	**1.74**	**1.43**	**2.46**	**3.37**	**2.01**	**1.87**	0.72
	(1.82)	(2.37)	(2.08)	(3.62)	(3.46)	(2.38)	(2.19)	(0.94)
volmacd_diff_signal	**1.91**	**1.79**	**1.67**	**2.66**	**2.30**	0.39	0.61	0.58
	(2.29)	(2.45)	(2.61)	(3.44)	(2.67)	(0.46)	(0.71)	(0.65)
chaikin	1.30	0.98	**1.86**	**2.81**	**2.42**	1.12	1.02	0.58
	(1.69)	(1.51)	(2.35)	(3.71)	(3.44)	(1.68)	(1.50)	(0.86)
Volatility Indicators								
boll_low	**3.22**	**2.32**	**2.53**	**1.92**	1.13	**-2.08**	-1.49	-0.54
	(3.19)	(2.72)	(3.36)	(2.95)	(1.92)	(-2.28)	(-1.64)	(-0.62)
boll_mid	**3.34**	**2.83**	**1.81**	0.48	-0.16	**-3.50**	**-3.40**	**-1.88**
	(3.86)	(3.71)	(2.66)	(0.69)	(-0.22)	(-4.25)	(-4.08)	(-2.73)
boll_high	**3.19**	**2.43**	**1.91**	0.50	0.78	**-2.41**	**-2.59**	**-1.82**
	(4.59)	(3.17)	(2.38)	(0.67)	(0.89)	(-3.01)	(-3.19)	(-2.36)
boll_width	**1.90**	**2.46**	1.52	**2.07**	**2.57**	0.67	0.26	-0.63
	(3.12)	(3.39)	(1.89)	(2.38)	(2.45)	(0.72)	(0.28)	(-0.67)

Table 3: Univariate Portfolio Sorts

The table reports the average weekly return (in %) and t-statistics in parentheses, the weekly standard deviation (in %), and the annualized Sharpe ratio of value-weighted quintile portfolios that hold cryptocurrencies based on their rank with respect to the aggregate trend characteristic. Additionally, the alpha against the CCAPM (α^{CCAPM}) and the portfolio's exposure to the value-weighted market return (β^{CMKT}) as well as the alpha against the LTW model (α^{LTW}) and the exposures to the market (β^{CMKT}), size (β^{CSMB}), and momentum (β^{CMOM}) factors are reported. The table also reports the average market capitalization in million U.S. dollars, the average trading volume in million U.S. dollars, the average idiosyncratic volatility with respect to the market portfolio (in %), and the average cumulative return over the previous three weeks. Statistical significance at the 5% level is indicated by bold numbers. The study period is from April 2015 to May 2022.

	Portfolio Performance									Portfolio Characteristics			
Rank	Avg	Std	Shp	α^{CCAPM}	β^{CMKT}	α^{LTW}	β^{CMKT}	β^{CSMB}	β^{CMOM}	mcap	volume	ivol	ret_3_0
L	0.12	13.86	0.06	**-1.70**	**0.98**	**-1.51**	**0.95**	**0.12**	**-0.27**	134.59	229.64	0.11	-21.63
	(0.16)			(-3.70)	(23.76)	(-3.23)	(23.21)	(3.32)	(-6.64)				
2	0.93	13.56	0.49	-0.83	**0.94**	-0.82	**0.90**	**0.15**	**-0.22**	401.08	689.25	0.10	-6.55
	(1.32)			(-1.80)	(22.96)	(-1.74)	(22.05)	(4.24)	(-5.47)				
3	1.12	11.99	0.67	-0.57	**0.91**	**-0.99**	**0.85**	**0.16**	-0.00	986.88	936.25	0.09	4.49
	(1.79)			(-1.63)	(28.95)	(-2.63)	(25.94)	(5.62)	(-0.07)				
4	**2.72**	14.59	1.34	0.67	**1.10**	0.19	**1.03**	**0.09**	**0.14**	1,485.5	1,218.3	0.09	18.11
	(3.59)			(1.57)	(28.89)	(0.42)	(25.53)	(2.63)	(3.54)				
H	**3.98**	15.99	1.80	**2.10**	**1.01**	1.10	**0.92**	0.03	**0.52**	1,182.3	1,134.7	0.10	62.74
	(4.80)			(3.48)	(18.69)	(1.94)	(18.61)	(0.79)	(10.75)				
H-L	**3.87**	14.34	1.94	**3.80**	0.03	**2.62**	-0.03	-0.08	**0.79**				
	(5.19)			(5.03)	(0.50)	(4.22)	(-0.49)	(-1.79)	(14.88)				

Table 4: Cross-Sectional Regressions

The table reports average slope coefficients obtained from cross-sectional regressions of cryptocurrency returns on the aggregated trend characteristic and control characteristics. The regressions are estimated using the weighted least squares method (WLS) with the weights based on cryptocurrency market capitalizations. *CTREND* is the aggregate trend characteristic, *beta* is the CCAPM market beta calculated over the previous 365 days, *mcap* is the market capitalization, *illiq* is the Amihud (2002) illiquidity measure calculated over the previous week, *ivol* is the idiosyncratic volatility with respect to the CCAPM calculated over the previous 365 days, and *ret_*_0* are cumulative returns over the previous one to four weeks. Newey and West (1987) robust t-statistics are reported in parentheses. Statistical significance at the 5% level is indicated by bold numbers. The study period is from April 2015 to May 2022.

	1	2	3	4	5	6	7	8	9	10	11	12
Intercept	**0.08**	**0.09**	0.08	**0.08**	**0.08**	**0.08**	**0.09**	**0.09**	**0.05**	**0.07**	**0.08**	0.08
	(3.96)	(3.58)	(1.77)	(2.04)	(1.98)	(2.21)	(2.21)	(4.17)	(2.40)	(3.25)	(3.48)	(1.86)
CTREND	**2.36**	**2.34**	**2.03**	**2.07**	**2.05**	**2.15**	**2.13**	**2.94**	**2.00**	**2.56**	**2.74**	**2.62**
	(5.00)	(4.82)	(3.64)	(3.79)	(3.76)	(4.06)	(4.05)	(4.67)	(3.20)	(4.27)	(4.87)	(3.93)
beta		-0.02		-0.01	-0.01	-0.01	-0.01					-0.01
		(-1.35)		(-0.86)	(-0.83)	(-0.99)	(-1.03)					(-1.73)
mcap			-0.00	-0.00	-0.00	-0.00	-0.00					0.00
			(-0.35)	(-0.23)	(-0.14)	(-0.17)	(-0.26)					(0.72)
illiq					1.00		1.22					0.89
					(1.91)		(1.67)					(1.41)
ivol						0.01	-0.01					0.07
						(0.09)	(-0.15)					(1.10)
ret_1_0								-0.04				**-0.06**
								(-1.66)				(-2.97)
ret_2_0									**0.04**			0.03
									(2.10)			(1.43)
ret_3_0										0.01		0.01
										(0.78)		(0.48)
ret_4_0											0.00	0.00
											(0.27)	(0.06)

Table 5: Performance in Subperiods and Different Market States

The table reports the average weekly returns and abnormal returns of value-weighted CTREND quintile portfolios in subperiods by splitting the sample period into equal halves (Panel A), high and low cryptocurrency market volatility periods (Panel B), high and low cryptocurrency uncertainty periods (Panel C), and bull and bear markets (Panel D). The statistical significance of the average returns and alphas at the 5% level is indicated in bold font. All mean returns and alphas are reported in percentage terms. The study period is from April 2015 to May 2022.

	L	2	3	4	H	H-L	α^{CCAPM}	α^{LTW}
Panel A: Changes Over Time								
First half	0.94	1.94	1.72	**3.87**	**5.41**	**4.47**	**4.23**	**2.66**
	(0.89)	(1.66)	(1.77)	(3.03)	(3.81)	(3.50)	(3.24)	(2.48)
Second half	-0.72	-0.09	0.50	1.56	**2.55**	**3.26**	**3.32**	**2.38**
	(-0.74)	(-0.11)	(0.65)	(1.93)	(3.01)	(4.25)	(4.29)	(3.79)
Panel B: Market Volatility								
Low volatility	-0.52	0.52	1.21	**3.02**	**4.94**	**5.46**	**4.76**	**2.85**
	(-0.68)	(0.68)	(1.70)	(2.96)	(4.13)	(5.08)	(4.40)	(3.01)
High volatility	0.75	1.33	1.02	**2.42**	**3.02**	**2.27**	**2.48**	**2.20**
	(0.62)	(1.13)	(1.00)	(2.15)	(2.63)	(2.22)	(2.42)	(2.72)
Panel C: Cryptocurrency Market Uncertainty								
Low uncertainty	1.92	**2.25**	**2.37**	**4.17**	**6.14**	**4.22**	**4.24**	**2.42**
	(1.85)	(2.18)	(2.85)	(3.47)	(4.33)	(3.04)	(2.91)	(2.05)
High uncertainty	-1.29	-0.11	0.13	1.58	**2.29**	**3.59**	**3.54**	**2.89**
	(-1.31)	(-0.11)	(0.15)	(1.64)	(2.37)	(4.71)	(4.63)	(4.47)
Panel D: Past Market Performance								
Bear market	-0.81	0.02	0.23	1.12	**2.44**	**3.25**	**3.36**	**2.17**
	(-0.97)	(0.02)	(0.31)	(1.49)	(2.47)	(3.36)	(3.46)	(3.09)
Bull market	1.05	1.84	**2.01**	**4.33**	**5.53**	**4.49**	**4.19**	**3.14**
	(0.89)	(1.59)	(2.02)	(3.30)	(4.17)	(3.95)	(3.61)	(2.99)

Table 6: Factor Performance across Research Design Choices

The table reports median annualized Sharpe ratios of the CTREND factor and the LTW factors under alternative research designs. For each design choice, we hold a specific choice fixed and calculate the Sharpe ratios when varying all other research designs. We then calculate the median over the possible outcomes. The first column reports the design choice and the second column shows the option used to calculate the factors. For each design choice, the option that is used in the baseline calculation is shown first and highlighted in bold font. In total, we have 53,920 possible combinations. The study period is from April 2015 to May 2022.

		CTREND						LTW	
Choice	Option	FM	CFM	**CS-C-ENet**	POLS	CPOLS	C-ENet	CSMB	CMOM
Panel A: Dataset									
Outlier treatment	**Truncation at 0.5%**	0.67	1.28	1.27	1.45	1.39	1.42	0.80	0.94
Outlier treatment	Truncation at 1%	1.15	1.34	1.43	1.60	1.53	1.58	-0.28	0.77
Outlier treatment	Winsorization at 0.5%	0.49	1.19	1.23	1.43	1.34	1.37	1.33	0.87
Outlier treatment	Winsorization at 1%	0.85	1.41	1.42	1.55	1.57	1.56	0.79	0.99
Stablecoins	**exclude**	0.73	1.31	1.34	1.51	1.46	1.49	0.72	0.89
Stablecoins	include	0.78	1.31	1.34	1.52	1.46	1.49	0.74	0.89
MCAP filter	**≥$1 mio**	0.81	1.26	1.30	1.52	1.42	1.45	0.78	0.93
MCAP filter	≥$0 mio	1.08	1.29	1.37	1.53	1.51	1.49	0.59	0.59
MCAP filter	≥$2 mio	0.49	1.36	1.37	1.49	1.49	1.51	0.75	1.01
Price filter	**≥ $0**	1.17	1.53	1.64	1.89	1.62	1.73	1.27	0.94
Price filter	≥$1	0.35	1.16	1.13	1.19	1.34	1.29	0.41	0.88
Panel B: Trend Factor Construction									
Estimation window	**rolling**	0.91	1.32	1.29	1.36	1.41	1.43	0.73	0.89
Estimation window	expanding	0.37	1.30	1.40	1.62	1.53	1.54		
In-sample observations	**52**	0.83	1.35	1.38	1.54	1.50	1.54	0.75	0.89
In-sample observations	26	0.79	1.24	1.25	1.32	1.36	1.39	0.73	0.86
In-sample observations	78	0.72	1.34	1.36	1.54	1.51	1.52	0.74	0.92
In-sample observations	104	0.69	1.31	1.39	1.59	1.49	1.53	0.69	0.88
Implementation lag	**0**	0.94	1.35	1.46	1.76	1.57	1.61	0.72	0.90
Implementation lag	1	0.64	1.25	1.24	1.33	1.34	1.32	0.75	0.89
Breakpoints	**quintile**	0.71	1.30	1.34	1.51	1.43	1.49	0.73	0.89
Breakpoints	tertile	0.79	1.33	1.35	1.52	1.49	1.49		
Weighting	**value-weighted**	0.34	1.33	1.17	1.37	1.53	1.49	0.51	0.91
Weighting	equally weighted	1.15	1.30	1.47	1.71	1.40	1.48	0.92	0.85
Volume indicators	**include**	0.84	1.28	1.30	1.40	1.46	1.45	0.73	0.88
Volume indicators	exclude	0.67	1.33	1.39	1.62	1.47	1.51		
Panel C: CS-C-ENet									
Validation sample	**no**	0.76	1.31	1.47	1.51	1.46	1.49	0.73	0.89
Validation sample	yes			1.19					
Forecast weight	**equally weighted**	0.76	1.31	1.37	1.51	1.46	1.49	0.73	0.89
Forecast weight	θ-weighted			1.30					

Table 7: Frontier Expansion Test

The table reports generalized alphas (in %) and t-statistics in parentheses from a regression of the returns of the tangency portfolio $MVP_{M_1 \cup M_0}$ on the tangency portfolio return series MVP_{M_0}, where M_0 denotes a factor set (shown in the columns) and M_1 denotes another set of factors (shown in the rows). Newey and West (1987) adjusted standard errors are used to calculate the t-statistics and p-values. Alphas that are statistically significant at the 5% level are marked in bold. A significant positive alpha indicates that the span of the efficient frontier of the MVE portfolio MVE_{M_0} can be improved by adding the factors in the rows, meaning that the factors shown in the columns are not mean-variance efficient. All results are based on out-of-sample estimates over the period from April 2016 to May 2022.

	$CTREND$	$CMKT + CTREND$	$CMKT + CSMB + CTREND$	LTW
CMKT	**0.91**			
	(2.07)			
CSMB	**1.70**	**1.50**		
	(2.60)	(2.93)		
CMOM	0.20	0.23	0.37	
	(0.55)	(0.63)	(1.02)	
CTREND				**2.77**
				(3.80)

Table 8: The CTREND Factor Performance in Big and Liquid Cryptocurrencies

The table reports the performance of quintile trend portfolios for the 50%, 30%, 20%, and 10% largest (Panel A) and most liquid (Panel B) cryptocurrencies. The last column of each panel reports the quintile portfolio returns for the 100 largest and most liquid cryptocurrencies, respectively. Specifically, at the beginning of each week t, cryptocurrencies are included in the portfolios only if their market capitalization (Amihud (2002) illiquidity measure) is above (below) the p-th percentile in week $t-1$. The table reports the average weekly return and t-statistics in parenthesis for the quintile portfolios as well as the average return of the hedge portfolio and the abnormal returns against the CCAPM and LTW three-factor model. Statistical significance at the 5% level is indicated by bold numbers. The study period is from April 2015 to May 2022.

	Panel A: Market Capitalization					Panel B: Liquidity				
	50%	30%	20%	10%	Top100	50%	30%	20%	10%	Top100
L	-0.03	0.33	0.50	-0.06	0.39	-0.23	0.09	0.31	-0.04	0.39
	(-0.04)	(0.36)	(0.46)	(-0.07)	(0.54)	(-0.30)	(0.09)	(0.28)	(-0.04)	(0.52)
2	1.33	1.21	1.01	0.55	0.86	1.25	1.70	**1.92**	0.82	1.20
	(1.68)	(1.43)	(1.21)	(0.67)	(1.30)	(1.54)	(1.91)	(2.06)	(0.96)	(1.70)
3	0.76	1.36	1.39	1.55	**1.58**	0.49	0.61	1.03	0.85	**1.36**
	(1.08)	(1.65)	(1.67)	(1.68)	(2.45)	(0.74)	(0.81)	(1.30)	(1.02)	(2.12)
4	**3.36**	**3.59**	**3.14**	**2.24**	**2.96**	**3.21**	**3.86**	**3.29**	**2.19**	**3.20**
	(3.88)	(3.73)	(3.41)	(2.57)	(3.73)	(3.57)	(3.62)	(3.33)	(2.46)	(3.85)
H	**3.80**	**3.79**	**3.24**	**2.44**	**3.79**	**4.13**	**3.74**	**3.13**	**2.16**	**3.68**
	(4.26)	(3.88)	(3.37)	(2.59)	(4.44)	(4.69)	(3.92)	(3.28)	(2.57)	(4.45)
H-L	**3.84**	**3.46**	**2.74**	**2.51**	**3.39**	**4.36**	**3.65**	**2.83**	**2.20**	**3.30**
	(5.00)	(4.17)	(2.94)	(3.01)	(4.49)	(5.62)	(4.21)	(2.87)	(2.76)	(4.36)
α^{CCAPM}	**3.70**	**3.36**	**2.81**	**2.52**	**3.30**	**4.27**	**3.58**	**2.97**	**2.34**	**3.29**
	(4.76)	(3.99)	(2.97)	(2.99)	(4.31)	(5.42)	(4.06)	(2.98)	(2.94)	(4.27)
α^{LTW}	**2.64**	**2.70**	**2.85**	**2.02**	**2.19**	**3.31**	**3.29**	**3.08**	**1.97**	**2.28**
	(4.19)	(4.04)	(3.61)	(3.18)	(3.53)	(5.07)	(4.32)	(3.50)	(3.18)	(3.62)

Table 9: CTREND Portfolios and Transaction Costs

The table reports the average gross (Avg^{gross}) and net (Avg^{net}) returns and t-statistics in parentheses of trend quintile portfolios assuming fixed costs of (I) 40bps for the short and 30bps for the long leg (Bianchi et al., 2022), (II) 50bps for the short and 40bps for the long leg, and (III) 60bps for the short and 50bps for the long leg. The table also reports the required portfolio turnover (in %) (Gu et al., 2020), breakeven transaction costs (in %) that set the net return to exactly zero (BETC), and the breakeven transaction cost rate for which the net return is not statistically significant at the 5% level (BETC 5%). Panel A reports the results for the full sample of cryptocurrencies, while Panel B shows the statistics for only the largest 100 cryptocurrencies per week. Statistical significance at the 5% level is indicated by bold numbers. The study period is from April 2015 to May 2022.

	Avg^{gross}	Avg^{net} (I)	Avg^{net} (II)	Avg^{net} (III)	TO	BETC	BETC 5%
Panel A: All Cryptocurrencies							
L	0.12	-0.33	-0.47	-0.62	74.09	0.08	0.00
	(0.16)	(-0.45)	(-0.66)	(-0.86)			
2	0.93	0.45	0.29	0.13	79.89	0.58	0.00
	(1.32)	(0.64)	(0.41)	(0.18)			
3	1.12	0.65	0.50	0.34	77.30	0.72	0.00
	(1.79)	(1.05)	(0.80)	(0.55)			
4	**2.72**	**2.27**	**2.12**	**1.97**	75.21	1.80	0.82
	(3.59)	(2.99)	(2.80)	(2.60)			
H	**3.98**	**3.61**	**3.48**	**3.36**	62.84	3.17	1.86
	(4.80)	(4.34)	(4.19)	(4.03)			
H-L	**3.87**	**2.90**	**2.62**	**2.35**	68.46	1.41	0.88
	(5.19)	(3.89)	(3.53)	(3.16)			
Panel B: Largest 100 Cryptocurrencies							
L	0.38	-0.04	-0.18	-0.32	69.68	0.27	0.00
	(0.52)	(-0.06)	(-0.25)	(-0.44)			
2	0.83	0.35	0.19	0.04	79.11	0.52	0.00
	(1.26)	(0.54)	(0.30)	(0.06)			
3	**1.59**	1.11	0.96	0.80	78.70	1.01	0.20
	(2.46)	(1.73)	(1.48)	(1.24)			
4	**2.91**	**2.47**	**2.32**	**2.17**	74.22	1.95	0.91
	(3.68)	(3.12)	(2.94)	(2.75)			
H	**3.78**	**3.38**	**3.24**	**3.11**	66.74	2.83	1.56
	(4.41)	(3.94)	(3.79)	(3.63)			
H-L	**3.40**	**2.45**	**2.17**	**1.90**	68.21	1.25	0.70
	(4.48)	(3.22)	(2.86)	(2.50)			

Online Appendices for "A Trend Factor for the Cross-Section of Cryptocurrency Returns"

[FOR ONLINE PUBLICATION ONLY]

Content

Appendix A provides a description of the characteristics and technical indicators analyzed in the study.

Appendix B reports additional figures and tables from the study. Figure B.1 illustrates the distribution of Sharpe ratios under alternative research designs based on value-weighted portfolios only. Figure B.2 plots the cumulative returns on factor portfolios. Table B.1 details the calculation of cryptocurrency characteristics. Table B.2 reports the return characteristics of factor returns. Table B.3 reports the results of bivariate portfolio sorts. Table B.4 analyzes the CTREND performance for different types of cryptocurrencies. Table B.5 shows the performance of insignificant anomalies. Table B.6 documents the impact of research design choices on value-weighted anomaly portfolios. Table B.7 reports the univariate sorts evaluated using asset pricing factors from alternative sources. Table B.8 presents the performance of anomaly portfolios used in asset pricing tests. Table B.9 displays abnormal returns on various long-short portfolios unexplained by the TREND model.

Finally, Appendix C reports the variable importance for the CTREND signal.

Appendix A. Technical Signals

This appendix describes the calculation of technical indicators. Except for scaling, which we employ to avoid size effects, we use only the standard definitions and default settings that can be found in numerous textbooks on technical analysis (e.g., Murphy, 1999; Ciana, 2011).

A. Helper Functions

- Simple moving average: We define the simple moving average of variable X as

$$SMA_t(X, L) = \frac{1}{L-1} \sum_{l=0}^{L} = X_{t-l} \tag{A.1}$$

  with L denoting the lag length.

- Exponential moving average: We define the exponential moving average of variable X as

$$EMA_t(X, L) = \alpha P_t + (1 - \alpha) EMA_{t-1} \tag{A.2}$$

  with L denoting the lag length and α denoting a smoothing parameter, which we set to $1/(1 + L)$. If no EMA_{t-1} is available, we initialize the calculation with the closing price at time $t - 1$.

B. Momentum Oscillators

- *rsi*: The relative strength index is defined based on the ratio of the average gains to the average losses over a 14-day period. Define a gain as

$$G_t = \begin{cases} P_t - P_{t-1} & \text{if } P_t > P_{t-1} \\ 0 & \text{otherwise} \end{cases} \tag{A.3}$$

  and a loss as

$$L_t = \begin{cases} P_{t-1} - P_t & \text{if } P_t < P_{t-1} \\ 0 & \text{otherwise} \end{cases} \tag{A.4}$$

Thus, the rsi is defined as:

$$rsi_t = 100 - \frac{100}{1 + \frac{\bar{G}_t}{\bar{L}_t}} \tag{A.5}$$

with $\bar{G}_t$ and $\bar{L}_t$ denoting the average gains and losses over the 14-day period.

- *stochRSI*: The stochastic relative strength index is defined as the difference between the current rsi_t and the lowest rsi_t over the previous 14 days divided by the RSI range:

$$stochRSI_t = \frac{rsi_t - L_t}{H_t - L_t} \tag{A.6}$$

with L_t and H_t denoting the lowest and highest rsi over a 14-day period.

- *stochK*: The stochastic %K is defined as the difference between the current closing price P_t and the lowest price over the previous 14 days divided by the price range:

$$stochK_t = \frac{P_t - LL_t}{HH_t - LL_t} \tag{A.7}$$

with LL_t and HH_t denoting the lowest low and highest high prices over the 14-day period.

- *stochD*: The stochastic %D is defined as the 3-day moving average of *stochK*, i.e.,

$$stochD_t = SMA\left(stochK,\ 3\right) \tag{A.8}$$

- *cci*: The commodity channel index is derived as follows: First, we calculate the "typical price", which is the average of closing price P_t, high price H_t, and low price L_t, i.e.,

$$X_t = \left(P_t + H_t + L_t\right)/3. \tag{A.9}$$

We then compute an SMA of X of length $L = 20$ and calculate the average absolute deviation of the typical price from the moving average within the 20-day period

$$AvgDev_t = \sum_{l=0}^{L-1} |X_{t-l} - SMA(X, 20)_t| \tag{A.10}$$

Finally, we calculate the *cci* as the deviation of the current typical price from its moving average divided by the average deviation:

$$cci_t = \frac{X_t - SMA(X, 20)_t}{0.015 AvgDev_t} \tag{A.11}$$

with 0.015 being a scaling constant.

C. Moving Average Indicators

- *sma_∗d*: We define the simple moving average (SMA) of the daily closing prices P of lag length $*$ as $SMA(P, *)$, following the definition of SMA in equation (A.1). To mitigate scaling issues and to ensure stationarity of the SMAs, we scale the $SMA(P, *)_t$ by the current closing price, i.e., $sma\_{*}d = SMA(P, *)_t / P_t$.

- *macd*: We define the moving average convergence/divergence as the difference of a 12-day exponential moving average (EMA) of daily closing prices and a 26-day EMA, scaled by the 12-day EMA:

$$macd_t = \frac{EMA\,(P, 12) - EMA\,(P, 26)}{EMA\,(P, 12)} \tag{A.12}$$

- *macd_diff_signal*: We define the difference of the *macd* to its signal line as:

$$macd\_diff\_signal_t = macd_t - EMA\,(macd, 9) \tag{A.13}$$

D. Volume Indicators

- *volsma_∗d*: We define the simple moving average (SMA) of the daily dollar trading volume V of lag length $*$ as $SMA(V, *)$, following the definition of SMA as in equation (A.1). To mitigate scaling issues and to ensure stationarity of the SMAs, we scale the $SMA(V, *)_t$ by the current trading volume, i.e., $volsma\_{*}d = SMA(V, *)_t / V_t$.

- *volmacd*: We define the volume moving average convergence/divergence as the difference of a 12-day exponential moving average (EMA) of the daily dollar trading volume and a 26-day EMA, scaled by the 12-day moving average:

$$volmacd_t = \frac{EMA\,(V,12) - EMA\,(V,26)}{EMA\,(V,12)} \tag{A.14}$$

- *volmacd_diff_signal*: We define the difference of the *volmacd* to its signal line as:

$$volmacd\_diff\_signal_t = volmacd_t - EMA\,(volmacd, 9) \tag{A.15}$$

- *chaikin*: We define the Chaikin money flow indicator as follows: First, we calculate the accumulation distribution value for each period t:

$$AD_t = \frac{(P_t - L_t) - (H_t - P_t)}{H_t - L_t} V_t \tag{A.16}$$

with P_t, L_t, and H_t denoting the closing, low, and high price of each day t, respectively, and V_t being the dollar trading volume on day t. Then, *chaikin* is the sum of the AD_t values over the previous $L = 21$ days divided by the sum of the dollar trading volume over the same period

$$chaikin_t = \frac{\sum_{l=0}^{L-1} AD_{t-l}}{\sum_{l=0}^{L-1} V_{t-l}} \tag{A.17}$$

E. Volatility Indicators

- *boll_low*: The lower Bollinger band is defined as the (unscaled) middle Bollinger band *boll_mid* minus two standard deviations of daily closing prices. To mitigate scaling issues and to ensure stationarity, we scale the lower Bollinger band by the current closing price:

$$boll\_low_t = \frac{boll\_mid_t - 2\sigma}{P_t} \tag{A.18}$$

with σ denoting the 20-day standard deviation of daily closing prices.

- *boll_mid*: The middle Bollinger band is defined as the 20-day SMA of daily closing prices P scaled by the current closing price, i.e.,

$$boll\_mid_t = \frac{SMA(P,20)_t}{P_t} \tag{A.19}$$

- *boll_high*: The upper Bollinger band is defined as the (unscaled) middle Bollinger band *boll_mid* plus two standard deviations of daily closing prices. To mitigate scaling issues and to ensure stationarity, we scale the upper Bollinger band by the current closing price:

$$boll\_high_t = \frac{boll\_mid_t + 2\sigma}{P_t} \tag{A.20}$$

  with σ denoting the 20-day standard deviation of daily closing prices.

- *boll_width*: The Bollinger band width is defined as the difference between the upper and lower Bollinger bands, divided by the middle Bollinger band:

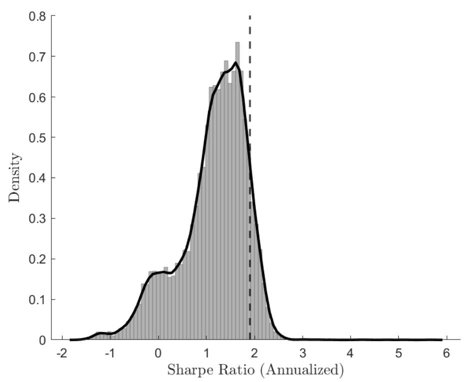
$$boll\_width_t = \frac{boll\_high_t - boll\_low_t}{boll\_mid_t} \tag{A.21}$$

Appendix B. Additional Figures and Tables

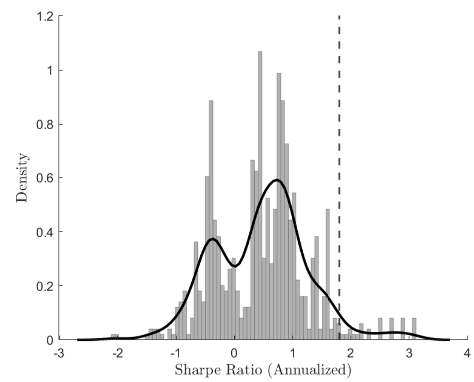
Figure B.1: Distribution of Sharpe Ratios Under Alternative Research Designs (Value-Weighted Portfolios Only)

The figure shows the distribution of Sharpe ratios under alternative research designs. Specifically, (a) shows the density plot of the Sharpe ratios for the CTREND factor for 26,960 combinations, (b) shows the density plot of the CSMB factor, (c) shows the density plot of the CMOM factor, and (d) compares the performance of the CTREND factor estimated with CS-C-ENet with alternative estimation methods and the CSMB and CMOM factors under 3,072 alternative research designs.

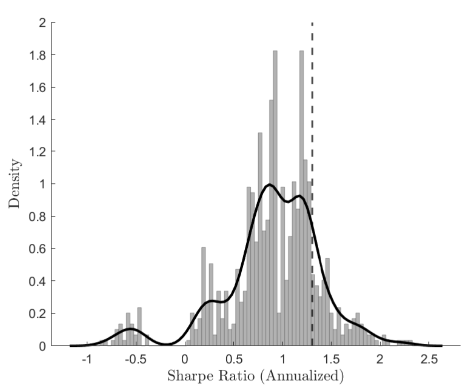
(a) Density Function CTREND



(b) Density Function CSMB



(c) Density Function CMOM



(d) Comparison With Other Factors

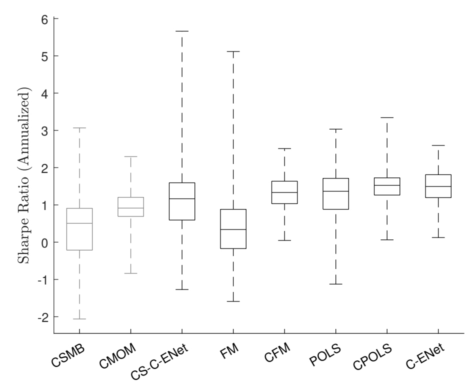


Figure B.2: Comparison of Cumulative Factor Returns

The figure shows the cumulative factor returns of the CMKT, CSMB, CMOM, and CTREND factors over the period from April 2015 to May 2022. All values are expressed in percentage terms.

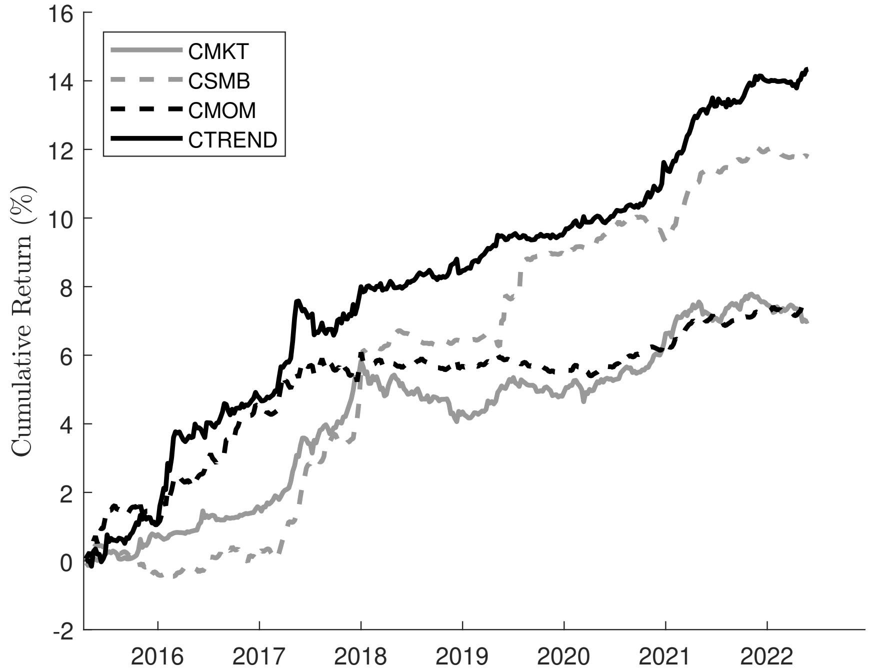


Table B.1: Cryptocurrency Characteristics

The table presents details on the cryptocurrency characteristics used to form the anomaly portfolios. *Symbol* indicates the running symbol used in the text.

Characteristic	Symbol	Description and Reference
Panel A: Momentum		
Momentum	ret_*_0	Cumulative returns over the past 1, 2, 3, and 4 weeks, including the last week (Jegadeesh and Titman, 1993).
Momentum	ret_4_1	Cumulative returns over the past 4 weeks, excluding the last week (Jegadeesh and Titman, 1993).
Panel B: Size		
Age	age	Number of days with available return data (Barry and Brown, 1984).
Max. Price	maxdprc	Maximum closing price during the previous week (George and Hwang, 2004).
Market Value	mcap	Mean market capitalization during the previous week (Banz, 1981).
Price	prc	Closing price at the end of the previous week (Miller and Scholes, 1982).
Panel C: Liquidity		
Amihud Illiquidity	illiq	Amihud illiquidity measure. Sum of absolute returns divided by the US-Dollar quoted volume over the previous 7 days (Amihud, 2002).
$-Volume	prcvol	Mean US-Dollar quoted trading volume during the previous week (Chordia et al., 2001).
Std. $-Volume	stdprcvol	Rolling 30-day standard deviation of the US-Dollar quoted trading volume (Chordia et al., 2001).

Table B.1: **Cryptocurrency Characteristics (continued)**

Characteristic	Symbol	Description and Reference
Scaled Volume	volscaled	US-Dollar quoted trading volume scaled by market capitalization (Chordia et al., 2001).
Volume	volume	Mean base quoted trading volume during the previous week (Chordia et al., 2001).
Panel D: Volatility		
Beta	beta	Beta coefficient obtained from a 365-day rolling CCAPM regression (Fama and MacBeth, 1973).
Beta Squared	beta2	Squared beta coefficient obtained from a 365-day rolling CCAPM regression (Fama and MacBeth, 1973).
Delay	delay	Improvement in the R^2 obtained from a 365-day rolling CCAPM regression including two lagged values as explanatory variables, compared to a market regression without lags (Hou and Moskowitz, 2005).
Expected Shortfall	es	Expected shortfall calculated over the previous 90 days (Bianchi and Babiak, 2022).
Idiosyncratic Skewness	iskew	Idiosyncratic skewness obtained from a 365-day rolling market regression (Harvey and Siddique, 2000; Chen et al., 2022).
Idiovolatility	ivol	Idiosyncratic risk obtained from a 365-day rolling CCAPM regression (Ang et al., 2006).
Maximum Return	maxret	Maximum daily return during the previous 7 days (Bali et al., 2011).
Prospect Theory Value	ptv	Prospect theory value of a cryptocurrency's historical daily return distribution over the previous 365 days (Barberis et al., 2016).
Return Volatility	retvol	Return standard deviation (Ang et al., 2006) calculated over the previous 7 days.

Table B.1: Cryptocurrency Characteristics (continued)

Characteristic	Symbol	Description and Reference
Salience Theory Value	stv	Salience theory value of a cryptocurrency's historical daily return distribution over the previous 365 days (Cosemans and Frehen, 2021).
Short-term Return Skewness	skew1	Return skewness calculated over the previous 7 days (Bali and Cakici, 2010).
Long-term Return Skewness	skew2	Return skewness calculated over the previous 365 days (Bali and Cakici, 2010).
Value at Risk (5%)	var	90-day historical value-at-risk (5%).

Table B.2: Descriptive Statistics of Asset Pricing Factor Returns

Panel A of the table reports the average weekly return (in %), the weekly standard deviation (in %), the annualized Sharpe ratio, skewness, and excess kurtosis for the CTREND factor and the factors proposed in Liu et al. (2022). The numbers in parentheses are t-statistics. Panel B reports the Pearson-product moment pairwise correlation coefficients of factor returns. The sample period runs from April 2015 to May 2022.

	Panel A: Performance					Panel B: Correlations			
	Avg	Std	Shp	Skew	Kurt	CMKT	CSMB	CMOM	CTREND
CMKT	**1.89** (3.29)	11.06	1.23	0.23	1.42		0.11	0.07	0.02
CSMB	**3.18** (4.78)	12.81	1.79	3.59	18.68			0.11	-0.01
CMOM	**1.98** (3.40)	11.26	1.27	1.10	3.16				0.61

Table B.3: Bivariate Portfolio Sorts

The table reports the average weekly returns (in %) and t-statistics in parentheses of value-weighted CTREND portfolios from two-way independent sorts. Cryptocurrencies are sorted into two groups based on the control variables indicated in the first column and three CTREND subsets. The intersection forms portfolios from independent double sorts. We report average returns on portfolios with a consistent level of the control variables but different levels CTREND. The table also presents alphas for the CCAPM and LTW models. Values that are significantly different from zero at the 5% level are in bold font. The study period is from April 2015 to May 2022.

	Trend Forecasts				Abnormal Returns	
	Low	Mid	High	High-Low	α^{CCAPM}	α^{LTW}
beta	0.81	1.12	**3.85**	**3.04**	**2.96**	**1.96**
	(1.15)	(1.91)	(4.91)	(4.61)	(5.00)	(3.64)
mcap	**1.50**	**1.86**	**3.52**	**2.02**	**2.02**	**0.85**
	(2.26)	(2.90)	(4.67)	(3.81)	(3.78)	(2.49)
illiq	**1.45**	**1.56**	**2.87**	**1.42**	**1.43**	0.62
	(2.26)	(2.51)	(4.25)	(2.90)	(2.81)	(1.67)
ivol	0.86	**1.75**	**3.09**	**2.23**	**2.23**	**1.31**
	(1.22)	(2.48)	(3.72)	(3.17)	(3.55)	(2.19)
ret_1_0	0.77	**1.55**	**3.87**	**3.10**	**2.99**	**2.39**
	(1.11)	(2.42)	(4.63)	(4.87)	(4.96)	(4.76)
ret_2_0	0.46	**1.49**	**2.69**	**2.22**	**2.14**	**1.62**
	(0.67)	(2.34)	(3.46)	(3.82)	(4.24)	(3.45)
ret_3_0	0.15	**1.47**	**2.06**	**1.90**	**1.83**	**1.28**
	(0.23)	(2.34)	(3.05)	(3.80)	(3.95)	(2.80)
ret_4_0	0.27	**1.48**	**2.50**	**2.23**	**2.09**	**1.38**
	(0.40)	(2.37)	(3.47)	(4.13)	(4.34)	(3.06)

Table B.4: CTREND Performance Depending on Cryptocurrency Type

The table reports the performance of quintile trend portfolios constructed from the full sample of cryptocurrencies and for subsets of coins and tokens, respectively. The table reports the average weekly return and t-statistics in parenthesis for the quintile portfolios as well as the average return of the hedge portfolio and the abnormal returns against the CCAPM and LTW three-factor model. The study period is from April 2015 to May 2022.

	Full	Coins	Tokens
Low	0.12	0.56	-0.28
	(0.16)	(0.78)	(-0.28)
2	0.93	0.97	-0.06
	(1.32)	(1.27)	(-0.07)
3	1.12	1.09	1.72
	(1.79)	(1.66)	(1.36)
4	**2.72**	**3.08**	1.54
	(3.59)	(3.91)	(1.47)
High	**3.98**	**3.86**	**2.88**
	(4.80)	(4.41)	(2.72)
H-L	**3.87**	**3.31**	**3.16**
	(5.19)	(4.31)	(2.93)
α^{CCAPM}	**3.80**	**3.16**	**3.23**
	(5.03)	(4.06)	(2.97)
α^{LTW}	**2.62**	**1.91**	**3.13**
	(4.22)	(2.95)	(3.23)

Table B.5: Insignificant Anomaly Strategy Returns

The table reports the average weekly portfolio returns (in %) and t-statistics of quintile portfolios based on cryptocurrency characteristics. Quintile portfolios are constructed by ranking cryptocurrencies by their characteristics (from low to high) and assigning them into portfolios based on the quintile distribution. The portfolios are value-weighted and rebalanced weekly. A zero-investment portfolio takes a short position in cryptocurrencies in the low and a long position in cryptocurrencies in the high portfolio. The sample period is from April 2015 to May 2022.

Char	L	2	3	4	H	H - L
age	**1.99**	**1.65**	**2.48**	**1.94**	**1.88**	-0.11
	(2.09)	(2.01)	(3.41)	(2.73)	(3.28)	(-0.13)
ret_8_0	**2.16**	**1.73**	**2.03**	**2.57**	**3.02**	0.85
	(2.49)	(2.81)	(2.90)	(3.42)	(3.24)	(0.91)
ret_16_0	**2.31**	**2.11**	**1.78**	**2.19**	**2.85**	0.54
	(3.12)	(3.13)	(2.61)	(2.90)	(3.09)	(0.61)
ret_50_0	**1.61**	**2.11**	**2.37**	**2.06**	**1.84**	0.23
	(2.47)	(2.83)	(2.87)	(2.62)	(2.24)	(0.33)
ret_100_0	**2.47**	**1.61**	**2.13**	**1.92**	**1.70**	-0.77
	(3.29)	(2.32)	(2.53)	(2.35)	(2.03)	(-0.90)
volume	**2.14**	**2.15**	**2.06**	**1.64**	**1.90**	-0.25
	(3.18)	(3.06)	(3.03)	(2.39)	(3.30)	(-0.50)
illiq	**1.89**	**2.00**	**2.00**	**2.15**	**1.93**	0.04
	(3.30)	(2.74)	(2.84)	(2.88)	(2.83)	(0.07)
beta	**1.89**	**2.27**	**3.00**	**2.21**	1.41	-0.48
	(2.37)	(3.36)	(3.78)	(2.76)	(1.80)	(-0.56)
beta2	**1.91**	**2.29**	**2.99**	**2.23**	1.41	-0.50
	(2.40)	(3.37)	(3.77)	(2.78)	(1.80)	(-0.58)
ivol	**1.91**	**2.60**	**2.41**	0.64	1.83	-0.08
	(3.30)	(3.11)	(2.74)	(0.78)	(1.82)	(-0.09)
iskew	**1.97**	**2.67**	**1.75**	**2.45**	**1.98**	0.01
	(3.25)	(3.36)	(2.11)	(2.84)	(2.20)	(0.01)
retvol	**2.00**	**2.47**	**2.86**	**1.65**	1.22	-0.78
	(3.26)	(3.22)	(3.13)	(2.00)	(1.27)	(-0.89)
skew1	1.11	1.00	**3.13**	**2.53**	**2.42**	1.32
	(1.86)	(1.64)	(3.71)	(3.17)	(2.83)	(1.91)
skew2	**2.01**	**2.58**	1.16	**2.23**	**2.03**	0.02
	(3.46)	(3.33)	(1.55)	(2.52)	(2.20)	(0.03)
maxret	**1.50**	**2.43**	**2.73**	**2.65**	1.27	-0.23
	(2.58)	(3.22)	(3.38)	(2.96)	(1.29)	(-0.26)
delay	**2.14**	**2.00**	**1.98**	**2.29**	**1.28**	-0.86
	(3.09)	(2.43)	(2.46)	(2.35)	(2.33)	(-1.55)
var90d	1.33	1.40	1.31	**2.59**	**1.89**	0.56
	(1.41)	(1.65)	(1.53)	(3.16)	(3.35)	(0.76)
es90d	**1.89**	**2.57**	**2.41**	1.61	0.60	-1.28
	(3.37)	(2.90)	(2.55)	(1.71)	(0.60)	(-1.55)
ppt	**2.39**	**3.33**	**1.77**	**1.76**	**1.90**	-0.48
	(2.73)	(3.89)	(2.12)	(2.66)	(2.66)	(-0.65)
stv	0.74	**2.00**	**2.60**	**3.17**	1.60	0.86
	(1.10)	(3.27)	(3.82)	(3.55)	(1.67)	(1.02)

Table B.6: Factor Performance Depending on Research Design Choices without Equal-Weighting

The table reports median annualized Sharpe ratios of the CTREND factor and the LTW factors under alternative research designs without the option to create equally weighted factor portfolios. For each design choice, we hold a specific choice fixed and calculate the Sharpe ratios when varying all other research designs. We then calculate the median over the possible outcomes. The first column reports the design choice and the second column shows the option used to calculate the factors. For each design choice, the option that is used in the baseline calculation is shown first and highlighted in bold font. In total, we have 26,960 possible combinations. The study period is from April 2015 to May 2022.

		CTREND						LTW	
Choice	Option	FM	CFM	**CS-C-ENet**	POLS	CPOLS	C-ENet	CSMB	CMOM
Panel A: Dataset									
Outlier treatment	**Truncation at 0.5%**	0.33	1.36	1.18	1.34	1.55	1.56	0.54	1.02
Outlier treatment	Truncation at 1%	0.49	1.39	1.14	1.41	1.60	1.54	-0.43	0.89
Outlier treatment	Winsorization at 0.5%	0.31	1.31	1.17	1.28	1.51	1.49	1.03	0.90
Outlier treatment	Winsorization at 1%	0.28	1.25	1.15	1.46	1.49	1.46	0.60	1.00
Stablecoins	**exclude**	0.30	1.33	1.17	1.37	1.52	1.50	0.47	0.91
Stablecoins	include	0.37	1.33	1.16	1.36	1.53	1.49	0.51	0.92
MCAP filter	**≥$1 mio**	0.23	1.38	1.17	1.50	1.52	1.52	0.47	1.08
MCAP filter	≥$0 mio	0.70	1.29	1.17	1.28	1.57	1.48	0.51	0.59
MCAP filter	≥$2 mio	0.25	1.38	1.15	1.38	1.48	1.50	0.52	1.11
Price filter	**≥$0**	0.72	1.61	1.53	1.67	1.69	1.79	0.87	1.11
Price filter	≥$1	0.04	1.06	0.91	1.03	1.29	1.21	0.32	0.88
Panel B: Trend Factor Construction									
Estimation window	**rolling**	0.44	1.34	1.09	1.10	1.48	1.43	0.51	0.91
Estimation window	expanding	-0.04	1.32	1.23	1.53	1.59	1.58		
In-sample observations	**52**	0.42	1.34	1.14	1.39	1.53	1.50	0.51	0.91
In-sample observations	26	0.26	1.26	1.00	1.01	1.43	1.40	0.56	0.89
In-sample observations	78	0.34	1.35	1.20	1.43	1.56	1.54	0.47	1.00
In-sample observations	104	0.33	1.35	1.28	1.53	1.57	1.57	0.46	0.92
Implementation lag	**0**	0.38	1.39	1.28	1.53	1.62	1.57	0.51	0.98
Implementation lag	1	0.31	1.19	1.04	1.25	1.41	1.38	0.49	0.86
Breakpoints	**quintile**	0.29	1.30	1.13	1.34	1.45	1.44	0.51	0.91
Breakpoints	tertile	0.38	1.35	1.20	1.39	1.60	1.57		
Volume indicators	**include**	0.20	1.20	1.08	1.25	1.47	1.43	0.51	0.91
Volume indicators	exclude	0.48	1.40	1.27	1.52	1.57	1.56	0.47	0.93
Panel C: CS-C-ENet									
Validation sample	**no**	0.34	1.33	1.39	1.37	1.53	1.49	0.51	0.91
Validation sample	yes			0.83					
Forecast weight	**equally weighted**	0.34	1.33	1.37	1.37	1.53	1.49	0.51	0.91
Forecast weight	θ-weighted			0.66					

Table B.7: Univariate Portfolio Sorts - Alternative Factor Data

The table reports the average weekly return (in %) and t-statistics in parentheses, the weekly standard deviation (in %), and the annualized Sharpe ratio of value-weighted quintile portfolios that hold cryptocurrencies based on their rank of the aggregate trend characteristic. Additionally, the alpha against the CCAPM (α^{CCAPM}) and the portfolio's exposure to the value-weighted market return (β^{CMKT}) as well as the alpha against the LTW model (α^{LTW}) and the exposures to the market (β^{CMKT}), size (β^{CSMB}), and momentum (β^{CMOM}) factors are reported. The CSMB factor is constructed from single tertile sorts with respect to the market capitalization and the CMOM factor is constructed using double-sorts based on market capitalization and three-week momentum, as described in LTW. The table also reports the average market capitalization in million U.S. dollars, the average trading volume in million U.S. dollars, the average idiosyncratic volatility with respect to the market portfolio (in %), and the average cumulative return over the previous three weeks. Values that are statistically significant at the 5% level are marked in bold font. The study period is from April 2015 to May 2022.

	Portfolio Performance									Portfolio Characteristics			
Rank	Avg	Std	Shp	α^{CCAPM}	β^{CMKT}	α^{LTW}	β^{CMKT}	β^{CSMB}	β^{CMOM}	mcap	volume	ivol	ret_3_0
L	0.12	13.86	0.06	**-1.70**	**0.98**	**-1.76**	**1.00**	**0.27**	**-0.32**	134.59	229.64	0.11	-21.63
	(0.16)			(-3.71)	(23.87)	(-4.21)	(27.34)	(6.39)	(-8.89)				
2	0.93	13.56	0.49	-0.82	**0.94**	**-0.90**	**0.96**	**0.26**	**-0.30**	401.08	689.25	0.10	-6.55
	(1.32)			(-1.79)	(22.98)	(-2.11)	(25.80)	(5.97)	(-7.99)				
3	1.12	11.99	0.67	-0.56	**0.91**	**-1.04**	**0.91**	**0.26**	**-0.06**	986.88	936.25	0.09	4.49
	(1.79)			(-1.62)	(29.01)	(-3.11)	(31.33)	(7.76)	(-1.96)				
4	**2.72**	14.59	1.34	0.67	**1.10**	-0.01	**1.10**	**0.22**	**0.13**	1,485.45	1,218.26	0.09	18.11
	(3.59)			(1.59)	(29.00)	(-0.01)	(30.69)	(5.32)	(3.58)				
H	**3.98**	15.99	1.80	**2.11**	**1.01**	0.85	**0.98**	**0.15**	**0.58**	1,182.33	1,134.71	0.10	62.74
	(4.80)			(3.49)	(18.73)	(1.73)	(22.93)	(3.00)	(13.61)				
H-L	**3.87**	14.34	1.94	**3.80**	0.03	**2.61**	-0.01	**-0.12**	**0.90**				
	(5.19)			(5.03)	(0.50)	(4.69)	(-0.28)	(-2.16)	(18.72)				

Table B.8: Anomaly Strategy Returns

The table reports the average weekly portfolio returns (in %) and t-statistics of quintile portfolios based on cryptocurrency characteristics. Quintile portfolios are constructed by ranking cryptocurrencies by their characteristics (from low to high) and assigning them to portfolios based on the quintile distribution. The portfolios are value-weighted and rebalanced weekly. A zero-investment portfolio takes a short position in cryptocurrencies in the low and a long position in cryptocurrencies in the high portfolio. The table also reports the risk-adjusted return against the CCAPM and the three-factor model proposed in Liu et al. (2022). Statistical significance at the 5% level is indicated by bold numbers. The sample period is from April 2015 to May 2022.

Char	L	2	3	4	H	H - L	α^{CCAPM}	α^{LTW}
Size Strategy Returns								
mcap	**5.29**	**2.36**	**1.85**	**1.64**	**1.89**	**-3.40**	**-3.39**	**-1.46**
	(6.56)	(3.10)	(2.58)	(2.36)	(3.29)	(-5.98)	(-5.86)	(-3.29)
prc	**4.68**	**2.25**	**2.19**	**1.96**	**1.86**	**-2.81**	-1.95	0.18
	(3.59)	(2.45)	(2.64)	(2.39)	(3.30)	(-2.57)	(-1.80)	(0.17)
maxdprc	**4.65**	**2.14**	**2.02**	**2.14**	**1.86**	**-2.79**	-1.89	0.23
	(3.56)	(2.34)	(2.44)	(2.57)	(3.29)	(-2.55)	(-1.76)	(0.22)
Momentum Strategy Returns								
ret_1_0	0.84	1.01	**1.79**	**3.12**	**2.86**	**2.02**	**2.03**	0.88
	(1.13)	(1.39)	(2.70)	(4.46)	(3.18)	(2.35)	(2.33)	(1.09)
ret_2_0	0.19	1.21	**1.40**	**2.77**	**3.79**	**3.60**	**3.40**	**1.83**
	(0.25)	(1.64)	(2.11)	(3.81)	(4.21)	(4.09)	(3.81)	(2.47)
ret_3_0	0.73	1.07	**2.19**	**2.15**	**3.88**	**3.15**	**3.14**	**1.35**
	(1.00)	(1.45)	(3.05)	(3.03)	(4.19)	(3.56)	(3.49)	(1.99)
ret_4_0	0.86	0.93	**1.92**	**2.70**	**2.99**	**2.13**	**2.03**	0.62
	(1.18)	(1.28)	(2.94)	(3.67)	(3.26)	(2.53)	(2.37)	(0.89)
ret_4_1	0.91	1.03	**2.97**	**2.09**	**2.38**	1.47	1.26	0.18
	(1.25)	(1.49)	(3.80)	(3.05)	(2.65)	(1.82)	(1.55)	(0.27)
Volume Strategy Returns								
prcvol	**4.19**	**2.59**	**2.69**	**2.14**	**1.88**	**-2.31**	-1.85	0.96
	(3.30)	(3.04)	(3.03)	(2.43)	(3.29)	(-2.15)	(-1.71)	(0.98)
volscaled	**4.23**	**2.78**	**1.87**	**2.64**	**1.83**	**-2.41**	-1.93	-0.13
	(3.65)	(2.60)	(2.30)	(3.01)	(3.27)	(-2.44)	(-1.95)	(-0.14)
stdprcvol	**3.58**	**2.79**	**2.55**	**2.50**	**1.88**	**-1.71**	**-1.61**	0.55
	(3.66)	(2.90)	(2.95)	(2.73)	(3.29)	(-2.16)	(-2.00)	(0.77)

Table B.9: TREND Model Alphas

The table reports alphas (in %) and t-statistics in parentheses from a regression of hedge portfolio returns on a three-factor model that includes the CMKT, CSMB, and CTREND factors. The study period is from April 2015 to May 2022.

	α^{TREND}		α^{TREND}		α^{TREND}
Panel A: Anomaly Alphas					
Size Anomalies		**Momentum Anomalies**		**Volume Anomalies**	
mcap	**-1.57** (-3.38)	ret_1_0	-1.08 (-1.59)	prcvol	1.47 (1.47)
prc	0.58 (0.55)	ret_2_0	0.22 (0.32)	volscaled	0.35 (0.36)
maxdprc	0.71 (0.68)	ret_3_0	-0.44 (-0.69)	stdprcvol	0.58 (0.77)
		ret_4_0	-1.07 (-1.67)		
		ret_4_1	-1.01 (-1.43)		
Panel B: Technical Indicator Alphas					
Momentum Oscillators		sma_50d	0.82 (1.32)	volsma_100d	0.62 (0.91)
rsi	0.97 (1.85)	sma_100d	1.22 (1.84)	volsma_200d	0.67 (1.03)
stochRSI	0.38 (0.51)	sma_200d	1.35 (1.91)	volmacd	-0.53 (-0.71)
stochK	**1.06** (1.98)	macd	-0.87 (-1.31)	volmacd_diff_signal	-0.29 (-0.32)
stochD	0.61 (1.02)	macd_diff_signal	-0.58 (-0.68)	chaikin	-0.14 (-0.21)
cci	0.82 (1.34)				
		Volume Indicators		**Volatility Indicators**	
Moving Averages		volsma_3d	-0.34 (-0.50)	boll_low	0.48 (0.55)
sma_3d	0.31 (0.37)	volsma_5d	-0.36 (-0.55)	boll_mid	0.14 (0.27)
sma_5d	-0.33 (-0.43)	volsma_10d	-0.07 (-0.09)	boll_high	-0.45 (-0.62)
sma_10d	1.06 (1.77)	volsma_20d	0.13 (0.16)	boll_width	-1.32 (-1.38)
sma_20d	0.41 (0.72)	volsma_50d	0.06 (0.09)		

Table B.10: Extended Portfolio Holding Periods

The table reports average weekly returns (in %) and t-statistics in parentheses of zero-investment portfolios for holding periods ranging from one to six weeks. The portfolios buy (sell) the quintile of cryptocurrencies with the highest (lowest) expected return, as implied by the variable in the first column. The study period is from April 2015 to May 2022.

	1	2	3	4	5	6
CTREND	**3.87**	**2.34**	**2.35**	**1.55**	0.03	-0.53
	(5.19)	(3.08)	(3.03)	(2.10)	(0.05)	(-0.67)
ret_1_0	**2.02**	1.56	1.37	0.08	0.57	-0.58
	(2.35)	(1.82)	(1.60)	(0.09)	(0.76)	(-0.75)
ret_2_0	**3.60**	**2.17**	**1.97**	**1.75**	0.26	-0.81
	(4.09)	(2.64)	(2.21)	(2.27)	(0.31)	(-0.95)
ret_3_0	**3.15**	**1.88**	**1.63**	0.80	-0.49	0.16
	(3.56)	(2.25)	(2.01)	(1.01)	(-0.61)	(0.20)
ret_4_0	**2.13**	1.53	0.61	0.57	-0.57	0.36
	(2.53)	(1.71)	(0.88)	(0.72)	(-0.76)	(0.53)

Appendix C. Variable Importance

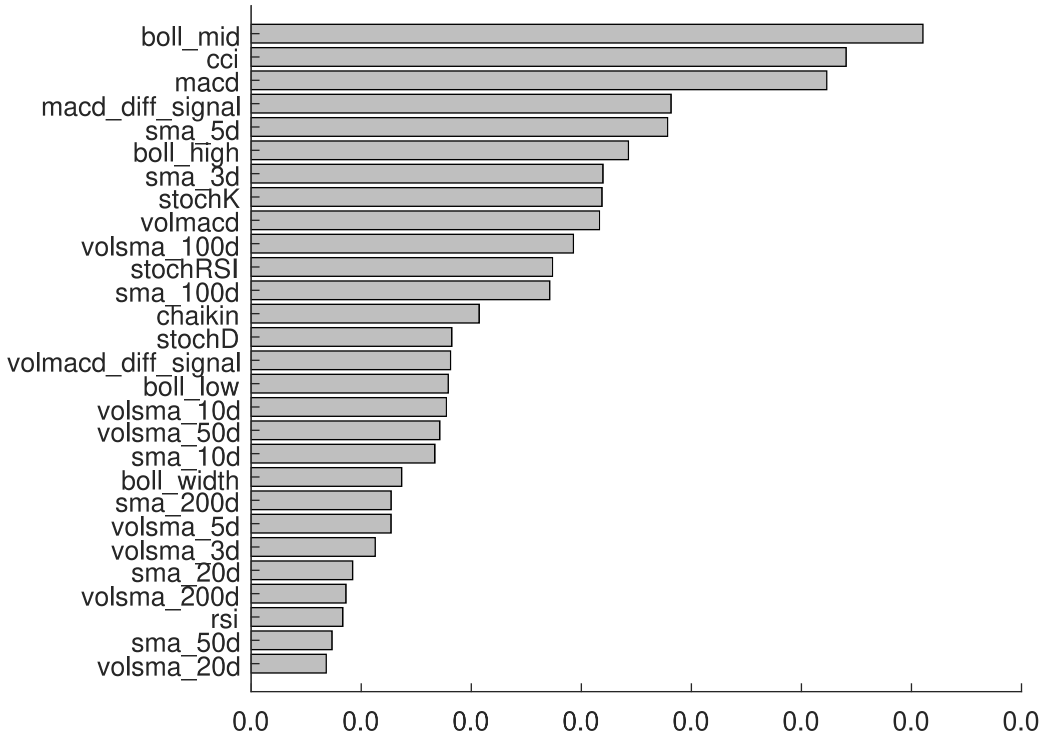
The CTREND variable aggregates multiple technical signals into one aggregate trend measure. However, does it extract the information from all of them? Or does the predictive performance depend on a handful of crucial variables? To shed light on this issue, we assess the contribution of particular technical indicators using partial dependence plots (PDPs).

Our method follows the approach suggested by Greenwell et al. (2018) and Han et al. (2023). The partial dependence value (PDV) $\hat{f}_{j,t+1}$ of a technical indicator j at time $t+1$ is calculated following Greenwell et al. (2018). Denote $K_{j,t+1}$ as the number of unique observations for which the technical indicator j at time t and the return at time $t+1$ are not missing, and $N_{j,t+1}$ is the number of assets for which the j-th technical indicator at time t and the return at time $t+1$ are observed. Note that, generally, $K_{j,t+1} = N_{j,t+1}$ for continuous variables. For each unique observation $k = 1, \ldots, K_{j,t+1}$, the actual observations of the technical indicator $z_{i,j,t}$ $\forall i = 1, \ldots, N_{j,t+1}$ are replaced by observation $z_{k,j,t}$. Then, the slopes obtained from the estimation using the actual data are used to obtain an $N_{t+1} \times 1$ vector of return estimates at time $t+1$, i.e., $\hat{f}_{j,t+1}$. Repeating this for each unique observation, we obtain an $N_{t+1} \times K_{j,t+1}$ matrix of PDVs. We then calculate the cross-sectional average of the PDVs and obtain the standard deviation of the PDVs, which we denote as $\sigma_{j,t+1}$. According to Greenwell et al. (2018), a higher standard deviation indicates that the predicted returns fluctuate more in response to the j-th technical indicator, suggesting a greater contribution of the indicator to the aggregate trend characteristic. If the indicator is not important at all, $\sigma_{j,t+1}$ equals zero, which is also the value we assign if the elastic net does not select a technical indicator. Finally, we average over the series of $\sigma_{j,t+1}$ and obtain the average importance score $\bar{\sigma}_j$ of the j-th technical indicator (Han et al., 2023).

Figure C.3 depicts the importance ranking. By far the most important technical indicators are *boll_mid*, *cci*, and *macd*; however, other indicators such as *macd_diff_signal*, *sma_5d*, *boll_high*, *sma_3d*, or *volmacd* also have high importance scores. The findings reveal that the aggregate trend characteristic extracts information from the entire spectrum of technical indicators: momentum oscillators, moving averages, as well as price, volume, and volatility indicators.

Figure C.3: Average Variable Importance

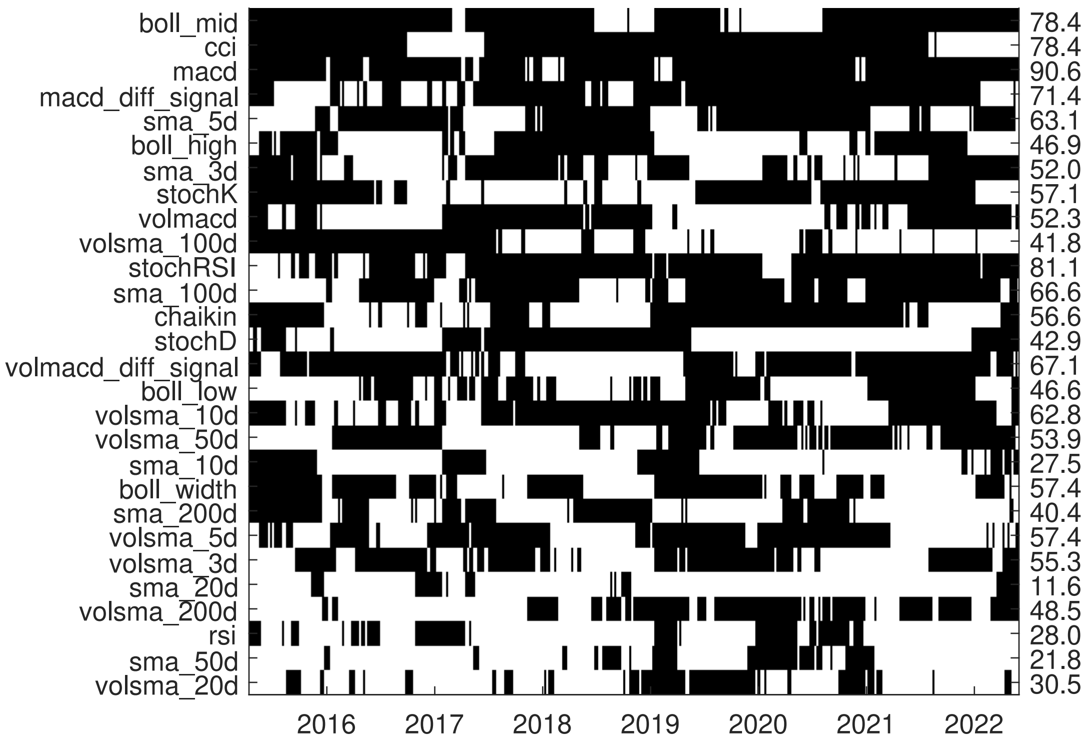
The figure shows the importance ranking for all 28 technical indicators within the aggregate CTREND signal. Importance is gauged according to Greenwell et al. (2018) and Han et al. (2023). Indicators are ranked in descending order from the most to the least important indicator. The sample period is from April 2015 to May 2022.



Next, we analyze which predictors are selected by the CS-C-ENet over time to see if the selected set of predictors is persistent and if the aggregate trend prediction is sparse in only a few indicators. Figure C.4 shows the selection of the CS-C-ENet over time and reports the proportion in which a particular indicator was selected. The findings generally align with the variable importance measures reported above. The four most important indicators, *boll_mid*, *cci*, *macd*, and *macd_diff_signal*, are selected in more than 70% of all weeks, with the *macd* indicator being selected in more than 90% of all weeks. Overall, most indicators are picked in more than 50% of all weeks, suggesting that the set of predictors in the aggregate trend characteristic is highly persistent. Interestingly, the average number of indicators selected per week is 15, indicating that the CTREND factor is not sparse, i.e., it captures information from many technical indicators.

Figure C.4: Indicator Selection Over Time

The figure shows the predictor selection of the CS-C-ENet over time. The black shades indicates that a technical indicator was selected by the CS-C-ENet in a particular week, while the white shades means that the indicator was not selected. The right y-axis shows the proportion (in %) of weeks in which an indicator was selected. Technical indicators are sorted according to the importance ranking shown in Figure C.4. The sample period is from April 2015 to May 2022.



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