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Catching Crypto Trends

A Tactical Approach for Bitcoin and Altcoins

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Abstract

In recent years, cryptocurrencies have attracted significant attention from both retail traders and large institutional investors. As their involvement in digital assets grows, so does their interest in active and risk-aware investment frameworks. This paper applies a well-established trend-following methodology, successfully deployed for decades in traditional asset classes, to Bitcoin, and then extends the analysis to a comprehensive, survivorship bias-free dataset covering all cryptocurrencies traded since 2015, to evaluate whether its robustness persists in the emerging digital asset space. We propose an ensemble approach that aggregates multiple Donchian channel-based trend models, each calibrated with different lookback periods, into a single signal, as well as a volatility-based position sizing method. This model, applied to a rotational portfolio of the top 20 most liquid coins, achieved notable net-of-fees returns, with a Sharpe ratio above 1.5 and an annualized alpha of 10.8% versus Bitcoin. While assessing the impact of transaction costs, we propose a straightforward yet effective portfolio technique to mitigate these expenses. Finally, we investigate correlations between crypto-focused trend-following strategies and those applied to traditional asset classes, concluding with a discussion on how investors can execute the proposed strategy through both on-chain and off-chain implementations.

Keywords: Trading Systems, Algo Trading, Momentum, Trend-Following, Cryptocurrencies, Risk Management, Technical Analysis, Decentralized Exchanges, Blockchain, Decentralized Finance

1 Introduction

The cryptocurrency market has rapidly evolved from a niche innovation into a significant segment of the global financial system. As noted by Harvey et al. (2022), the total market capitalization of cryptocurrencies stood at approximately $1.0 trillion as of July 2022, nearly half the value of all U.S. currency in circulation at the time. By March 2025, this figure had surpassed $3.0 trillion, driven by the launch of new digital assets and a broad increase in the valuation of existing cryptocurrencies. While Bitcoin and Ethereum continue to dominate the market, together accounting for approximately 75% of total capitalization, more than 100 cryptocurrencies now individually exceed a $1 billion market capitalization, underscoring the expanding depth and diversity of the crypto ecosystem.

For years, the crypto space remained highly volatile and was largely overlooked by institutional asset managers, with participation dominated by retail investors pursuing either speculative gains or long-term fundamental convictions. This dynamic began to shift with the introduction of Bitcoin futures on the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE) in 2017, followed by the approval of Bitcoin Futures ETFs by the U.S. Securities and Exchange Commission (SEC) in 2021. These milestones paved the way for growing institutional interest, prompting many to incorporate cryptocurrencies into their portfolios, whether through small passive allocations or more actively managed strategies.

Governments and large corporations have also started to recognize and adopt cryptocurrencies, exploring their use as alternative payment methods, settlement layers, or even as strategic assets in treasury management. As the market matures and regulatory frameworks continue to evolve, the need for robust, adaptable investment approaches becomes increasingly clear, particularly for those wishing to avoid the risks inherent in a static, long-term buy-and-hold position.

Because of their high liquidity, substantial volatility, absence of conventional valuation anchors, and a participant base prone to emotion-driven decisions, cryptocurrencies offer fertile ground for systematic trading methods. In particular, trend-following strategies may capitalize on sustained price trends or parabolic moves.

The primary objective of this paper is to backtest and evaluate classic trend-following approaches within the cryptocurrency market. We begin with a base model applied to Bitcoin and subsequently extend the analysis to a broader set of liquid digital assets. The base model is constructed as an ensemble of short and long-term trend signals, designed to capture different types of momentum and trend dynamics across various time horizons. Transaction costs are also carefully examined, with particular attention given to rebalancing methodologies intended to reduce unnecessary turnover and mitigate trading fees.

With this paper, we aim to provide investors and speculators with a valuable resource to better understand the risks and opportunities inherent in crypto markets, enabling them to embrace a new, volatile asset class without incurring the implicit risk of a passive buy-and-hold approach.

Throughout the analysis, we restrict attention to a long-only implementation of the trend-following model. This choice reflects the institutional reality that most market participants engage with cryptocurrencies from a structurally long-biased perspective. Moreover, the estimation of short-selling costs, particularly for less liquid tokens, remains highly uncertain, rendering long-short backtests sensitive to modeling assumptions and less informative for practical deployment. Nevertheless, a symmetric long-short extension of the model has also demonstrated favorable performance in historical simulations. Comprehensive results and further portfolio construction considerations for the long-short version are presented in the Appendix.

***Disclaimer**: While this study presents a comprehensive analysis of trend-following strategies applied to digital assets, all results are derived from historical backtests. As such, they reflect past market dynamics and should not be interpreted as guarantees of future performance. The profitability and robustness of the proposed approach are inherently dependent on the persistence of trending behavior in cryptocurrency markets—an aspect that may evolve over time. Readers and investors should remain mindful that future outcomes may differ substantially from those observed in this retrospective evaluation.*

2 Literature Review

Over the past three decades, extensive research has documented the pervasive and significant presence of momentum across diverse asset classes, industries, and time horizons. Momentum is commonly characterized as the tendency for asset prices to continue moving in the same direction they have recently taken. Broadly, momentum can be categorized into time-series momentum and cross-sectional momentum. In this paper, we focus on time-series momentum, often referred to as trend-following.

Academic literature has long established evidence of profitable trend-following across traditional markets (Moskowitz et al., 2012), spanning centuries (Hurst et al., 2017; Lempérière et al., 2014), multiple economic environments (Daniel and Moskowitz, 2016), as well as in U.S. industries (Zarattini and Antonacci, 2024), US stocks (Zarattini et al., 2025) and intraday frequencies (Zarattini et al., 2024). These studies collectively highlight the robustness and adaptability of momentum-based strategies under various market conditions, suggesting that psychological and behavioral factors, such as investor herding or slow information diffusion, may contribute to persistent price trends (Jegadeesh and Titman, 1993; Barberis et al., 1998).

Within the realm of cryptocurrencies, recent work (Rozario et al., 2020; Harvey et al., 2022; Le et al., 2023; Fraikin et al., 2024) has begun to document the existence of momentum effects similar to those observed in more traditional asset classes. Jia et al. (2022) find evidence for the existence of a momentum factor using weekly data, while Fieberg et al. (2023) report that momentum is among the most relevant anomalies in the cross-section of cryptocurrency returns. Liu et al. (2022) show that a 3-factor model including market, size, and momentum captures a large fraction of variation in the cross-section of expected cryptocurrency returns.

Nonetheless, much of this research either centers exclusively on Bitcoin, potentially introducing selection bias, or employs trend-following techniques that diverge markedly from real-world applications. Furthermore, the nascent literature often omits critical details about transaction costs, order execution, and portfolio rebalancing, all of which can significantly impact the net profitability of systematic strategies.

Our paper aims to contribute to and expand upon the existing literature by empirically testing a diversified trend-following approach across multiple cryptocurrencies and time horizons. To offer a more practical perspective, we explicitly account for transaction costs, liquidity constraints, and operational details related to strategy implementation. By illustrating how a systematic trend-following strategy can be adapted to real-world crypto trading, we hope to provide actionable insights for investors and speculators who want to participate into this emerging and volatile asset class.

3 Database

We construct a survivorship bias-free dataset using data from CoinMarketCap, comprising 21,616 individual cryptocurrencies spanning the period from January 2010 to March 2025. To ensure consistency with our research objectives, we exclude stablecoins, wrapped tokens, and tokens primarily associated with NFT collectibles.

Our final dataset is a daily panel of OHLCV data (Open, High, Low, Close, and Volume) for the entire cross-section of eligible cryptocurrencies. The data is aggregated across multiple exchanges, as outlined in the official CoinMarketCap documentation.[1]

4 Trend-Following Model

Over the years, technical analysts and quantitative researchers have introduced hundreds of indicators and methodologies aimed at identifying trends in asset prices across various markets and timeframes. Despite the abundance of approaches, many of them introduce unnecessary complexity, making the resulting signals harder to interpret and significantly more vulnerable to overfitting. In our view, the true edge in trend-following systems lies only marginally in the specific indicator chosen to detect the trend itself. Rather, it is the formulation of effective exit criteria and the consistent application of robust risk

[1]According to the methodology described in the official documentation, CoinMarketCap aggregates price and volume data from numerous exchanges.

management techniques that play a far more critical role in shaping long-term profitability and resilience across market regimes.[2]

4.1 Entry and Exit Criteria

Consistent with methodologies outlined in prior studies (Zarattini and Antonacci, 2024; Zarattini et al., 2025), we employ Donchian Channels, a widely recognized technical indicator originally developed by Richard Donchian in the late 1950s. Donchian, a leading figure in managed futures and commodities trading, initially applied this tool, calibrated with a 20-day window, in his market newsletters.

Donchian Channels comprise three primary components: an upper boundary marking the highest high, a lower boundary marking the lowest low, and a middle boundary calculated as the midpoint between these extremes. Traders utilize these channels to discern prevailing market trends, volatility, and potential reversal points. Specifically, a breakout above the upper boundary signals bullish sentiment, whereas a breach below the lower boundary indicates bearish momentum.

Furthermore, the distance between the upper and lower bands of the Donchian Channel serves as an indicator of asset volatility. A broader channel denotes elevated volatility and larger price movements, whereas a narrower channel indicates relatively stable or consolidating market conditions.

Historically, Donchian Channels gained significant recognition through the 1980s experiment by Richard Dennis and William Eckhardt, famously known as the *Turtle Traders* experiment. In this initiative, novice traders successfully demonstrated the profitability of systematic, rules-based trading utilizing Donchian Channels and other trend-following techniques.

Mathematically, we define the boundaries of the Donchian Channels as follows:

[2] Inspired by research conducted by Tom Basso in the late 1990s, we backtested a trend-following system based on randomly generated entry signals. The results, which support the notion that the choice of trend indicator may be secondary to position management and exits, are presented on the Concretum Research X page: `https://x.com/ConcretumR/status/1638446734807375872`

$$\begin{aligned}
\text{DonchianUp}_t^n &= \max\left\{\text{Close}_t, \text{Close}_{t-1}, \ldots, \text{Close}_{t-n+1}\right\} \\
\text{DonchianDown}_t^n &= \min\left\{\text{Close}_t, \text{Close}_{t-1}, \ldots, \text{Close}_{t-n+1}\right\} \\
\text{DonchianMid}_t^n &= 0.5 * \left(\text{DonchianUp}_t^n + \text{DonchianDown}_t^n\right)
\end{aligned}$$

A trend-following system is constructed such that as soon as the closing price hits the upper boundary of the Donchian Channel, a new long position is established. Each position is then maintained until the first closure below a trailing stop which is updated daily according to the following formula

$$\text{TrailingStop}_{t+1}^n = \max\left(\text{TrailingStop}_t^n, \text{DonchianMid}_t^n\right)$$

In line with trend-following habits, we never allow the trailing stop to be updated downward. In practice, the prevailing Trailing Stop used in day $t+1$ is the maximum between the Trailing Stop used in day t and the middle line of the Donchain channel computed at the end of day t.[3]

To better illustrate the mechanics of the trend-following model, Figure 1 provides a graphical example of how a few historical trades would have unfolded when applying the Donchian-based entry and exit rules to Bitcoin. The chart displays the upper and lower Donchian Channel boundaries (green and red lines), the closing price of Bitcoin (black line), and the corresponding trailing stop (red dotted line) that dynamically adjusts over time. Entry points are marked with colored triangles, in green when price crosses the upper Donchian threshold, in red while exits are triggered by a close below the active trailing stop. This visualization clearly demonstrates how the system systematically captures upward momentum while enforcing disciplined exits to protect against reversals.

[3] For newly opened positions, the initial trailing stop is set equal to the midpoint of the Donchian Channel at the time of entry.

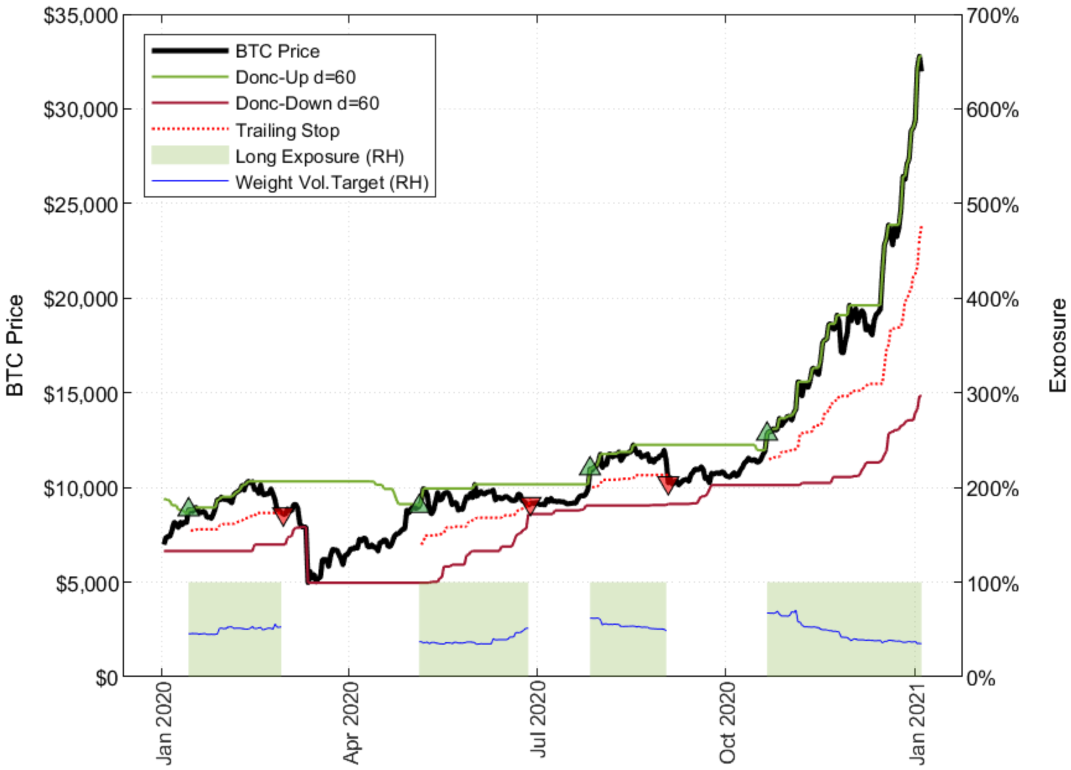

Figure 1: Illustrative example of the long-only trend-following model applied to Bitcoin between January 2020 and January 2021. The model is calibrated using 60-day Donchian Channels for trend signals and employs a volatility targeting scheme based on a 3-month rolling window of daily returns. The portfolio is scaled to achieve an annualized target volatility of 25%. The chart highlights the entry and exit signals, as well as the dynamic position sizing over the life of each trade. Data source: `https://www.coinmarketcap.com`.

4.2 Position Sizing

Similar to other asset classes, cryptocurrencies exhibit persistence in volatility and due to the high level of returns variability, investors should be better-off by stabilizing return streams by using risk management techniques as suggested by Goodall and Tarek (2024).

We thus size a trend position such as the target annualized volatility is 25%. In mathematical terms, at the end of day t, a trend position is sized as

$$w_t = \frac{25\%}{\sigma_t},$$

where σ_t is the 90-day annualized volatility of the returns of the underlying asset computed on day t. To prevent excessive leverage, we do not allow the allocation to exceed 200%.

The lower part of Figure 1 shows the resulting position exposure, depicted by the blue line and computed using a volatility targeting framework, plotted against the right-hand axis. As shown, the exposure dynamically adjusts over the life of each trade in response to changes in Bitcoin's return volatility. Periods of elevated volatility result in smaller position sizes, whereas calmer market regimes allow for increased exposure. This approach is intended to ensure a more stable portfolio-level risk profile over time.

However, this figure also highlights one of the key drawbacks of applying volatility scaling to trend-following strategies. While the technique effectively stabilizes portfolio volatility, it may also hinder full participation in large trending moves. Specifically, if return volatility rises during a strong directional trend, as observed during the sharp uptrend that began in late 2020, the scaling mechanism reduces exposure just when the opportunity for outsized returns is highest. This creates a structural trade-off between risk management and trend participation.

Throughout this research project, we have tested alternative position-sizing methodologies that are less sensitive to this effect and allow for greater participation in strong trends. The potential for performance improvement is notable, although a full discussion of these methods lies outside the scope of the present paper.[4]

4.3 An Ensemble Trend Model

The effectiveness of a trend-following strategy can vary significantly depending on the length of the look-back window used to compute Donchian Channels. Shorter windows (e.g., 5 days) tend to capture quick, short-lived price movements, while longer windows (e.g., 360 days) are better suited for identifying persistent, slower-moving trends that

[4] For readers interested in this topic, we explored these alternative techniques in traditional asset classes in a dedicated article available on our website: www.concretumgroup.com/position-sizing-in-trend-following-comparing-volatility-targeting-volatility-parity-and-pyramiding/.

may be driven by fundamental factors.

To explore the impact of trend horizon selection, we evaluate strategy performance across a range of look-back periods: specifically, 5, 10, 20, 30, 60, 90, 150, 250, and 360 days. For each look-back window n, the optimal portfolio weight at the end of day t is defined as:

$$w_t^n = \min\left(\frac{0.25}{\sigma_t}, 200\%\right) \times \text{Pos}_t^n,$$

where σ_t represents the 3-month annualized volatility of the underlying asset, and Pos_t^n is the binary trading signal determined as follows:

$$\text{Pos}_t^n = \begin{cases} 1 & \text{if } \text{Close}_t = \text{DonchianUp}_t(n) \\ 0 & \text{if } \text{Close}_t \leq \text{TrailingStop}_t \\ \text{Pos}_{t-1}^n & \text{otherwise.} \end{cases}$$

The daily return on day t for the portfolio employing an n-day Donchian Channel is given by:

$$r_t^n = w_{t-1}^{\mathrm{n}} \times \text{ret}_t^{\text{asset}}$$

Consistent with best practices in systematic trend-following, we implement a model ensemble that diversifies across multiple trend horizons. Conceptually, the final portfolio, referred to as the *Combo* portfolio, is constructed as an equal-weighted aggregation of N sub-portfolios, each driven by a different trend signal length. The aggregate portfolio weight on day t is given by:

$$w_t^{\text{Combo}} = \frac{1}{N}\sum_{i=1}^{N} w_t^{\mathrm{n}_i},$$

where $n_i \in \{5, 10, 20, 30, 60, 90, 150, 250, 360\}$. The return for the *Combo* portfolio on day t is computed as:

$$\text{ret}_t^{\text{Combo}} = w_{t-1}^{\text{Combo}} \times \text{ret}_t^{\text{asset}}$$

5 Empirical Results on Bitcoin

We begin our empirical analysis by evaluating the historical performance of each individual trend-following model, as well as the ensemble approach, on Bitcoin, the most prominent and widely traded cryptocurrency. The backtest period begins in January 2015 and extends through March 2025.

This preliminary analysis serves two main purposes. First, it allows us to assess the behavior and robustness of various trend signal horizons in a single-asset setting before generalizing the framework to a broader multi-asset crypto portfolio. Second, Bitcoin's relatively long and uninterrupted trading history, combined with its dominance in market capitalization and liquidity, provides a natural benchmark for evaluating the efficacy of trend-following techniques in digital assets.

Table 1 reports a comprehensive set of performance metrics for each model, including annualized return (CAGR), annualized volatility, Sharpe and Sortino ratios, maximum drawdown (MDD), the MAR ratio, annualized alpha and beta relative to Bitcoin itself. As seen in the results, models with short look-back periods (5 to 30 days) exhibited the strongest risk-adjusted returns, while the ensemble *Combo* model offered a solid overall profile with a Sortino ratio of 2.03, a Sharpe ratio of 1.58, a maximum drawdown of just 19% (versus >80% for Bitcoin passive exposure) and an annualized alpha of 14%. With the exception of the 150-day and 250-day models, all reported alphas were statistically significant in the historical sample, with p-values well below 2.5%.

In Table 2, we present trade-level statistics for each model. These include the total number of trades, hit ratio, average PnL and return per trade, maximum and minimum trade returns, drawdown of closed trades, and the gain-to-loss ratio. As expected, as the look-back horizon increases, the number of trades decreases significantly.

In Figure 2, we plot the equity curves for each individual trend-following model alongside the resulting *Combo* portfolio. To facilitate a risk-adjusted comparison, we also include a rescaled version of Bitcoin's price trajectory (black line), adjusted to match the ex-

Table 1: Performance of BTC trend-following models across various Donchian lookback windows. All models use Donchian Channels for trend signal generation and implement a daily volatility targeting scheme based on a 3-month rolling window of Bitcoin returns, targeting an annualized volatility of 25%. The *Combo* model refers to the ensemble approach described in Section 4.3. Metrics include CAGR, volatility, Sharpe and Sortino ratios, maximum drawdown (MDD), MAR (CAGR/MDD), annualized alpha, and beta versus BTC. The backtest period spans from January 1, 2015 to March 19, 2025. Transaction costs are not included. Alphas in **bold** are statistically significant at the 2.5% level. Data source: `https://www.coinmarketcap.com`.

Model	**CAGR**	**Vol.**	**Sharpe**	**Sortino**	**MDD**	**MAR**	**Alpha**	**Beta**
5d	36%	19%	1.66	1.87	25%	1.41	**19%**	0.16
10d	32%	18%	1.55	1.64	27%	1.19	**18%**	0.15
20d	34%	18%	1.60	1.60	26%	1.32	**19%**	0.16
30d	34%	19%	1.61	1.61	24%	1.41	**19%**	0.16
60d	28%	19%	1.30	1.25	19%	1.46	**13%**	0.17
90d	27%	20%	1.20	1.15	24%	1.12	**11%**	0.18
150d	21%	20%	0.99	0.97	29%	0.74	7%	0.19
250d	25%	20%	1.13	1.15	33%	0.76	9%	0.20
360d	29%	20%	1.28	1.27	34%	0.83	**12%**	0.18
Combo	30%	17%	1.58	2.03	19%	0.88	**14%**	0.17

Table 2: Trade-level statistics of BTC trend-following models across various Donchian lookback windows. Metrics include the number of trades, win rate, average PnL and return per trade, maximum and minimum trade returns, and the gain-to-loss ratio. *Unit* refers to PnL and returns assuming the strategy trades one BTC contract per signal, while all other return figures are computed at the portfolio level. The backtest period spans from January 1, 2015 to March 19, 2025. Transaction costs are not included. Data source: `https://www.coinmarketcap.com`.

Model	**Trades**	**Win Rate**	**AvgPnL × Unit**	**AvgRet × Unit**	**AvgRet**	**MaxRet**	**MinRet**	**Gain: Loss**
5d	292	41%	$229	2.8%	1.2%	29%	-5%	3.7
10d	156	40%	$380	4.7%	2.0%	34%	-5%	4.5
20d	78	47%	$730	10%	4.3%	45%	-6%	5.2
30d	49	49%	$1,493	17%	7.4%	69%	-5%	6.7
60d	28	46%	$3,137	27%	11%	89%	-7%	9.2
90d	20	60%	$4,266	35%	15%	84%	-9%	6.5
150d	15	60%	$3,804	47%	17%	90%	-11%	4.1
250d	9	78%	$4,902	126%	35%	111%	-11%	4.7
360d	5	80%	$12,648	477%	99%	350%	-10%	12.8

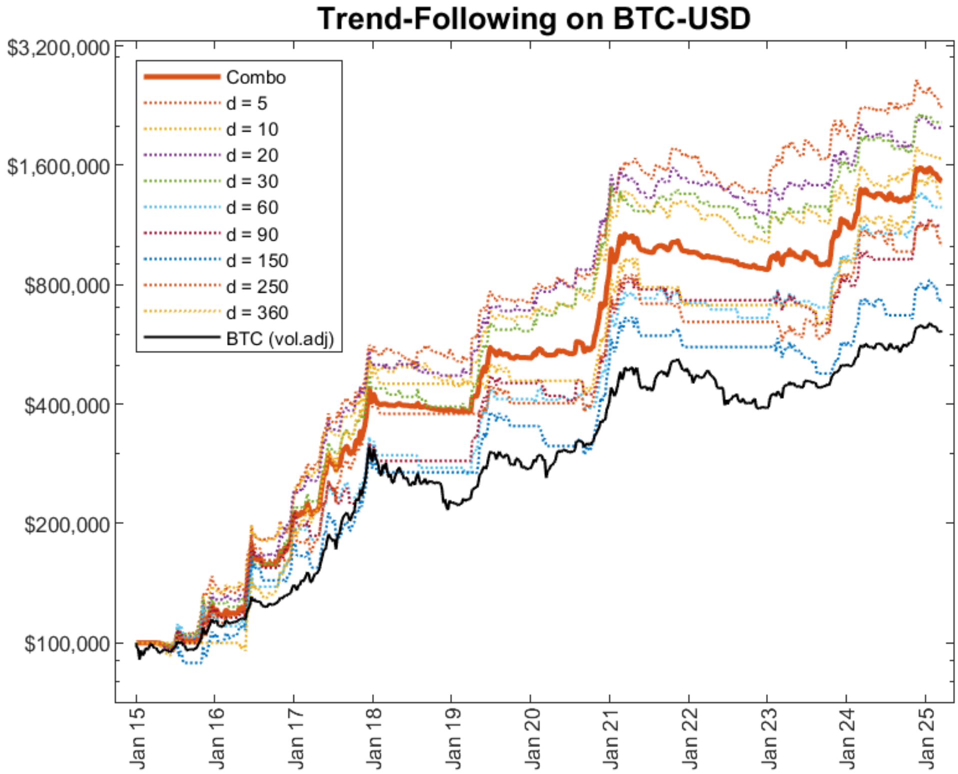

Figure 2: Cumulative equity curves of long-only trend-following models applied to Bitcoin, each calibrated using a different Donchian Channel look-back window. All strategies employ daily volatility targeting based on a 3-month rolling window of Bitcoin returns, scaled to a 25% annualized volatility target. The black line represents a passive long exposure in Bitcoin, rescaled to match the ex-post volatility of the ensemble *Combo* portfolio described in Section 4.3. The backtest spans from January 1, 2015, to March 19, 2025, and does not include transaction costs. Data source: `https://www.coinmarketcap.com`.

post volatility of the *Combo* portfolio. This normalization enables a more meaningful comparison between strategies operating at comparable levels of risk, highlighting the effectiveness of systematic trend-following in delivering superior risk-adjusted returns over passive exposure.

5.1 Transaction Costs and Advanced Portfolio Techniques

The results presented thus far do not account for transaction costs. In practice, however, trading fees can materially affect the performance of high-turnover strategies such as daily rebalanced trend-following systems. Following the methodology of Le et al. (2023), we assess the sensitivity of our results to transaction costs set at three conservative levels: 10 basis points (bps), 25 bps, and 50 bps. These values exceed the typical fee structure observed on major cryptocurrency exchanges, where Bitcoin trading costs are generally

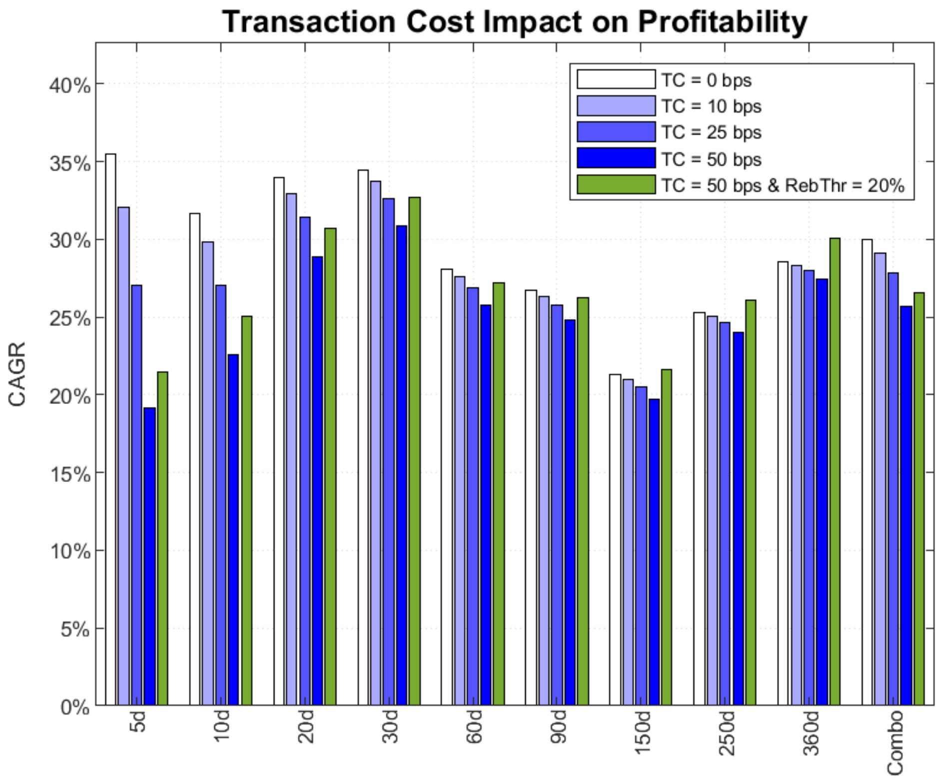

Figure 3: Impact of transaction costs on the annualized performance (CAGR) of Bitcoin trend-following models across different Donchian look-back windows. The *Combo* model refers to the ensemble approach described in Section 4.3. Each bar represents the compound annual growth rate under different transaction cost assumptions: 0, 10, 25, and 50 basis points (bps), following the methodology of Le et al. (2023). The green bars show results under a 50 bps cost combined with a 20% rebalance threshold, which helps reduce unnecessary turnover. All models use daily volatility targeting based on a 3-month rolling window, targeting a 25% annualized volatility. Backtest period: January 1, 2015 to March 19, 2025. Data source: `https://www.coinmarketcap.com`.

below 5 bps, thus providing a cautious view of cost impact.

As shown in Figure 3, profitability decreases as transaction costs increase, particularly for short-horizon models which require more frequent trading. For instance, at 50 bps, the CAGR of the 5-day model is significantly reduced (from 34% to 18%) while longer-term models are less affected. This confirms that excessive rebalancing may erode returns without delivering a commensurate improvement in risk-adjusted performance.

To mitigate this effect, we evaluate an enhancement inspired by Zarattini et al. (2025). Specifically, we implement a threshold-based rebalancing rule: the portfolio is only rebalanced if the difference between the current and target allocation exceeds 20%. This adjustment is applied exclusively to rebalancing activity driven by volatility targeting. It is important to distinguish that portfolio weights can change for two main reasons:

(i) A new entry or stop-loss trigger from the trend signal.

(ii) Changes in asset volatility that affect sizing under volatility targeting.

The threshold mechanism is applied only to the second case (i.e. volatility-induced rebalancing) while any signal-based adjustments, such as a fresh breakout or trailing stop event, result in an immediate position update regardless of the threshold.

The results show that introducing this rebalancing threshold under a 50 bps cost scenario would have led to a material recovery in performance, which can be estimated at approximately 100 basis points per year. As shown by the green bars in Figure 3, this simple enhancement helped restore a significant portion of the strategy's gross returns, thereby improving the historical viability of volatility-targeted trend-following in cost-sensitive implementations.

In the remainder of the paper, all results are presented net of a transaction cost of 10 basis points (in line with the estimates proposed by Liu and Tsyvinski (2021)) and incorporate a rebalancing threshold of 20% to limit unnecessary turnover.

6 Trend-Following on Other Cryptocurrencies

In this section, we extend the analysis previously conducted on Bitcoin to a broader universe that encompasses more than 10,000 cryptocurrencies traded over the past decade. The construction and filtering criteria of the full dataset are described in detail in Section 3.

As a first step, we identify the top 40 cryptocurrencies in our database based on their cumulative trading volume since inception. For each of these assets, we backtest the trend-following strategies across all signal lengths, incorporating a transaction cost of 10 basis points and applying a 20% rebalancing threshold to mitigate excessive turnover.

While we acknowledge that this study is affected by selection bias, given that we focus only on the most liquid and well-known cryptocurrencies, the objective is to give readers a clearer understanding of how trend-following models perform when applied to recognizable and historically significant digital assets.

The resulting performance statistics are presented in Table 3. Due to space constraints, we report results for the ensemble portfolio only. For detailed performance decomposition by individual trend signal horizon, interested readers are encouraged to contact the authors at info@concretumgroup.com.

7 A Diversified Trend-Following Program

While the preceding sections examine trend-following applied to individual assets such as Bitcoin or subsets of well-known cryptocurrencies, a more robust and resilient implementation should incorporate a dynamically selected, diversified set of tradable tokens. By continuously adapting the investment universe based on liquidity and activity filters, the portfolio becomes better positioned to capture idiosyncratic trends and to capitalize on price momentum in newly emerging or reactivated digital assets.

To this end, we construct and backtest a dynamic, cross-sectional trend-following program. The strategy applies the same signal generation and execution rules outlined in Section 4 to a rotating universe of eligible cryptocurrencies, with asset selection and rebalancing performed on a monthly basis.

7.1 Universe Construction and Filtering Criteria

At the end of each month, we identify the set of eligible assets using the following screening criteria:

Table 3: Performance statistics of the ensemble trend-following model (*Combo*) applied to a selection of major cryptocurrencies. The Combo model, described in Section 4.3, aggregates signals from multiple Donchian lookback windows and applies a volatility targeting scheme based on a 3-month rolling window, targeting 25% annualized volatility. Metrics reported include CAGR, volatility, Sharpe and Sortino ratios, maximum drawdown (MDD), and the MAR ratio (CAGR divided by MDD). The backtest starts in January 2015 or later, depending on the asset's listing date. Results include a 10 basis point transaction cost and a 20% rebalance threshold. Data source: `https://www.coinmarketcap.com`.

Name	**Symbol**	**From**	**CAGR**	**Vol.**	**Sharpe**	**Sortino**	**MDD**	**MAR**
Bitcoin	BTC	Jan-2015	30%	17%	1.56	1.23	19%	1.15
Ethereum	ETH	Aug-2015	27%	16%	1.51	1.22	15%	0.96
XRP	XRP	Jan-2015	18%	17%	1.00	0.97	14%	1.10
Bitcoin Cash	BCH	Jul-2017	7%	14%	0.48	0.42	19%	0.42
Litecoin	LTC	Jan-2015	11%	14%	0.72	0.53	29%	0.44
EOS	EOS	Jul-2017	7%	12%	0.53	0.27	19%	0.36
Solana	SOL	Apr-2020	27%	14%	1.68	1.64	12%	2.04
BNB	BNB	Jul-2017	17%	15%	1.06	0.99	17%	0.77
WETH	WETH	Jan-2018	10%	14%	0.67	0.49	15%	0.35
Cardano	ADA	Oct-2017	17%	14%	1.13	0.94	18%	0.88
TRON	TRX	Sep-2017	19%	21%	0.82	0.88	16%	1.21
Ethereum Classic	ETC	Jul-2016	16%	14%	1.08	0.76	14%	0.83
Dogecoin	DOGE	Jan-2015	24%	18%	1.20	1.21	15%	1.13
Chainlink	LINK	Sep-2017	15%	14%	0.99	0.72	19%	0.80
Polkadot	DOT	Aug-2020	7%	12%	0.60	0.41	17%	0.34
Bitcoin SV	BSV	Nov-2018	3%	12%	0.21	0.19	23%	0.22
Avalanche	AVAX	Sep-2020	22%	14%	1.49	1.37	12%	1.64
Shiba Inu	SHIB	Aug-2020	39%	55%	0.60	3.27	18%	6.64
Polygon	MATIC	Apr-2019	10%	13%	0.78	0.76	12%	0.49
Stellar	XLM	Jan-2015	14%	15%	0.86	0.85	19%	0.85
Neo	NEO	Sep-2016	17%	15%	1.00	0.80	20%	0.73
Cosmos	ATOM	Mar-2019	6%	12%	0.47	0.30	16%	0.28
Dash	DASH	Jan-2015	14%	14%	0.91	0.81	24%	0.85
Qtum	QTUM	May-2017	9%	13%	0.66	0.40	13%	0.42
Zcash	ZEC	Oct-2016	8%	13%	0.57	0.33	22%	0.35
Filecoin	FIL	Dec-2017	5%	13%	0.39	0.36	30%	0.39
Terra Classic	LUNC	Jul-2019	23%	15%	1.38	1.12	12%	0.74
Uniswap	UNI	Sep-2020	3%	10%	0.33	0.23	17%	0.21
Pepe	PEPE	Apr-2023	23%	14%	1.48	1.72	8%	1.47
NEAR Protocol	NEAR	Oct-2020	14%	13%	1.02	1.06	12%	1.18
Aave	AAVE	Oct-2020	5%	12%	0.43	0.32	11%	0.22
VeChain	VET	Aug-2018	14%	13%	1.03	0.84	11%	0.70
Monero	XMR	Jan-2015	11%	16%	0.67	0.53	35%	0.36
Fantom	FTM	Oct-2018	23%	14%	1.51	1.35	11%	1.04
Algorand	ALGO	Jun-2019	9%	14%	0.64	0.49	21%	0.46
OMG Network	OMG	Jul-2017	5%	12%	0.42	0.29	20%	0.33
Curve DAO Token	CRV	Aug-2020	4%	10%	0.42	0.33	15%	0.40
yearn.finance	YFI	Jul-2020	8%	13%	0.62	0.13	14%	0.52
OKB	OKB	May-2019	12%	15%	0.79	0.68	13%	0.68
THORChain	RUNE	Jul-2019	21%	14%	1.39	1.05	16%	1.21

- The asset must have been listed for at least 365 calendar days;
- It must not be a wrapped token, stablecoin, or collectible NFT;
- It must have recorded a median daily trading volume of at least $2 million over the preceding 30 days.

From the resulting filtered list, we rank cryptocurrencies by their median daily trading volume during the same month and retain only the top B assets. These selected tokens constitute the tradable universe for the subsequent month. This dynamic selection process ensures that the portfolio focuses on assets with sufficient liquidity, while also adapting over time to market evolution.

7.2 Portfolio Construction and Rebalancing

Capital is allocated equally across all selected assets, with each receiving one-B^{th} of the portfolio's total capital. For each asset, the ensemble trend-following strategy, as described in Section 4.3, is applied independently. The cross-sectional trend portfolio is rebalanced at the end of each month.

Formally, the assets under management (AUM) allocated on cryptocurrency i at the end of day t are given by:

$$\text{AUM}_{t,i} = \frac{\text{AUM}_{t_0}}{B} \cdot \prod_{s=t_0}^{t} \left(1 + \text{ret}_{s,i}^{Combo}\right)$$

where $\text{ret}_{s,i}^{Combo}$ denotes the return of the trend-following strategy applied to asset i on day s while AUM_{t_0} represents the asset under management at the beginning of the month.

To avoid exposure to illiquid or structurally compromised assets, we implement an exit rule based on two liquidity conditions. An asset is removed from the portfolio if:

- Its median daily trading volume over the past 30 days falls below $1 million; or
- Its median daily price change over the same period is less than 0.5%.

Table 4: Performance statistics of long-only diversified trend-following portfolios across different universe sizes, based on the strategy described in Section 7. Metrics include cumulative return (Tot.Ret.), compound annual growth rate (CAGR), annualized volatility (Vol.), Sharpe and Sortino ratios, maximum drawdown (MDD), MAR ratio (CAGR/MDD), and annualized alpha and beta relative to Bitcoin. The backtest includes a 10 basis point (bps) transaction cost and a 20% rebalance threshold, and spans the period from January 1, 2015 to March 19, 2025. Alphas in **bold** are statistically significant at the 2.5% level. Data source: `https://www.coinmarketcap.com`.

# Assets	Tot.Ret.	CAGR	Vol.	Sharpe	Sortino	MDD	MAR	Alpha	Beta
5	452%	18%	10%	1.44	1.77	14%	1.28	**9.7%**	0.10
10	438%	18%	9%	1.50	1.87	12%	1.44	**10.3%**	0.09
20	443%	18%	9%	1.57	1.97	11%	1.61	**10.8%**	0.08
30	404%	17%	8%	1.56	1.96	11%	1.54	**10.5%**	0.07
40	366%	16%	8%	1.53	1.92	11%	1.46	**9.9%**	0.07
50	359%	16%	8%	1.54	1.93	11%	1.44	**9.9%**	0.07

These exit rules are designed to eliminate stale, inactive, or manipulated tokens that no longer exhibit sufficient trading activity or price discovery dynamics.

Table 4 reports the performance of the long-only diversified trend-following program across portfolios of increasing breadth, ranging from 5 to 50 assets. Historical simulations indicate that performance improved with broader diversification up to approximately 20 assets, beyond which the marginal benefits of including additional cryptocurrencies diminished. The Sharpe ratio remained remarkably stable across all portfolio sizes, fluctuating only slightly around 1.5, suggesting that risk-adjusted returns are largely preserved once basic liquidity conditions are met. The Sortino ratio exhibited a similar pattern, peaking at 1.97 for the 20-asset portfolio.

The compound annual growth rate (CAGR) remains close to 18% for portfolios of up to 20 assets, before declining slightly. While volatility and maximum drawdown continue to decline modestly as the number of assets increases, the alpha versus Bitcoin peaks at 10.8% per year for the portfolio composed of 20 assets.

In Figure 4, we plot the Sharpe ratios of the trend-following strategy as a function of the number of crypto assets included in the portfolio. While the highest Sharpe ratios are observed in highly concentrated portfolios—peaking with as few as two assets—these

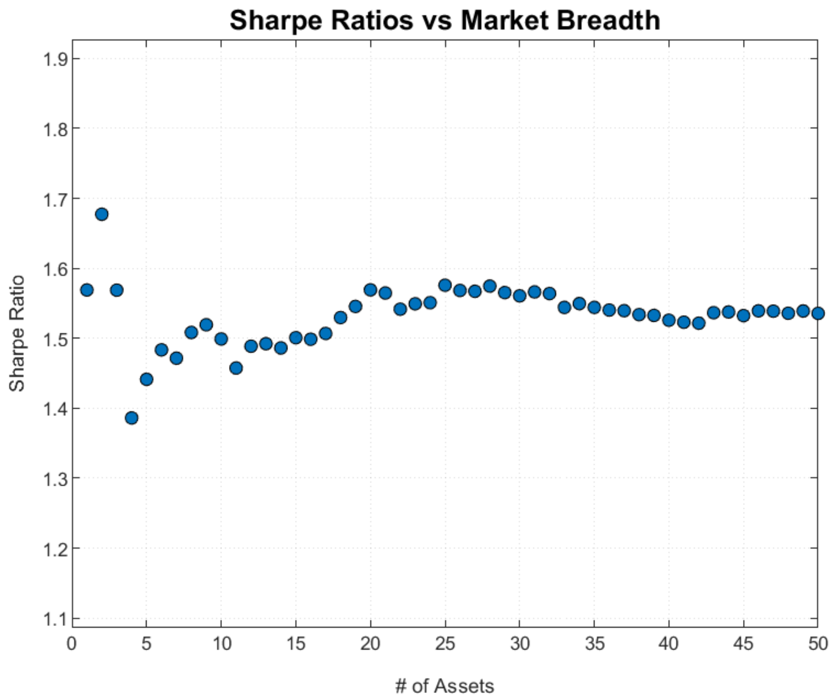

Figure 4: Sharpe ratios of the diversified trend-following strategy described in Section 7 as a function of the number of crypto assets included in the portfolio. Each point represents the performance of the portfolio when trading the top N cryptocurrencies ranked by median daily volume over the previous month. The strategy includes a transaction cost of 10 basis points and a 20% rebalance threshold. Backtest period: January 1, 2015 to March 19, 2025. Data source: `https://www.coinmarketcap.com`.

configurations are not desirable in practice. Although such setups may appear optimal *ex post*, they are typically associated with elevated idiosyncratic risk and limited diversification. A more balanced allocation, involving a broader cross-section of assets, provides greater robustness and aligns more closely with established principles of prudent portfolio construction.

Notably, beyond 20 assets, the Sharpe ratio stabilizes, suggesting that moderate diversification is sufficient to achieve most of the attainable benefits in terms of risk-adjusted performance. This reinforces the notion that trend-following in crypto does not require exhaustive breadth, but that some degree of diversification is essential to reduce single-asset risk while preserving strategy efficiency.

Taken together, these findings suggest that a diversified portfolio of approximately 10 to 20 cryptocurrencies may already represent an optimal balance between capturing broad

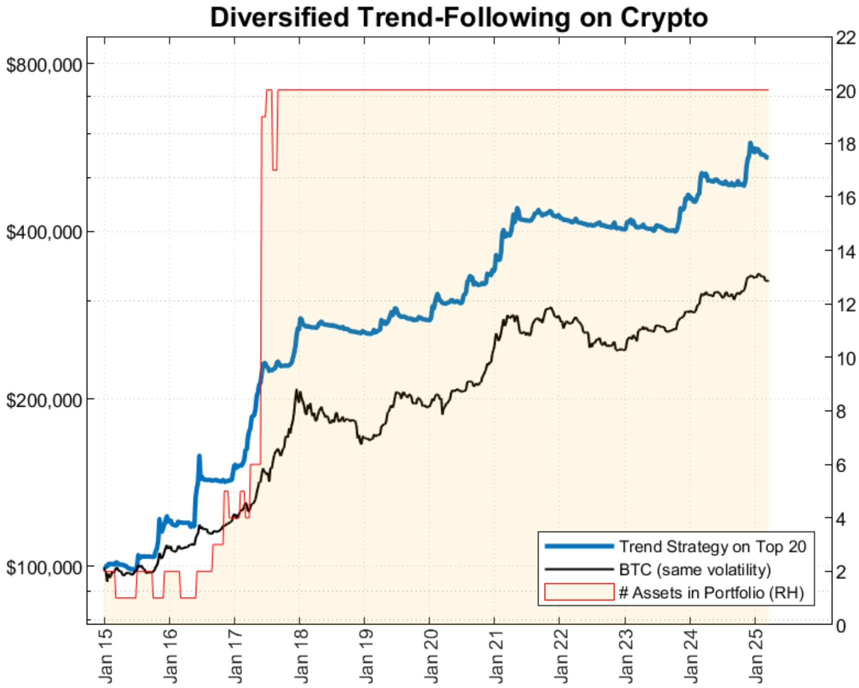

Figure 5: Performance of the diversified trend-following program described in Section 7, applied to the top 20 most liquid cryptocurrencies each month. The blue line shows the equity curve of the strategy, which includes a 10 basis point transaction cost and a 20% rebalance threshold. The black line represents a passive long exposure to Bitcoin, rescaled to match the volatility of the trend strategy. The red line (right axis) shows the number of eligible assets included in the portfolio over time. Backtest period: January 1, 2015 to March 19, 2025. Data source: `https://www.coinmarketcap.com`.

market trends and maintaining capital efficiency within a long-only trend-following framework. This range appears even more appropriate when considering that efforts to further diversify the portfolio by including a larger number of assets (e.g., 50 or more) would likely expose the portfolio to diminishing liquidity, wider bid-ask spreads, and higher transaction costs; factors that could offset or even outweigh the marginal benefits of additional diversification.

Figure 5 displays the equity curve of the long-only trend-following program applied to the 20 most liquid cryptocurrencies, selected each month based on their trailing 30-day trading volume. The total return path exhibits the characteristic *stair-step* behavior frequently observed in well-constructed trend-following systems: periods of consolidation or mild drawdown are followed by sharp, sustained advances. This pattern reflects the model's ability to endure low-trend regimes while remaining positioned to capture emergent momentum.

Superimposed on the chart, the red line (right axis) indicates the number of cryptocurrencies that met the program's eligibility and liquidity criteria and were included in the portfolio at each point in time. Notably, prior to mid-2017, the number of qualifying assets was below 20, underscoring the limited market depth in the early years of the crypto ecosystem. As the market matured and trading volumes increased across a broader range of assets, the strategy was able to operate with its full allocation, enabling greater diversification and more stable capital deployment.

7.3 Profitability versus Size

We investigate whether the profitability of the *Diversified Trend-Following Program* is influenced by the size of the underlying cryptocurrencies. Specifically, we ask: does trend-following tend to perform better when applied to highly traded assets?

To explore this, we construct ten distinct trend-following portfolios as detailed in Section 7. These portfolios are rebalanced monthly and are formed by ranking the tradable universe based on average daily trading volume over the preceding 30 days. Each portfolio includes 10 cryptocurrencies.

For instance, the portfolio labeled *D1* consists of the 10 most liquid cryptocurrencies; those ranked 1 to 10 by trading volume (with rank 1 indicating the highest volume). Conversely, *D10* includes less liquid assets, specifically those ranked 91 to 100. This decile-based approach allows us to assess the relationship between liquidity and trend-following performance across the cross-section of cryptocurrencies. To ensure each portfolio contains sufficiently liquid assets (defined as a median daily volume above $1 million), the backtest begins in January 2020.

Figure 6 reports the Sharpe ratios of the ten decile portfolios. The results indicate no meaningful size effect on the performance of trend-following strategies, at least when focusing on the top 100 most traded cryptocurrencies, dynamically selected on a monthly basis, and when evaluating returns on a risk-adjusted basis.

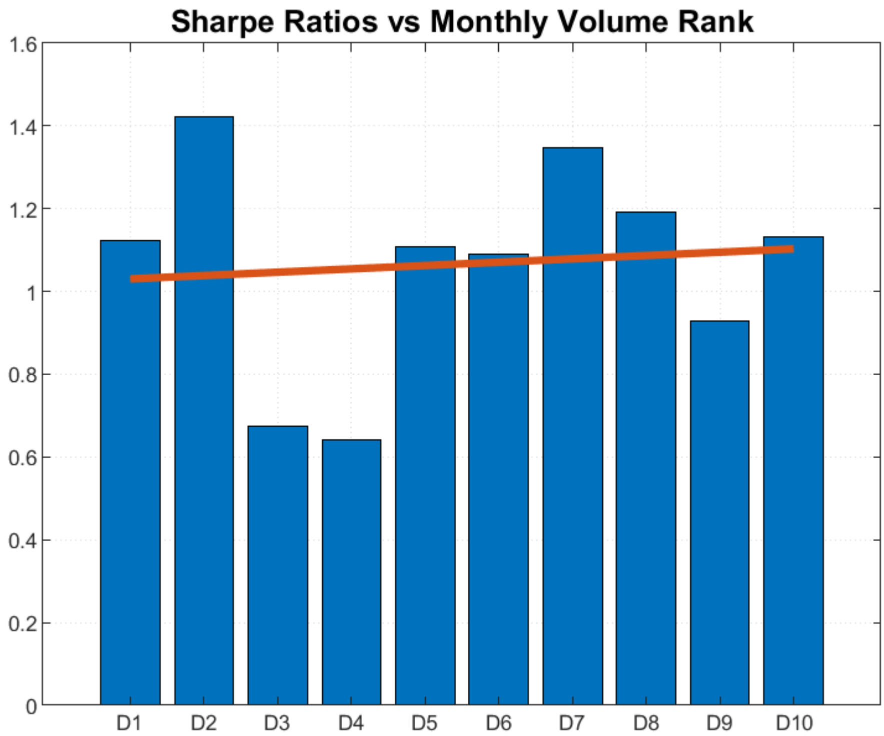

Figure 6: Sharpe ratios of the diversified trend-following strategy across liquidity deciles. The strategy is applied to the 100 most traded cryptocurrencies, selected at the end of each month. Assets are sorted each month into deciles based on their average daily trading volume over the preceding 30 days, with D10 containing the least liquid and D1 the most liquid assets. Each portfolio holds 10 cryptocurrencies. Backtest period: January 1, 2020 to March 19, 2025. Data source: `https://www.coinmarketcap.com`.

8 Crypto Trend versus Traditional CTAs

To assess the degree to which trend-following in cryptocurrency markets aligns with traditional trend-following strategies, we compare our diversified Trend-Following program applied to 20 assets with the SG Trend Index, a widely used benchmark representing the performance of large institutional managed futures programs across traditional asset classes.

We begin by examining the correlation between the two return series using a 6-month rolling window over the past decade. As shown in Figure 7, the correlation varies substantially over time, oscillating between slightly negative values and peaks exceeding +30%. The average rolling correlation over the sample period is approximately 7.4%, indicating a generally low linear relationship between the strategies.

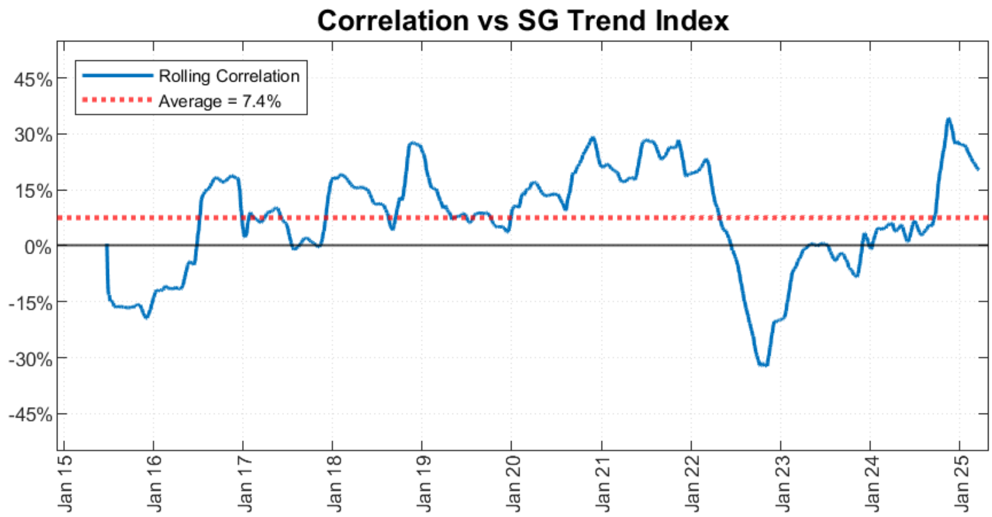

Figure 7: 6-month rolling correlation between the Crypto Trend strategy and the SG Trend Index. The Crypto Trend portfolio consists of the top 10 most traded cryptocurrencies from the previous month, rebalanced monthly with a 20% threshold and incorporating transaction costs of 10 basis points. The SG Trend Index (data source: Bloomberg) is a widely used benchmark that tracks the performance of major trend-following CTAs. Backtest period: January 1, 2015 to March 19, 2025. Crypto data source: `https://www.coinmarketcap.com`.

Importantly, there are extended periods, such as during 2015–2016 and again in 2022–2023, when the correlation turned negative or hovered near zero. These findings suggest that crypto trend-following offers meaningful diversification benefits when included in a broader trend-following allocation. The structural and behavioral characteristics of digital assets may explain the relatively distinct return profile observed in comparison to traditional trend programs.

In Figure 8, we compare the cumulative performance of the diversified crypto trend-following program and the SG Trend Index, with both series initialized at a base value of $100,000. The divergence is notable: while the SG Trend Index shows modest gains over the 10-year period, reflecting the relatively subdued trends in traditional asset classes, the crypto trend program delivers substantially stronger performance. This outperformance is particularly pronounced during major momentum phases in the digital asset space, such as in 2017, 2020–2021, and late 2023, underscoring the potential of trend-following models to capitalize on structural price dislocations and persistent directional moves in crypto markets.

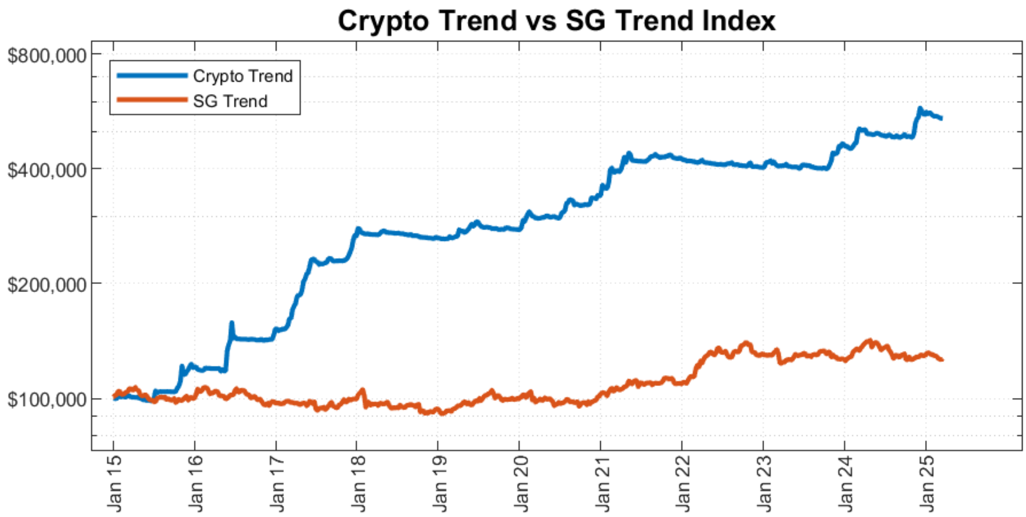

Figure 8: Cumulative performance of the Crypto Trend strategy versus the SG Trend Index. The Crypto Trend strategy allocates capital equally across the top 10 most traded cryptocurrencies each month, using a trend-following model with monthly rebalancing, a 20% rebalance threshold, and 10 basis points of transaction costs. Both strategies are initialized at $100,000. The SG Trend Index (data source: Bloomberg) reflects the aggregate performance of leading trend-following CTAs across traditional asset classes. Backtest period: January 1, 2015 to March 19, 2025. Crypto data source: `https://www.coinmarketcap.com`.

These historical findings suggest two key observations. First, trend-following in crypto has exhibited non-redundant exposure, offering return streams with limited correlation with traditional trend strategies. Second, the crypto market provides a uniquely dynamic environment in which well-designed trend-following systems can achieve substantial performance. As such, a crypto trend allocation may serve as a powerful complement to macro-oriented and managed futures strategies.

9 Managing Risks in Digital Asset Trading

Investing in crypto tokens involves additional risks compared to traditional financial assets. These risks largely stem from the fundamental trade-off between delegating custody to centralized exchanges versus managing assets independently using non-custodial wallets.

To better understand these risks, it is important to recall that ownership of crypto tokens is recorded directly on a blockchain, that is, a decentralized digital ledger recording transaction data.

Investors manage their holdings through specific software applications, commonly referred to as *non-custodial wallets* or *crypto wallets*. These wallets allow users to transfer tokens by sending a specified amount to the public address of the recipient. Crucially, the user retains full control over the assets, without relying on a third-party intermediary.

Furthermore, non-custodial wallets can be connected to Decentralized Finance (DeFi) applications, enabling interaction with smart contracts that power these protocols. Of particular relevance are decentralized exchanges (DEXs), which allow users to swap arbitrary quantities of token "A" for token "B". These transactions, known as *token swaps*, do not involve trading with a counterparty in the traditional sense. Instead, users interact with *liquidity pools*, which hold reserves of both tokens. Transaction prices are determined algorithmically based on the relative supplies of tokens in the pool, following rules embedded in the underlying smart contracts.

A trading strategy involving crypto tokens and the U.S. Dollar can typically be implemented in two ways:

1. **Via centralized exchanges.** The investor may purchase tokens directly from a centralized exchange, such as Binance or Kraken, using U.S. Dollars or other fiat currencies. Alternatively, the investor may transfer tokens to the exchange from her wallet. Within the exchange platform, crypto assets can be traded for other tokens or converted back to fiat, using a centralized limit order book to determine prices. This setup is similar to the structure of traditional financial exchanges. Algorithmic trading strategies can be implemented by calling the exchange's internal APIs.

2. **Via decentralized exchanges.** The investor may connect her wallet to a DEX, such as Uniswap or Hyperliquid, and execute token swaps through the application's user interface or via smart contract interaction. In this setup, tokens are never deposited to

the exchange; they remain under the user's control in the wallet. Since DEXs only support blockchain-native assets, they do not support direct trades against fiat currencies. Instead, investors obtain cash-equivalent exposure by swapping tokens for *stablecoins* – such as USDC or USDT – which are tokenized representations of fiat currencies. Automated trading strategies can be executed using Web3 libraries to interact with the relevant smart contracts on-chain.

To trade on a decentralized exchange, one must first initialize a wallet and fund it with crypto tokens or stablecoins. Typically, this involves buying tokens on a centralized exchange using fiat and then transferring them to the wallet by sending them to its public address.

Each of these trading modalities is associated with different risks and trade-offs. Trading on centralized exchanges exposes investors to *counterparty risk*, since assets are deposited under the exchange's custody. Exchanges may be subject to hacking attacks, or may mismanage or misappropriate user funds. Notable examples include the 2014 collapse of *Mt. Gox*, which lost over 650,000 bitcoins to a security breach, and the more recent failure of *FTX*, where client funds were allegedly misused by the platform itself.

In contrast, using decentralized exchanges avoids counterparty risk, as assets remain under the user's control. However, this setup shifts the responsibility for asset security entirely onto the user. If the private keys associated with a wallet are lost or compromised, access to the tokens is permanently lost, with no recourse or recovery mechanism.

Another layer of risk arises from the use of stablecoins as cash substitutes. While stablecoins like USDC and USDT aim to maintain a 1:1 peg to the U.S. Dollar, historical events have shown that de-pegging is possible, particularly during periods of market stress or liquidity imbalances. That said, in recent years, leading stablecoin issuers have improved transparency regarding their reserves, including regular attestation reports and enhanced regulatory compliance. Nevertheless, the risk of temporary or permanent deviation from the dollar peg cannot be ruled out.

Finally, transactions on decentralized exchanges are fully recorded on the public blockchain, including the sender's and recipient's wallet addresses. As a result, on-chain activity is transparent and publicly accessible, allowing third parties to analyze wallet behavior and, potentially, reverse engineer trading strategies. While transaction data on centralized exchanges is not public, these platforms could theoretically monitor or even monetize user activity for their own benefit.

Finally, centralized and decentralized exchanges may also differ in terms of trading fees, execution costs, slippage, and asset coverage. For a detailed discussion, see Barbon and Ranaldo (2024).

10 Conclusion

Cryptocurrencies have rapidly evolved from a niche technological innovation into a globally recognized asset class. As of early 2025, total market capitalization has surpassed $3 trillion, with over 100 tokens individually exceeding $1 billion in market value. While both retail and institutional investors are increasingly embracing digital assets, the inherent volatility and structural risks of crypto markets highlight the importance of adopting robust, adaptive, and risk-aware investment frameworks.

In this paper, we backtested a tactical trend-following approach rooted in a classic breakout methodology that has been successfully deployed in traditional asset classes for decades. Our strategy, built on an ensemble of Donchian Channel-based models with varying lookback horizons, consistently delivered strong risk-adjusted performance across both Bitcoin and a wide selection of altcoins.

On Bitcoin, shorter-horizon models (5 to 30 days) proved particularly effective, yielding Sharpe ratios near 1.60 and reducing drawdowns to roughly one-third of those experienced under a passive long position. The ensemble model, combining signals from nine different horizons, achieved a compound annual growth rate (CAGR) of 30%, a Sortino ratio of 2.03, and an annualized alpha of 14% versus Bitcoin.

Expanding the analysis to a broader universe of cryptocurrencies, we applied the same trend-following framework to rotational portfolios of the most liquid digital assets, rebalanced monthly. A diversified strategy targeting the top 20 most actively traded cryptocurrencies would have produced net-of-fees Sharpe ratio 1.57, a maximum drawdown of just 11%, and a statistically significant alpha of 11% relative to Bitcoin.

Taken together, our results suggest that a tactical trend-following approach in crypto markets may be particularly appealing to two types of investors: those seeking to enhance diversification within a traditional trend-following portfolio, and those looking to capture the upside potential of crypto markets while avoiding the severe drawdowns that have characterized passive exposure to many digital assets.

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Born in Venice, currently resides in Zurich, Switzerland. He holds a Master degree in pure mathematics from the University of Amsterdam and a PhD in finance from the University of Lugano. He is Assistant Professor of Financial Technology at the FSI Center of the University of St.Gallen, Switzerland and at the Swiss Finance Institute. His research interests include asset pricing, monetary policy, fintech, blockchain, and machine learning. He is also head of AI at Concretum Research, and lead developer for the R-Candles web application.

Carlo Zarattini

Originally from Italy, Carlo Zarattini currently resides in Lugano, Switzerland. After completing his mathematics degree in Padova, he pursued a dual master's in quantitative finance at Imperial College London and USI Lugano. He formerly served as a quantitative analyst at BlackRock, where he developed volatility and trend-following trading strategies. Carlo later established Concretum Research, assisting institutional clients with both high and medium-frequency quantitative strategies in stocks, futures, and options. Additionally, he founded R-Candles.com, the first backtester for discretionary technical traders.

Alberto Pagani

Based in Piacenza, Italy, Alberto Pagani holds a bachelor's degree in management engineering from the University of Parma. In 2020, he was included in the National Registry of Excellence by the Ministry of Education, University, and Research (MIUR), and in 2022 he received the Young Students Fund Award (MIUR), honoring high-achievers in STEM disciplines. As of 2024, he is pursuing a master's degree in supply chain management. Driven by a strong interest in finance and mathematics, his research focuses on quantitative investment strategies, particularly trend-following and volatility-based approaches.

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Appendix. Long-Short Implementation

The long-only trend-following strategy described in Section 4.3 can be extended to a long-short framework by allowing the position to turn negative when downward breakouts occur. Specifically, the binary position signal $\mathrm{Pos}_t^n \in \{-1, 0, 1\}$ is modified to account for both upward and downward Donchian Channel breakouts.

The updated signal rule is defined as:

$$\mathrm{Pos}_t^n = \begin{cases} 1 & \text{if } \mathrm{Close}_t = \mathrm{DonchianUp}_t^n \\ -1 & \text{if } \mathrm{Close}_t = \mathrm{DonchianDown}_t^n \\ 0 & \text{if } \mathrm{Close}_t \leq \mathrm{TrailingStop}_t^n \text{ and } \mathrm{Pos}_{t-1}^n = 1 \\ 0 & \text{if } \mathrm{Close}_t \geq \mathrm{TrailingStop}_t^n \text{ and } \mathrm{Pos}_{t-1}^n = -1 \\ \mathrm{Pos}_{t-1}^n & \text{otherwise.} \end{cases}$$

The trailing stop mechanism is also adjusted to be direction-aware. For long positions, the trailing stop evolves as:

$$\mathrm{TrailingStop}_{t+1}^n = \max\left(\mathrm{TrailingStop}_t^n, \mathrm{DonchianMid}_t^n\right),$$

whereas for short positions, it follows:

$$\mathrm{TrailingStop}_{t+1}^n = \min\left(\mathrm{TrailingStop}_t^n, \mathrm{DonchianMid}_t^n\right).$$

The portfolio weight remains volatility-targeted and direction-sensitive, computed as:

$$w_t^n = \min\left(\frac{0.25}{\sigma_t}, 200\%\right) \times \mathrm{Pos}_t^n,$$

where σ_t is the 3-month rolling annualized volatility of the asset. The daily return of the n-day strategy remains:

$$r_t^n = w_{t-1}^{\mathrm{n}} \times \mathrm{ret}_t^{\mathrm{asset}}.$$

The ensemble *Combo* portfolio aggregates the signals of N models as before:

$$w_t^{\mathrm{Combo}} = \frac{1}{N}\sum_{i=1}^{N} w_t^{\mathrm{n}_i}, \quad n_i \in \{5, 10, 20, 30, 60, 90, 150, 250, 360\},$$

$$\mathrm{ret}_t^{\mathrm{Combo}} = w_{t-1}^{\mathrm{Combo}} \times \mathrm{ret}_t^{\mathrm{asset}}.$$

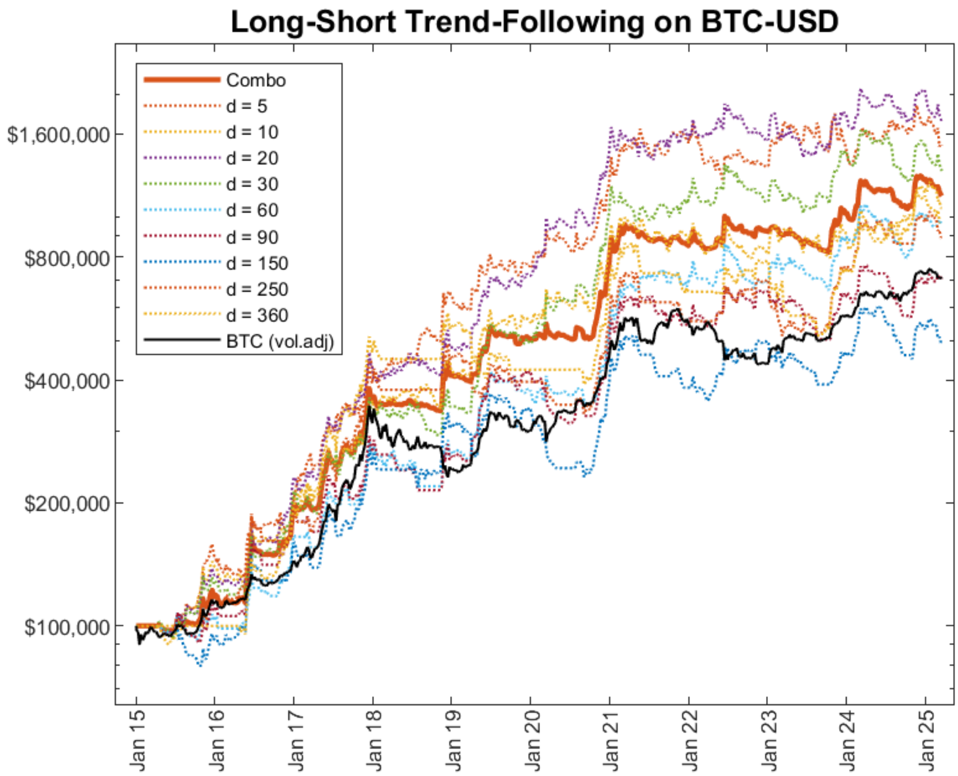

Figure 9: Cumulative equity curves of long-short trend-following models applied to Bitcoin, each calibrated using a different Donchian Channel look-back window. All strategies employ daily volatility targeting based on a 3-month rolling window of Bitcoin returns, scaled to a 25% annualized volatility target. The black line represents a passive long exposure in Bitcoin, rescaled to match the ex-post volatility of the ensemble *Combo* portfolio described in Section 4.3. The backtest spans from January 1, 2015, to March 19, 2025, and does not include transaction costs. Data source: `https://www.coinmarketcap.com`.

Table 5: Performance of BTC long-short trend-following models across various Donchian lookback windows. All models use Donchian Channels for signal generation and implement a daily volatility targeting scheme based on a 3-month rolling window of Bitcoin returns, targeting an annualized volatility of 25%. The *Combo* model refers to the ensemble approach described in Section 4.3. Metrics include CAGR, volatility, Sharpe and Sortino ratios, maximum drawdown (MDD), MAR (CAGR/MDD), annualized alpha, and beta versus BTC. The backtest period spans from January 1, 2015 to March 19, 2025. Transaction costs are not included. Alphas in **bold** are statistically significant at the 2.5% level. Data source: `https://www.coinmarketcap.com`.

Model	CAGR	Vol.	Sharpe	Sortino	MDD	MAR	Alpha	Beta
5d	30%	26%	1.05	1.53	28%	1.07	**30%**	0.00
10d	25%	25%	0.91	1.22	24%	1.02	**25%**	0.00
20d	32%	24%	1.15	1.47	27%	1.20	**29%**	0.02
30d	29%	24%	1.05	1.31	27%	1.04	**26%**	0.03
60d	25%	24%	0.94	1.13	29%	0.85	**20%**	0.07
90d	21%	24%	0.81	0.94	28%	0.75	14%	0.10
150d	17%	23%	0.67	0.78	39%	0.43	10%	0.10
250d	24%	22%	0.96	1.06	33%	0.73	12%	0.15
360d	26%	22%	1.04	1.13	43%	0.61	**15%**	0.14
Combo	27%	18%	1.31	1.78	19%	0.63	**20%**	0.07

Table 6: Trade-level statistics of BTC long-short trend-following models across various Donchian lookback windows. Metrics include the number of trades, win rate, average PnL and return per trade, maximum and minimum trade returns, and the gain-to-loss ratio. *Unit* refers to PnL and returns assuming the strategy trades one BTC contract per signal, while all other return figures are computed at the portfolio level. The backtest period spans from January 1, 2015 to March 19, 2025. Transaction costs are not included. Data source: `https://www.coinmarketcap.com`.

Model	Trades	Win Rate	AvgPnL × Unit	AvgRet × Unit	AvgRet	MaxRet	MinRet	Gain: Loss
5d	591	37%	\$90	1.3%	0.5%	29%	-7%	2.82
10d	304	34%	\$141	2.1%	0.9%	34%	-7%	3.45
20d	144	41%	\$356	5%	2.3%	45%	-7%	3.68
30d	98	39%	\$573	8%	3.4%	69%	-9%	4.27
60d	50	39%	\$1’782	15%	6%	89%	-7%	5.44
90d	35	41%	\$1’961	17%	8%	84%	-12%	4.71
150d	23	48%	\$1’735	26%	10%	90%	-12%	3.36
250d	12	67%	\$4’289	93%	26%	111%	-12%	4.97
360d	7	57%	\$8’897	340%	68%	350%	-13%	12.68

Table 7: Performance statistics of long-short diversified trend-following portfolios across different universe sizes, based on the strategy described in Section 7. Metrics include cumulative return (Tot.Ret.), compound annual growth rate (CAGR), annualized volatility (Vol.), Sharpe and Sortino ratios, maximum drawdown (MDD), MAR ratio (CAGR/MDD), and annualized alpha and beta relative to Bitcoin. The backtest includes a 10 basis point (bps) transaction cost and a 20% rebalance threshold, and spans the period from January 1, 2015 to March 19, 2025. Alphas in **bold** are statistically significant at the 2.5% level. Data source: `https://www.coinmarketcap.com`.

# Assets	Tot.Ret.	CAGR	Vol.	Sharpe	Sortino	MDD	MAR	Alpha	Beta
5	340%	16%	11%	1.09	1.38	18%	0.85	**13.9%**	0.02
10	358%	16%	10%	1.18	1.52	16%	0.99	**15.0%**	0.01
20	363%	16%	10%	1.24	1.61	13%	1.20	**15.5%**	0.00
30	339%	16%	10%	1.23	1.61	12%	1.27	**15.3%**	0.00
40	314%	15%	10%	1.20	1.57	12%	1.22	**14.9%**	0.00
50	303%	15%	10%	1.19	1.57	12%	1.19	**14.8%**	-0.01

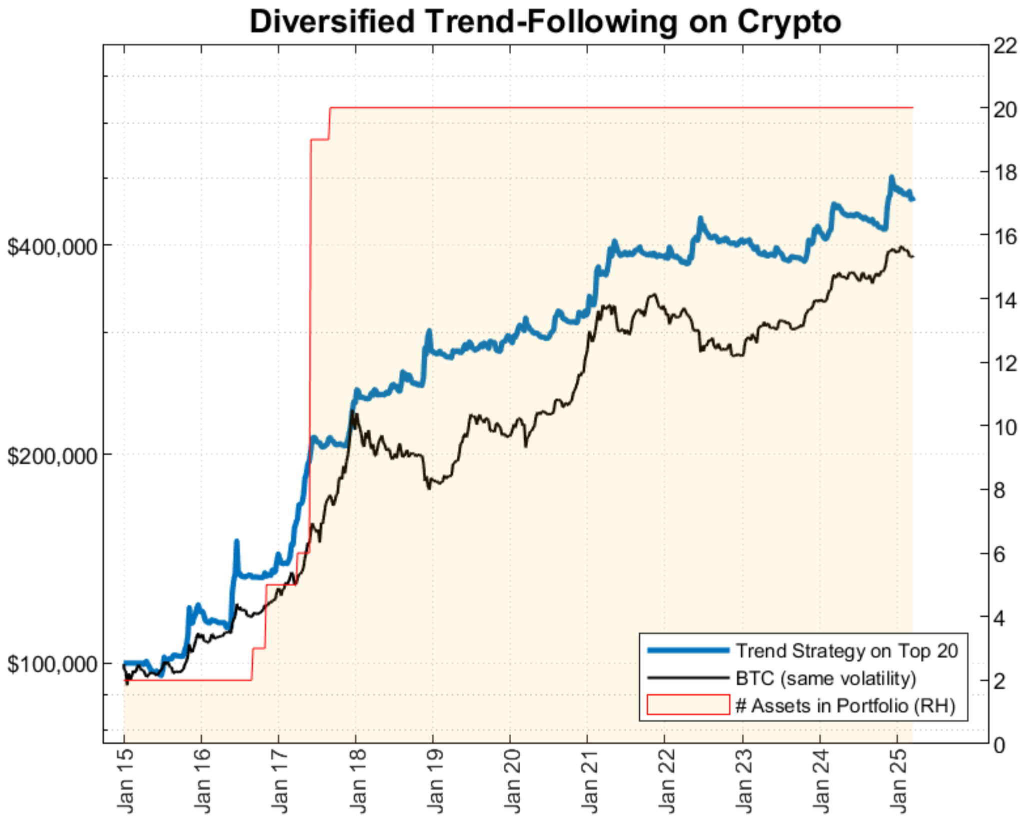

Figure 10: Performance of the long-short diversified trend-following program described in Section 7, applied to the top 20 most liquid cryptocurrencies each month. The blue line shows the equity curve of the strategy, which includes a 10 basis point transaction cost and a 20% rebalance threshold. The black line represents a passive long exposure to Bitcoin, rescaled to match the volatility of the trend strategy. The red line (right axis) shows the number of eligible assets included in the portfolio over time. Backtest period: January 1, 2015 to March 19, 2025. Data source: `https://www.coinmarketcap.com`.