Testing the Trend Factor:

Applications Across Asset Classes



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CANDIDATES:

137, 158, 103, 147

Abstract

This term paper investigates the applicability and performance of the trend factor, a quantitative investment strategy, in both traditional stock markets and the emerging cryptocurrency market. Using a Python-based implementation, we tested the factor on CRSP stock data from January 2011 to December 2020 and on Binance cryptocurrency futures data from January 2020 to July 2024. The paper analyzes the trend factor's ability to identify profitable patterns across asset classes and its effectiveness during periods of market stability and crises, such as the COVID-19 pandemic. Additionally, we examine the impact of transaction costs, revealing their significant influence on the strategy's profitability. As part of the research, we conducted an interview with Dr. Oliver Blaskowitz, a portfolio manager with expertise in quantitative strategies, to gain professional insights into the practical challenges of applying the trend factor in real-world scenarios. The findings highlight the strategy's potential while addressing its limitations in unconventional markets like cryptocurrencies.

Word Count: 5875

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List of Abbreviations

AMEX American Stock Exchange

CAPM Capital Asset Pricing Model

CRSP Center for Research in Security Prices

COVID-19 Coronavirus Disease 2019

ETF Exchange-Traded Fund

MA Moving Average

MDD Maximum Drawdown

NYSE New York Stock Exchange

OTC Over-The-Counter

SR Sharpe Ratio

WR Win Rate

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1 Introduction

When analyzing firms using various pricing models, the anomaly of momentum persists among models such as CAPM and the Fama-French three-factor model. However, these models have difficulties explaining these anomalies. The momentum anomaly itself shows that past performance significantly impacts future performance (Schwert, 2003).

There are three distinct momentum anomalies, which Han, Zhou, and Zhu (2016) incorporate into a model to develop a trend factor that can drive or contribute to investment decisions. The first and second anomalies are based on the overreaction hypothesis proposed by Bondt and Thaler (1985), which states that "most people overreact to unexpected and dramatic events."

The first is the short-term reversal effect, which relates to unusual changes in security prices within relatively short time frames (daily, weekly, monthly). These spikes or drops tend to reverse themselves in subsequent periods. Consequently, "investing fads" - investments driven by trends and media attention rather than financial fundamentals - create investment opportunities through irrational price movements, as investors can profit from the subsequent return to intrinsic value (Lehmann, 1990).

The second anomaly is the long-term reversal effect, which focuses on over-reaction within a three to five-year time frame. The long-term reversal effects behave similarly to the short-term effects, with minor divergences attributed to differences in the nature of information concerning the firm's short-term and long-term prospects, as well as systematic biases of investors (Titman & Jegadeesh, 1993; Bondt & Thaler, 1985).

The third anomaly is the momentum effect, which occurs over an intermediate time frame (3 to 12 months) and is primarily driven by the lead-lag effect. This effect describes the delay in price response to firm-specific information, and is not seen as sustainable. (Titman & Jegadeesh, 1993).

Building upon methodology used by Han et al. (2016), this paper has two major goals. The first is to replicate their model to test its current applicability, and the second is to explore whether their approach also works for unconventional asset classes. To achieve these objectives, we chose two different datasets.

2 Reconstructing the trend factor

2.1 Data

Han et al. (2016) utilized a dataset from the Center for Research in Security Prices (CRSP), which covers the daily stock prices from January 2, 1926, through December 31, 2014, for domestic (US-based) common stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and the Nasdaq stock market. However, following Titman and Jegadeesh (1993), they applied two filters:

stocks had to have a share price exceeding $5 (price filter) and could not be in the smallest decile by NYSE breakpoints (size filter). Han et al. (2016) later concluded these restrictions merely aided model management without improving performance - in fact, the opposite is true, as the sharpe ratio of the model without the filters is 0.64 compared to 0.47 with the filters.

Using this filtered dataset, they tested their trend factor across the entire period, and assessed tail risk by focusing on intervals pre-defined by CRSP as expansions or recessions. They placed particular emphasis on the 2007-2009 financial crisis to test the trend factor's robustness.

To review the models current applicability the dataset of CRSP was also selected, to ensure data consistency and to minimize discrepancies between the data used by this paper and the data used by (Han et al., 2016), while the selected timeframe for this paper is between the January 3rd 2011 and December 31st 2020. Additionally, we also separately analyze the time period beteween January 1st 2020 and July 1st 2020 to test the trend factor in an extreme scenarios, namely the COVID-19 pandemic. However, the size and price filters used by Han et al. (2016) and Titman and Jegadeesh (1993) were not used in the construction of our model, to increase the amount of considered stocks, which in return should improve the validity of our model.

The validity should improve as (Han et al., 2016) figured that the performance of the model is considerably better without filters, as previously explained. Additionally, the research of (Gu, Sun, Xiong, & Xu, 2024) proclaims that information uncertainty — which is high in firms that the models price and size filter secludes — drastically effects the precision of price information, leading investors to rely on trend signals, further improving the results of the trend factor.

To evaluate the model's broader applicability, we selected cryptocurrencies as an alternative asset class. Their structural properties - decentralized 24/7 trading, minimal regulation, and heightened volatility - present a challenging test case while retaining key similarities with stocks, such as price trends and market sentiment, that enable momentum modeling. Moreover, cryptocurrencies are characterized by significant levels of information uncertainty (Almeida, Dionísio, Vieira, & Ferreira, 2022), which should improve the results, based on (Gu et al., 2024), as previously expanded upon. We focused specifically on cryptocurrency futures data, the predominant derivative instrument for short positions in crypto markets. Rather than daily intervals, we analyzed 4-hour price signals, partly due to the limited historical data available (cryptocurrencies gained significant market presence only around 2020) and partly to test the trend factor's efficacy over shorter horizons. The data was sourced from Binance, the market's largest cryptocurrency exchange at the time of writing, and stretches from January 1st 2020 to July 31st 2024, ensuring comprehensive coverage.

2.2 Methodology

The trend factor as constructed by Han et al. (2016) is a way of ranking the analyzed assets through their expected performance estimated by cross-sectional regressions on normalized average prices across different lags. First they get the average price for each lag $L \in \mathcal{L}$ for each asset a

$$A_{a,t,L} = \frac{P^t_{a,d-L+1} + P^t_{a,d-L+2} + \cdots + P^t_{a,d-1} + P^t_{a,d}}{L} \tag{1}$$

where $P^t_{a,d}$ is the closing price of asset a on the last moment d of the holding period t, which for them is the last day of each month, since they rebalance their portfolio monthly. We will be building the same trend factor with higher granularity data, so d will come to represent the last 4-hour period of day t. The averages are then normalized by the last price

$$\tilde{A}_{a,t,L} = \frac{A_{a,t,L}}{P^t_{a,d}} \tag{2}$$

These normalized averages are then used in a cross-sectional regression of the returns $r_{a,t}$ of the assets $a = 1, \ldots, n$, where n is the number of assets

$$r_{a,t} = \beta_{0,t} + \sum_{L \in \mathcal{L}} \beta_{L,t} \tilde{A}_{a,t-1,L} + \epsilon_{a,t} \tag{3}$$

Note that when regressing the returns of period t, only normalized averages constructed with data up to $t-1$ are used, in order to make the regression forward-looking.

In order to predict the performance of each asset, not only the parameters of the last regression are used, but an expected future value for each $\beta_{L \in \mathcal{L}}$ is constructed by averaging its values across the last 12 regressions obtained with the last 12 holding periods

$$E_t[\beta_{L,t+1}] = \frac{1}{12} \sum_{m=1}^{12} \beta_{L,t+1-m} \tag{4}$$

Han et al. (2016, p. 363) show that this smoothing action is crucial for the predictive performance of the trend factor. The predictions made with these expected betas compute what Han et al. (2016) call the expected return in period $t+1$, but really is an expected performance, because they don't include the intercept

$$E_t[\lambda_{a,t+1}] = \sum_{L \in \mathcal{L}} E_t[\beta_{L,t+1}] \tilde{A}_{a,t,L} \tag{5}$$

where $E[\lambda_{a,t+1}]$ is the expected performance of asset a in period $t+1$. The reason they ignore the intercept is that the trend factor is meant only as a measure to rank assets relative to each other, and so including the intercept in the prediction would not change the resulting ranking as it contributes equally to the expected return of each asset (when including the intercept we would actually be computing the expected return).

In addition to using this approach for portfolio construction we attempt at improving it by using the intercepts of the regressions as a source of information. For that we also calculate an expected value for the intercept

$$E_t[\beta_{0,t+1}] = \frac{1}{12}\sum_{m=1}^{12}\beta_{0,t+1-m} \tag{6}$$

We use the intercept to compute expected returns

$$E_t[r_{a,t+1}] = E_t[\beta_{0,t+1}] + E_t[\lambda_{a,t+1}] \tag{7}$$

and we adapt the portfolio construction in two ways. If the expected intercept is positive, we only buy assets that have an expected return that is higher than it, and we short only assets that have a negative expected return. When the intercept is negative, we only short assets that have an expected return lower than the intercept and only buy assets that have a positive expected return. The assumption behind this choice is that the intercept represents a kind of expected market return, and so we try to select only asset that are expected to beat it, be it in an upward or downward movement, and more in general to only buy and sell assets that are expected to move in the direction we would like them to move.

$$\begin{cases} \text{if } E_t[\beta_{0,t+1}] > 0 : \begin{cases} \text{Long if: } E_t[r_{a,t+1}] > E_t[\beta_{0,t+1}] \\ \text{Short if: } E_t[r_{a,t+1}] < 0 \end{cases} \\ \\ \text{if } E_t[\beta_{0,t+1}] < 0 : \begin{cases} \text{Long if: } E_t[r_{a,t+1}] > 0 \\ \text{Short if: } E_t[r_{a,t+1}] < E_t[\beta_{0,t+1}] \end{cases} \end{cases}$$

2.3 Implementation

In this subsection, we outline the process of translating the methodology into code. The trend factor was implemented using Python along with several supporting libraries to ensure efficiency. This implementation simulates portfolio returns by combining short-, intermediate-, and long-term moving averages (MAs).

2.3.1 Portfolio Class Overview

We implemented a 'Portfolio' class that manages the tracking and computation of returns for long and short positions. Upon calling the 'update' method, the existing positions are cleared after their respective returns are calculated, and the new positions are stored with their associated entry prices. This iterative mechanism ensures that portfolio changes are efficiently managed, allowing the simulation to progress step-by-step.

2.3.2 Trend factor Initialization

We constructed a 'Trend_factor' class that encapsulates the simulation logic, focusing on the dynamic computation of trend signals using a set of predefined lag

periods. These lag periods dictate the window sizes for moving averages, spanning from 3 to 1,000 days. Those signals represent the price trends of the underlying stock across daily, weekly, monthly, quarterly, as well as 1-year, 2-year, 3-year, and 4-year intervals. However, due to the shorter duration covered by the cryptocurrency data provided, we needed to adjust the lags to range from 3 to 140 days.

The 'stepsize' parameter determines the rebalancing frequency, while the 'smoothing_factor' controls the number of historical coefficients used to compute expected performances. This ensures that trend signals are informed by both recent and long-term dynamics. Additionally, to the modification of lags, the smoothing factor for the cryptocurrencies was set to 42 instead of 12, and the stepsize was reduced to 6 instead of the original 20. The initialization phase includes a bootstrap process to calculate initial coefficients ('betas') for each lag. The coefficients are derived through linear regression on historical data, where returns serve as the dependent variable, whereas the lagged moving averages act as explanatory variables.

We constructed two classes that prepare the respective datasets by cleaning, filtering, and transforming them into suitable formats for analysis. This approach allows us to smoothly integrate our data into our implementation. Besides preparation, the classes also enable the representation of our dataset in order to provide an overview. For instance, the 'CryptoData' class extracts Bitcoin-related columns and visualizes their average prices, while the 'Stocks' class offers tools for examining correlations and plotting individual stock trends.

2.3.3 Signal Generation and Moving Averages

To generate trend signals we wrote a method that computes returns and price averages over a fixed interval ('lag'). The regression that is fed these signals forms the basis for identifying assets with the highest and lowest expected performances.

2.3.4 Simulation

Building on this, we provided a simulation that iteratively updates the portfolio by identifying long and short positions based on expected performances. This process is automated across the data's time span.

3 Stocks

3.1 Testing Model Applicability

Since market conditions change over time and a lot has happened since 2016, we backtest the model on the same CRSP dataset, however, extending it up to December 31st 2020. This subsection analyzes the metrics and rations resulting from the backtest. Table 1 provides an overview of the results.

Metric	Value
Cumulative Return	11.9048
Average Return	1.0401
Standard Deviation	0.0400
Skew of Returns	0.975
Kurtosis of Returns	0.332
Sharpe Ratio	1.0209
Maximum Drawdown	-0.0254
Win Rate	0.9048

Table 1: Performance metrics stocks

The statistical analysis of the trend factor following the CRSP dataset shows promising results. With an average return of 4.01% per month (calculated as a geometric mean) and a cumulative return of 1090.48% over the entire time-horizon of the dataset, the backtest suggests that the trend-following strategy effectively captures market movements.

The positive skew of the returns is easy to see in Figure 1, and shows that there are clearly more positive than negative returns and also more extreme positive than negative values. The extremely low kurtosis is likely caused by the low sample size of holding periods, since we are testing the factor over a relatively modest timeframe.

However, returns always have to be seen in relation to their associated risk, since the two are fundamentally interconnected in determining the attractiveness and viability of an investment. Therefore, we also consider risk-measuring metrics.

The first metric is the standard deviation, which has a value of 4%. The constructed portfolio's standard deviation indicates that the results are relatively stable and can be considered conservative when compared to conventional portfolios. The stability of the model is crucial for its success, as it indicates that the strategy effectively forecasts market trends and achieves long-term sustainable performance.

The next metric is the sharpe ratio, which we use primarily due to its industry influence (Scholz, 2007) and its use as a performance metric in (Han et al., 2016). It is calculated as the ratio of excess returns, using the arithmetic mean, to standard deviation. The returned value signals if the associated risk of an investment is considered reasonable, in relation to its expected return. A value above 1 indicates that the risk of the investment is reasonable for the related pay-off, while an investment with a sharpe ratio below 1 is considered to be suboptimal. When calculating the sharpe ratio we get a value of 1.02, which emphasizes the trend factor's ability to deliver modest returns for each unit of risk undertaken.

To further analyze the performance of the model, in relation to its risk, we analyzed the maximum drawdown. With a value of -2.54% the trend-following approach shows how well it is equipped to adapt to unfavorable market conditions. This suggests that the trend factor portfolio generates positive returns rather consistently.

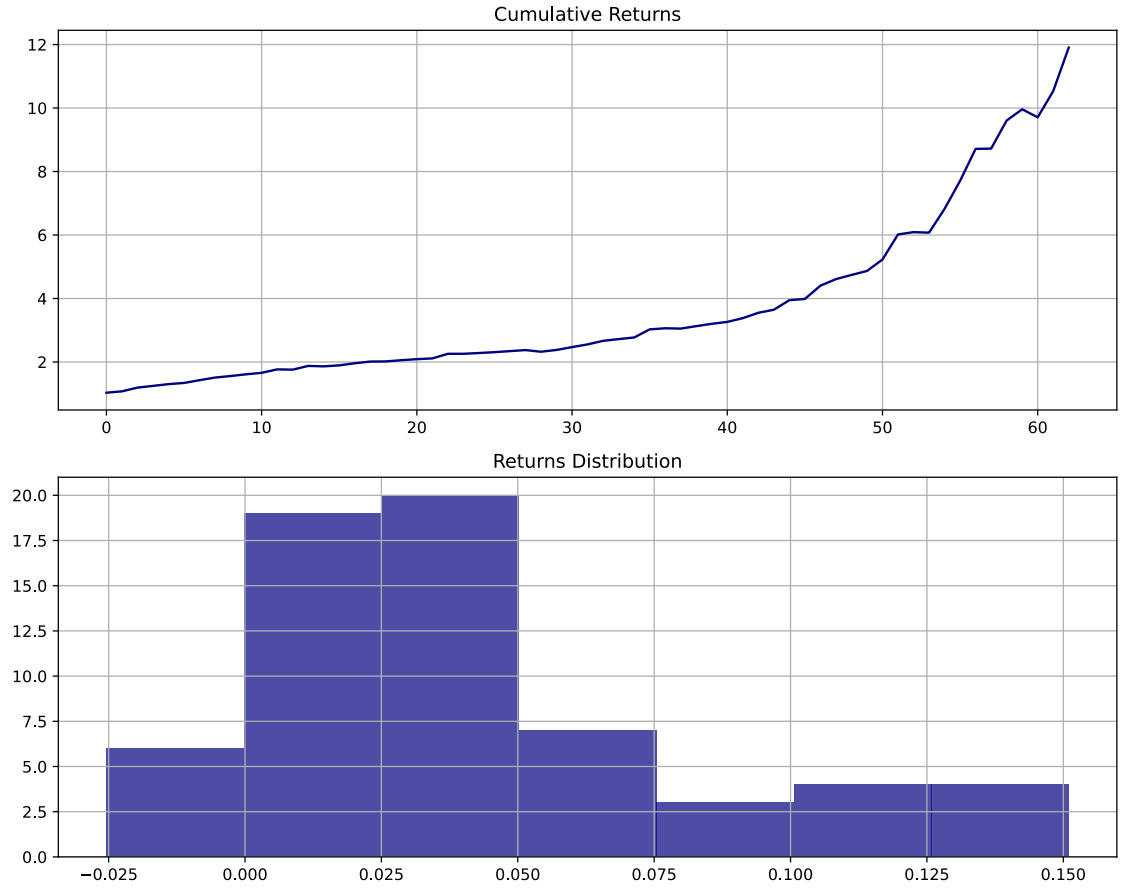


Figure 1: Cumulative returns and returns distribution of stock portfolio

The win rate is a metric that analyzes how many of the formed portfolios result in periods that create positive returns. Here, the win rate is about 90%. This high success rate is a testament to the effectiveness of the trend factor in identifying profitable market trends and avoiding unfavorable conditions.

In conclusion, the backtest has demonstrated the continued pertinence of the trend factor in the conventional stock market.

3.2 Analysis of Crisis Periods

Han et al. (2016) found that the trend factor performed exceptionally well during recessions and financial crises, compared to the market and even other factors. Therefore, it was interesting for us to investigate whether the trend factor demonstrates the same behavior during the COVID-19 pandemic, which caused significant economic and financial disruptions. To achieve this, we designed our framework to allow for focused analysis of specific periods. To conduct the analysis, we refined our dataset by restricting it exclusively to stock data from the year 2020. Table 2 summarizes the key statistics.

In general, the trend factor demonstrates strong performance during the COVID-

Metric	Value
Cumulative Return	2.2711
Average Return	1.0707
Standard Deviation	0.0822
Sharpe Ratio	0.8931
Win Rate	0.9167
Maximum Drawdown	-0.0026

Table 2: Performance metrics stocks COVID-19

19 crisis, as reflected in its cumulative return. Over the 13-month period, the strategy achieved a total gain of 127.11%. The geometric mean of the monthly returns, at 7.07%, further underscores this achievement, particularly when compared to the entire sample period, where the average return is notably lower at just 4.01%. These results align with the findings of Han et al. (2016).

The elevated standard deviation of 8.22%, which is double that of the complete sample period, indicates a greater exposure of the portfolio to heightened market volatility. This observation is consistent with the findings of Han et al. (2016), suggesting that the trend factor tends to perform more effectively under conditions of greater information uncertainty, as indicated by proxies such as idiosyncratic volatility. However, the sharpe ratio of 0.89, being below 1, indicates suboptimal risk-adjusted performance, suggesting that the returns may not fully justify the level of risk undertaken.

Nonetheless, when compared to the sharpe ratio of 0.15 reported during the financial crisis from December 2007 to June 2009 in the original study, the trend factor demonstrates a significantly stronger performance. Additionally, in contrast to its performance during other recessionary periods, the trend factor exhibits notably better results in this instance. The win rate of 91.67%, coupled with the maximum drawdown of -0.26%, reflects an impressive balance of consistent returns and strong risk control.

Research indicates that during such volatile periods, the performance of various strategies can vary significantly. For instance, a study by Kaminski (2020) found that pure trend-following strategies and faster systems tended to outperform multi-strategy and slower approaches during the 2020 crisis. This suggests that the adaptability and speed of trend-following models are crucial factors in their effectiveness amid rapidly changing market conditions. However, it is essential to acknowledge potential limitations. The COVID-19 crisis was marked by unprecedented and rapid market dynamics, which may challenge the robustness of trend-following strategies (Morgan, 2024). Similar to findings in the "Best-of-Two"-strategy (Ardia, Boudt, Hartmann, & Nguyen, 2022), where rapid market downturns and recoveries exposed shortcomings in its responsiveness, our trend factor model may also face challenges in adapting to extreme volatility and abrupt shifts in market conditions.

4 Cryptocurrencies

4.1 Applying the trend factor to an alternative asset class

As cryptocurrencies represent a fundamental different market, the applicability and translatability of the trend factor provide good insight into its robustness and universality. In this subsection, we analyze this exact suitability of the trend factor for alternative asset classes. Table 3 provides an overview of the results.

Metric	Value
Cumulative Return	2.9743
Average Return	1.0007
Standard Deviation	0.0128
Skew of Returns	0.4630
Kurtosis of Returns	4.4330
Sharpe Ratio	0.0592
Maximum Drawdown	-0.3565
Win Rate	0.5162

Table 3: Performance metrics cryptocurrencies

We obtain mixed results, especially, when comparing them to those of the factor applied to traditional stocks.

When applying the model to cryptocurrencies, we obtain an average return of 0.07% per day and a cumulative return of 197.43%. This suggests that the model is also capable of performing well in the cryptocurrency market, identifying and capitalizing on market trends. The skew is slightly positive, reinforcing the same point, and there is some excess kurtosis, meaning the distribution of returns is peaked with long tails. Hence, there are more extreme events, both positive and negative, than a normal distribution would predict.

However, as previously acknowledged, returns must always be considered in relation to their associated risk, in order to provide a comprehensive representation. The standard deviation of the returns is 1.28%, which is significantly lower than 4.00% when applied to regular stocks. This suggests that the model is able to generate on average positive returns over short daily timeframes for cryptocurrencies. Here it is important to acknowledge that the holding period (the frequency of portfolio updates) likely contributes significantly to the disparity. With a sharpe ratio of just 0.0592, the performance of the factor is rather poor with regard to the risk taken. In addition, the short time horizon of the cryptocurrency dataset, prevents the exploitation of long-term momentum effects.

The high value of the maximum drawdown of 35.65% further highlights the difficulties the trend model has in predicting market movements for cryptocurrencies. This is particularly evident when compared to the maximum drawdown of the trend factor applied to regular stocks, which is only 2.54%. This disparity highlights the inadequacy of the trend factor model in evaluating assets that deviate from conven-

tional market patterns, like cryptocurrencies, as these assets exhibit extraordinary volatility and unpredictable, random market movements.

We also see a difference compared to the results with stocks in the win rate. With a win rate of 50.62%, the factor barely surpasses random chance, indicating that the model lacks the ability to accurately identify profitable trends in the cryptocurrency market. This may be linked to the extreme market characteristics of cryptocurrencies, such as high volatility, frequent reverses in trends, and high noise.

To conclude, the test demonstrates that the model can be applied to cryptocurrencies. However, the returned results are significantly inferior to those of its traditional counterparts.

5 Incorporating the intercept

The information provided by the intercepts of the cross-sectional regressions is incorporated in two ways in the portfolio construction process. First, instead of performance, returns are calculated. Additionally, if the expected intercept is positive, we only buy assets that have an expected return that is higher than it, and we short only assets that have a negative expected return. When the intercept is negative, we only short assets that have an expected return lower than the intercept and only buy assets that have a positive expected return.

The resulting performance differs significantly from the simple implementation of the trend factor. With stocks, the cumulative return shoots up to an impressive 1876.54% with an average monthly return of 4.85%. With cryptocurrencies the cumulative return raises to 501.26% with an average daily return of 0.11%. However, for both asset classes the standard deviation increases too, leading to a worse risk-adjusted performance. For stocks the sharpe ratio decreases to 0.91 and for cryptocurrencies to 0.047.

Interestingly with stocks this version of the trend factor has a lower win rate of 84%, suggesting that the excess returns are generated by a relative minority of big winners and not a consistently higher performance. With cryptocurrencies the win rate stays approximately the same.

6 The influence of market volatility on the profitability of the trend factor

The study by Gu et al. (2024) investigates how stock market volatility influences the profitability of trend-following investment strategies. They suggest that during volatile market conditions, fundamental analysis may become less precise, prompting investors to rely more heavily on trend signals, thereby enhancing the effectiveness of trend-following strategies. Analyzing data from 1931 to 2022, the authors find that the trend factor yields significantly higher risk-adjusted returns following periods of elevated market volatility. We aimed to build upon these findings and

adapt them to our datasets. To validate our code and examine whether there is a correlation between returns and standard deviation—using the stock data as affirmed in Gu et al. (2024)—we decided to begin with a linear regression analysis of the features within the CRSP dataset.

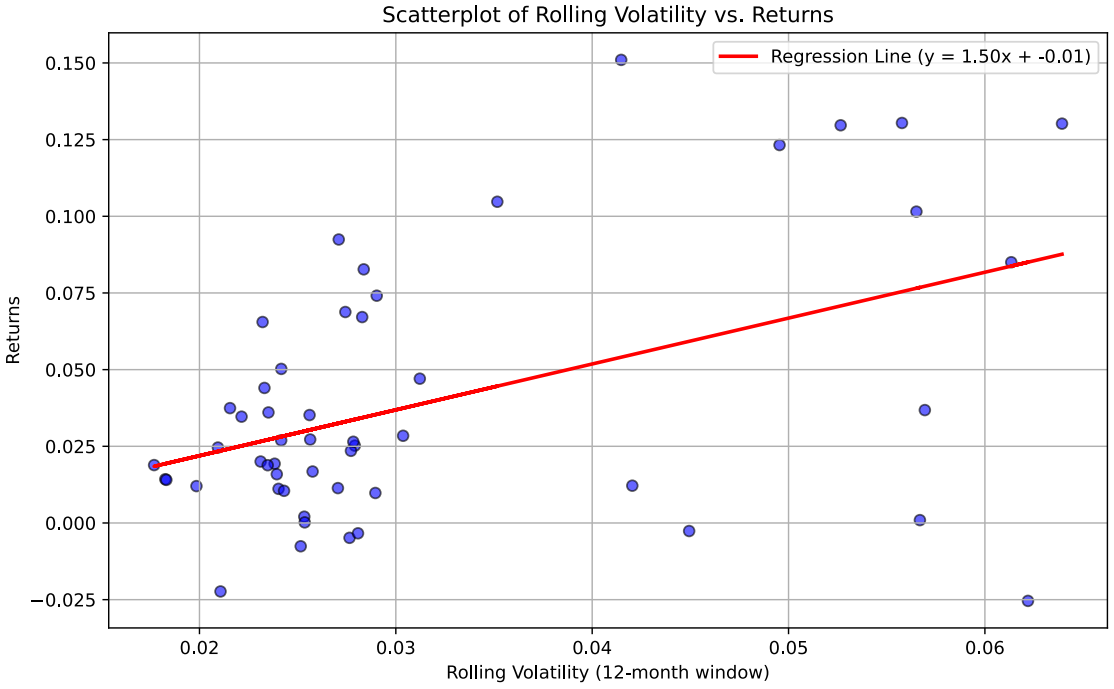


Figure 2: Correlation between market volatility and trend factor returns of stock portfolio

The correlation coefficient of 0.4568 indicates a tendency for returns to increase as market volatility rises, though the relationship is relatively likely not statistically significant, due to the low number of holding periods. This correlation supports the notion that the trend factor may perform better in more volatile environments, albeit with considerable variability in the data.

To explore whether a similar connection exists between market volatility and trend factor performance in the cryptocurrency market, we conducted the same analysis. A correlation coefficient of 0.0619, which is nearly zero, indicates no linear relationship between rolling volatility and returns in this dataset. Unlike the previous correlation of 0.4568 observed in stock data, the crypto data provides no evidence that increased volatility correlates with higher or lower returns. This lack of relationship is further illustrated in the plot, where the regression line is almost flat, underscoring the absence of a trend.

This absence of correlation might indicate that cryptocurrency markets do not follow the same patterns as traditional stock markets. Crypto markets are often more speculative, with price movements driven by factors unrelated to volatility, such as market sentiment, technological adoption, regulatory developments, or macroeconomic news (Koutmos, 2018).

An additional observation is the lower range of volatility in the crypto dataset.

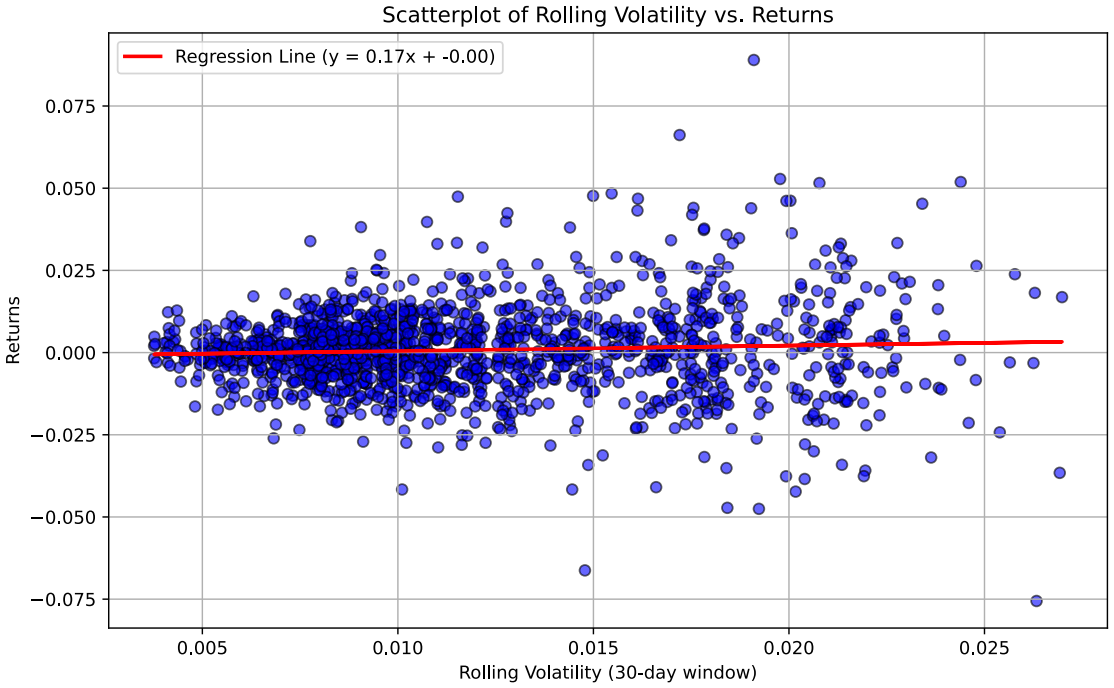


Figure 3: Correlation between market volatility and trend factor returns of cryptocurrency portfolio

Compared to the stock dataset, volatility levels are slightly lower, with the majority of values falling below 0.08. In the stock-based trend factor portfolio, a moderate positive correlation suggested that returns tended to increase during periods of heightened volatility. In contrast, for cryptocurrencies, returns appear to be independent of volatility.

While the trend factor portfolio in traditional stock markets exhibited a moderate positive correlation, suggesting improved performance during more volatile periods, the absence of such a relationship in crypto returns raises questions about the applicability of traditional assumptions to these markets. This divergence underscores the need to critically examine the limitations of our analysis in investigating the correlation between market volatility and the profitability of the trend factor in cryptocurrencies. Several factors constrain both the interpretation and broader relevance of our findings.

Initially, the relatively narrower range of volatility observed in the cryptocurrency dataset compared to stock data (Figure 3) might have constrained our ability to detect meaningful correlations. Traditional stock datasets exhibit a broader spectrum of volatility conditions, allowing for a clearer analysis of trends during extreme market events. Furthermore, cryptocurrencies, being a relatively new financial instruments, lack the extensive historical data available for traditional stock markets. The study by Gu et al. (2024), which analyzes nearly a century of stock data, benefited from robust datasets to establish statistically significant relationships. In contrast, cryptocurrency markets, with only about a fraction of that amount of data, may suffer from limited sample sizes, reducing the statistical power of our findings.

Unlike stock markets, where volatility is often tied to macroeconomic indicators and corporate fundamentals, cryptocurrency markets are driven by speculative behavior, sentiment, and non-economic factors such as media influence, technological trends, and regulatory announcements (Koutmos, 2018). These distinct drivers may explain the absence of a strong correlation between volatility and trend factor returns in our analysis.

7 Implementation in practice

7.1 Expert Interview

To gain deeper insights into the challenges and opportunities of applying the trend factor in portfolio management, we conducted an expert interview with Dr. Oliver Blaskowitz, an experienced portfolio manager specializing in quantitative strategies.

Dr. Oliver Blaskowitz is a seasoned portfolio manager with over 15 years of experience in capital markets, specializing in quantitative investment strategies and megatrends. Currently serving as Senior Portfolio Manager at Berliner Volksbank eG, he previously worked as a Fund Manager at Apo Asset Management GmbH and co-founded the Robo-Advisor growney. Dr. Blaskowitz holds a Ph.D. in Econometrics from the University of Kiel, is a certified CIIA investment analyst, and has lectured at Humboldt University in Berlin.

He has kindly agreed to share his thoughts on the trend factor discussed in the paper and compare it to the strategies he uses in his own work. The entirety of the interview can be found in the appendix.

Dr. Blaskowitz explained that, because the trend factor is a rule-based strategy that relies only on price data, unlike fundamental strategies that include earnings or balance sheet metrics, it doesn't account for the bigger economic picture. He also mentioned that transaction costs, especially for small-cap stocks, can reduce its returns significantly. These costs vary across time and asset types, making them difficult to compare. A main reason he can't use the trend factor in his current strategy is that it needs special licenses and tools to access and process the data. He also mentioned that, if used, he would allocate no more than 5% of his portfolio to the trend factor to maintain diversification.

In crises, Dr. Blaskowitz said the trend factor performs well during long-term downturns, like the dot-com bubble, where trends take time to form. However, it might struggle in fast-moving crises like COVID-19 because it can't react quickly enough. He compared this to Scalable Capital's Volatility approach, which also failed to adjust during the pandemic's rapid market changes. To improve, he suggested breaking the trend factor into short-, medium-, and long-term components to see how each works in different situations. Adding real time volatility indicators could also make it more responsive.

When it comes to cryptocurrencies, Dr. Blaskowitz pointed out some possible challenges. Unlike traditional assets, which are influenced by supply and demand

alongside economic fundamentals, Bitcoin's supply is fixed at 21 million. This means its price is entirely driven by demand. In today's market, this demand is heavily influenced by social media platforms like TikTok, Instagram, and YouTube, as well as finfluencers and news cycles. Such speculative behavior and media-driven hype make cryptocurrencies particularly vulnerable to bubbles. Unlike stocks, there's no value-based correction mechanism to stabilize prices when they deviate from intrinsic worth. Because of this, long-term momentum strategies don't work as well. He recommended combining short-term and long-term momentum measures, such as five-day and 12-month cycles, to better capture the price patterns in crypto markets.

To make the trend factor more useful for cryptocurrencies, he suggested creating synthetic datasets or using proxies like high-volatility small-cap stocks to simulate longer histories. Sentiment analysis could also help, using tools like natural language processing to track trends on social media and in the news.

However, Dr. Blaskowitz emphasized that transaction costs remain the trend factor's biggest limitation. These costs significantly impact its practicality in real-world portfolio management. In the next section, we will address this issue with adjustments to our model.

7.2 Incorporating transaction costs into trend factor analysis

Our expert interview highlighted the critical importance of accounting for transaction costs. High turnover rates in trend-following strategies can significantly impact net returns in real-world applications, especially for cryptocurrencies. To address the crucial role of transaction costs shaping net returns due to the daily portfolio updates required in this context, we integrated transaction cost estimates into our evaluation framework, ensuring a more realistic assessment of the strategy's profitability.

For stocks, we applied a transaction cost estimate of 0.1%, which aligns with typical rates in equity trading. The results revealed that transaction costs substantially impact performance. The cumulative return, for instance, dropped to 954.44%, illustrating the compounding negative effect of trading expenses over the sample period. Although the average return was only slightly reduced to 3.81%, the sharpe ratio fell to 0.971, indicating a notable decline in risk-adjusted returns. Despite these reductions, the maximum drawdown remained relatively low at -2.74%, and the win rate stayed high at 87.3%, demonstrating the strategy's resilience in identifying profitable trends and minimizing significant losses even with the added friction of transaction costs.

Cryptocurrencies proved to be significantly more sensitive to transaction costs compared to stocks, highlighting their higher turnover rates and market dynamics. To quantify this impact, we refined our trend factor model by incorporating a transaction cost estimate of 0.02%, based on data from major trading platforms, and calculated the key performance metrics, as shown in Table 5.

Metric	Value
Cumulative Return	10.5444
Average Return	1.0381
Standard Deviation	0.0400
Sharpe Ratio	0.9709
Win Rate	0.5162
Maximum Return	0.8731

Table 4: Performance metrics stocks with transaction costs

In comparison to the previous results, the inclusion of transaction costs has a profound effect on the profitability and efficiency of the cryptocurrency portfolio, as mostly reflected in its cumulative return. Over the entire sample period, the strategy's total gain of 195.98% decreased to less than a third, reaching 56.37%. This significant reduction illustrates the compounding negative impact of transaction costs on long-term profitability.

The average daily return decreases marginally, from 0.07% to 0.03%. Even though the difference seems negligible on a daily basis, over time, this reduction compounds and significantly influences the cumulative return, as seen above. The standard deviation however, remains constant at 1.28% in both scenarios, indicating that transaction costs do not influence the portfolio's overall volatility. This suggests that while the risk levels are consistent, the cost of trading reduces profitability. The sharpe ratio is halved, decreasing from 0.0590 in the original portfolio to 0.02806. This highlights a significant reduction in risk-adjusted returns, implying that the portfolio becomes less efficient at converting risk into reward when transaction costs are considered. The win rate decreases slightly, from 51.62% to 49.63%. This shows a small but notable reduction in the proportion of trades that are profitable when transaction costs are factored in, contributing to the diminished overall performance. The maximum drawdown worsens substantially, increasing from -35.65% to -53.64%, making it approximately 1.5 times larger. This indicates that the inclusion of transaction costs not only reduces profitability but also increases the depth of potential losses.

Metric	Value
Cumulative Return	1.56373
Average Return	1.0003
Standard Deviation	0.0128
Sharpe Ratio	0.02806
Win Rate	0.4963
Maximum Drawdown	-0.5364

Table 5: Performance metrics cryptocurrencies with transaction costs

While our estimates are based on available information, such as a transaction cost of 0.02% (per website), we acknowledge that these values may vary depending

on specific trading conditions and platforms. This adjustment aims to provide a more realistic understanding of the trend factor's performance in the cryptocurrency market, reflecting the practical challenges associated with high trading frequency.

8 Conclusion

The trend factor shows great potential as a systematic investment tool. It uses price data to predict performance and has delivered strong results in traditional stock markets. It takes advantage of momentum anomalies like short-term reversals, long-term reversals, and intermediate momentum. Our backtesting confirmed its ability to generate strong returns, especially during stable periods or crises where trends develop abruptly. For example Our test over the COVID-19 pandemic showed that it still performed very well.

Our analysis of the trend factor's relationship with cryptocurrency volatility revealed several limitations. One of the biggest challenges is the lack of historical data. Unlike stock markets, which have decades of reliable data, cryptocurrencies have only been around for about 10 years. We used data from the most recent 4 years of this period, as they represent the peak of cryptocurrency popularity and market activity. This small sample size makes it harder to draw strong, statistically reliable conclusions.

Another issue is the nature of cryptocurrency markets. Unlike stocks, where volatility is often tied to fundamentals or economic indicators, crypto markets are heavily influenced by speculative behavior, media trends and social sentiment. Our interview partner Dr. Blaskowitz pointed out that this makes cryptocurrencies very sensitive to hype and sudden price changes.

Transaction costs are another key issue. High turnover in trend-following strategies can significantly reduce returns, especially for small-cap stocks. For stocks, the inclusion of a 0.1% transaction cost demonstrated a notable impact on cumulative returns, which dropped to 10.54. While the average return was only marginally reduced to 1.038, the Sharpe ratio fell to 0.971, signaling reduced risk-adjusted performance. Despite this, the strategy proved resilient, maintaining a relatively low maximum drawdown of -2.74% and a high win rate of 87.3%. This indicates that the trend factor remains effective in identifying profitable trends and managing losses even under transaction cost constraints. Cryptocurrencies, however, were much more affected by transaction costs due to their higher turnover and volatility. With a 0.02% transaction cost, cumulative returns dropped dramatically from 195.98% to 56.37%. The sharpe ratio was cut in half, and maximum drawdowns increased from -35.65% to -53.64%, making losses much deeper. While daily return volatility stayed the same, the strategy became less efficient at turning risk into reward. This supports what our expert Dr. Blaskowitz highlighted during the interview: transaction costs are a major challenge for applying the trend factor in real-world scenarios.

References

Almeida, D., Dionísio, A., Vieira, I., & Ferreira, P. (2022). Uncertainty and risk in the cryptocurrency market. *Journal of Risk and Financial Management*, *15*(11). Retrieved from https://www.mdpi.com/1911-8074/15/11/532 doi: https://doi.org/10.3390/jrfm15110532

Ardia, D., Boudt, K., Hartmann, S., & Nguyen, G. (2022). Properties of the margrabe best-of-two strategy to tactical asset allocation. *International Review of Financial Analysis*, *81*, 101306.

Bondt, W. F. M. D., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, *40*(3), 793–805. Retrieved 2024-11-26, from http://www.jstor.org/stable/2327804

Gu, M., Sun, M., Xiong, Z., & Xu, W. (2024). Market volatility and the trend factor. *Finance Research Letters*, *65*, 105595. Retrieved from https://www.sciencedirect.com/science/article/pii/S1544612324006251 doi: https://doi.org/10.1016/j.frl.2024.105595

Han, Y., Zhou, G., & Zhu, Y. (2016). A trend factor: Any economic gains from using information over investment horizons? *Journal of Financial Economics*, *122*(2), 352-375. doi: https://doi.org/10.1016/j.jfineco.2016.01.029

Kaminski, K. M. (2020, September). Reflections on ten years in trend following [White Paper].
(Available at AlphaSimplex Insights)

Koutmos, D. (2018). Bitcoin returns and transaction activity. *Economics Letters*, *167*, 81–85.

Lehmann, B. N. (1990, 02). Fads, martingales, and market efficiency*. *The Quarterly Journal of Economics*, *105*(1), 1-28. Retrieved from https://doi.org/10.2307/2937816 doi: 10.2307/2937816

Morgan, J. P. (2024, December). *Market Volatility Continues to Surge as Virus Escalates.* J.P. Morgan. Retrieved from https://www.jpmorgan.com/insights/current-events/covid-19/market-volatility-covid19 ([Online; accessed 8. Dec. 2024])

Scholz, H. (2007). Refinements to the sharpe ratio: Comparing alternatives for bear markets. *Journal of Asset Management*, *7*(5), 347-357. doi: https://doi.org/10.1057/palgrave.jam.2250040

Schwert, G. (2003). Anomalies and market efficiency. *Handbook of the Economics of Finance*, *1*.

Titman, S., & Jegadeesh, N. (1993, 02). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, *48*, 65-91. doi: 10.1111/j.1540-6261.1993.tb04702.x

A Appendix

A.1 Interview with Dr. Oliver Blaskowitz

1. **Can you tell us about your current role and responsibilities as a portfolio manager?**

   I'm currently working in a fundamental discretionary investment team at Berliner Volksbank. Previously, I spent many years in a purely quantitative, rule-based setup, where decisions were derived from strict rules—metrics like volatility thresholds or return targets. Now, my role is more hands-on, focusing on bringing structure and some rule-based discipline into a discretionary environment. It's an interesting challenge because in a discretionary setup rules can be implemented but are often overridden by human judgment. My task is to create a framework where these rules are robust and actually followed.

2. **How does a rule-based approach differ from a fundamental discretionary approach?**

   Rule-based approaches are straightforward—you follow the data and predefined rules. For example, you might decide to invest only in stocks with a price-to-earnings ratio above a certain value. It's systematic, and there's no room for deviation. Fundamental discretionary investing, on the other hand, is more nuanced. Here, we analyze company fundamentals like price-to-book ratios, return on equity, or growth estimates. Then, based on this data and the overall narrative of the company, we form an opinion. It's more human and flexible but also less consistent compared to the strict discipline of a rule-based system.

3. **How would you define the trend factor?**

   The trend factor is a rule-based strategy that uses price data to identify patterns, without incorporating earnings or balance sheet metrics. It's strictly quantitative, meaning it can be backtested over decades with consistency. Essentially, it's a hybrid between momentum (tracking price trends) and value (identifying undervalued opportunities).

4. **What role do factors like Value, Momentum, and Low Volatility play in this strategy?**

   These factors are grounded in strong economic principles, which is why they continue to generate returns over time. Take value investing, for instance—it's based on the idea of buying something priced below its intrinsic value. Let me give you an example: imagine a pair of women's shoes in a store priced at €500. You'd only buy them if you think they're worth more to you, say €1,000. For me, those shoes would have a value of €0 because I don't need them. This is the essence of value investing: buying something that's worth more than what you're paying. Momentum works similarly, capturing

behavioral tendencies like the herd mentality, while low volatility appeals to investors looking for stable returns.

5. **How does the Trend Factor compare to these traditional factors?**

   The trend factor is interesting because it combines elements of both value and momentum. Like momentum, it captures trends, and like value, it focuses on mispricing—but with one key difference: it's strictly rule-based, using price data alone without incorporating fundamental metrics. It's a kind of hybrid strategy, but to make it effective, you'd need to hold positions for a longer period, just like value investing, where it often takes 2–5 years for the market to correct an undervaluation.

6. **Can the trend factor support fundamental analysis in investment decisions?**

   The trend factor, as it is backtested, is strictly rule-based and relies only on price data—no earnings, no balance sheet metrics. This makes it challenging to integrate directly into a discretionary framework, which typically emphasizes fundamental analysis. However, it could work as a complementary tool to identify market trends or validate discretionary decisions. For example, if a discretionary analysis points toward an undervalued stock, the trend factor could confirm whether the stock is also showing positive momentum. It's about finding a balance between these approaches to enhance decision-making.

7. **How would you integrate the Trend Factor into an investment strategy?**

   The key is simplicity. The Trend Factor is already appealing because it requires fewer inputs—just a single time series of price data per company instead of dozens of financial metrics. In practice, keeping things simple is crucial. Complex systems with huge databases, constant updates, and costly optimizations often don't deliver better results. Instead, a simple, well-designed system can achieve similar performance with far less effort and cost. For me, simplicity and diversification are the cornerstones of any successful strategy.

8. **Why do you emphasize simplicity and diversification in investment strategies?**

   There's wisdom in simplicity, supported by both empirical research and practical experience. Complex models may seem sophisticated, but they often face challenges like local optimization issues or high costs for data and infrastructure. Simpler methods can deliver almost the same forecast quality with far less hassle. Similarly, diversification is essential—it's not a new concept. The Babylonian Talmud, written over 2,000 years ago, advises splitting assets across different categories. The saying "don't put all your eggs in one basket" persists for a reason: it works.

9. **Would you integrate the Trend Factor into your strategy?**

If you're doing this professionally, you'd need to purchase licenses for the necessary data and meet other requirements. We don't have access to all of that at the moment, so I can't implement it in my current setup. Other firms might be able to. If I were to use it, I'd allocate, at most, around 5% to the Trend Factor, treating it as a separate component in a diversified portfolio.

10. **Do you know of any firms that are implementing the Trend Factor?**

    I don't know for sure, and even if someone is, they wouldn't advertise it. Quantitative firms like AQR, the Man Group with their AHL fund, or Wellington Management could be using it. In Europe, Robeco in Rotterdam is a leader in factor investing and publishes a lot of research—they might be integrating the Trend Factor as well.

11. **Given your experience in portfolio management, do you see opportunities for blending the trend factor with other quantitative strategies, such as factor investing or smart beta?**

    The literature on factor/smart beta investing is abundant. Numerous approaches in the "factor zoo" exist. From an academic point of view, it has to be shown that the trend factor has additional merits beyond existing approaches.

12. **How do transaction costs impact the Trend Factor's performance in practice?**

    Without accounting for transaction costs, the analysis has little relevance for practical applications. Transaction costs vary significantly over time. In the 1940s, they were much higher than today, where they've been reduced to just a few basis points. Realistically modeling these costs is complex because you'd need to adjust them for different time periods, asset types, and trading volumes. For instance, buying a large-cap stock like Nvidia has much lower implicit costs compared to a small-cap company with limited liquidity. Large trades can significantly impact the price of small caps, which adds another layer of complexity.

13. **How could transaction costs be implemented realistically in a Trend Factor model?**

    You'd need to vary transaction costs by period and by company size. For example, using a fixed estimate like 50 basis points for small caps and 5 basis points for large caps could be a reasonable approach for modern data. For academic validation of the Trend Factor, you could focus on more recent years, say post-2016, where transaction costs are relatively stable.

14. **Are there other weaknesses in the Trend Factor that should be considered for practical use?**

    One significant weakness is the lack of analysis across different market regimes or time periods. A simple way to address this would be to conduct a decade-by-decade analysis. For example, check whether the factor's performance is

consistent across ten-year periods. You might find that outperformance was much higher in the 1930s but has diminished over the decades. This kind of analysis could provide valuable insights into the robustness of the Trend Factor.

15. **What limitations exist in anayzing cryptocurrencies compared to traditional asset classes**

    Cryptocurrencies are entirely new from a financial perspective—Bitcoin has been around for about 10 to 15 years, which is a very short timeframe in financial academia. Unlike traditional assets, cryptos lack fundamental metrics like earnings or balance sheet data. Without these, it's impossible to apply a value-based approach or make comparisons between cryptos. For example, I can't say whether Bitcoin at $100,000 is "overvalued" compared to its own history or relative to Ethereum or Polkadot. Value approaches require such fundamental data, which cryptocurrencies simply don't provide.

16. **Can the Trend Factor, particularly long-term momentum, be applied to cryptocurrencies?**

    In theory, you could attempt to apply long-term momentum to cryptocurrencies, as the Trend Factor is essentially a value-momentum hybrid. However, there are practical limitations. Cryptos like Bitcoin have short histories—most coins have less than 10 years of data, and some have only a few years. For a 5-year momentum analysis, you need at least five years of data, leaving very little time for meaningful testing. This creates challenges in terms of sample size, statistical significance, and confidence in the results.

17. **What are the challenges in analyzing Bitcoin with the Trend Factor?**

    Bitcoin's unique structure adds complexity. Its supply is capped at 21 million, which means price is determined solely by demand. This demand is heavily influenced by media, social media, and FinFluencers, creating artificial or speculative bubbles. Unlike traditional assets, there's no fundamental correction mechanism like value metrics to anchor prices. This makes Bitcoin highly susceptible to hype-driven volatility, complicating the application of a Trend Factor or any value-related approach.

18. **What challenges do you see in building a dataset for cryptocurrencies to apply the Trend Factor?**

    Creating a dataset for cryptocurrencies is a significant challenge. First, you need to decide on the type of data—whether it's tick data, high-frequency data, or aggregated data like 30-second or daily intervals. Then there's the issue of the exchanges themselves. These aren't regulated markets like stock exchanges; they're OTC platforms like Coinbase or FTX, built with varying standards. Ensuring that timestamps are clean and aligned across time zones is another major hurdle. For example, closing prices differ between the U.S., Europe, and Japan due to time zone variations, and without proper adjustment, this can distort performance calculations and signals.

19. **Why does the trend factor perform well during crises?**

    The trend factor tends to perform well in crises, particularly those that develop over longer periods. In such cases, it identifies sustained drawdowns, exits the market, and avoids significant losses. For example, during a long-drawn-out crisis like the dot-com bubble, which unfolded over years, a 12-month momentum signal works effectively as it has enough time to detect and adjust to the downturn. However, its performance depends heavily on the type of crisis. In short, sharp events like the COVID-19 pandemic, which escalated within weeks, the trend factor may struggle—especially if it relies on longer-term momentum signals that are too slow to react to rapid market changes.

20. **How does the trend factor perform during crises compared to other investment strategies?**

    Every crisis is different, and what works in one might not work in another. Take Scalable Capital, for example. They used a volatility-based approach inspired by Professor Mittnik. The idea wasn't entirely new and has been around for a couple of decades. It worked pretty well during the 2009 financial crisis because that downturn played out over months, giving the model enough time to adjust equity exposure and reduce losses. But in 2020 with COVID-19, it was a completely different story. The crisis unfolded so quickly that the model didn't react fast enough. They ended up cutting equity exposure late, and then missed the recovery on the way back up. The Trend Factor has a similar issue—it can be great in long-term crises, where you have enough time to spot trends and make adjustments. But in short, sharp downturns like COVID-19, it might struggle.

21. **What changes could be made to the trend factor to make it work better during fast-moving crises?**

    One option is to break the trend factor into its components—short-term, medium-term, and long-term momentum—and analyze how each performs in different types of crises. A faster component, like a short-term reversal signal, could help respond to rapid market changes. For example, a 5-day or 1-month reversal might catch the quick movements better than a 12-month trend.

22. **How does the trend factor's performance relate to other investment factors like value or momentum during crises?**

    There's often overlap, especially with momentum. Long-term momentum tends to shine in prolonged crises because undervalued assets eventually develop momentum as prices recover.

23. **Are there any recommended papers for further reading?**

    Definitely. "Value and Momentum Everywhere" by AQR is an excellent resource. Robeco also publishes fantastic research on factor investing.