Exploit momentum in Cryptocurrency Market

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Abstract. Researchers put efforts into explanations of the momentum phenomenon and improvements of the momentum strategy since the emergence of momentum in 1993. Interested in anomalies appearing as exhibited in traditional asset markets, adequate studies are launched on the nascent phenomenon emergers in the last decade, the cryptocurrency market. Recent studies have shown that there is hardly any cross-sectional momentum in the cryptocurrency market. To explore the momentum anomaly additionally in the cryptocurrency market, this paper implemented a time-series momentum on cross-sectional winners for improvement. Previous studies have introduced detecting the turning point between long-term slow time-series factor and short-term fast time-series factor contributes to predicting the trend well. Furthermore, a threshold decided by a certain machine learning model suggests better performance. In this paper. A multilayer perceptron (MLP) is utilized to learn the weights of time-series factors. The combination of cross-sectional momentum and time-series momentum shows advantages and the MLP learned weighted strategy is preferable.

Keywords: Momentum Strategy, Cryptocurrency market.

1. Introduction

The momentum anomaly has drawn adequate attention since it has firstly reported by Jegadeesh and Titman in 1993 [1]. As a concept from physics, momentum means continuous trends. This anomaly indicates that the past performance of certain assets could be utilized to predict the future price and challenges the previous price random walk consensus. Despite the arguments about the explanations of momentum, academicians have made agreements about the existence of the momentum effect. Real estate investment trusts, corporate bonds, currencies, commodities, exchange-traded funds, mutual funds, and other traditional and alternative asset classes have all observed significant momentum effects [2].

The cryptocurrency market is a novel phenomenon since the introduction of bitcoin in 2008. Leveraging blockchain technology strengths including decentralization, tamper-proof, and transparency, and cryptocurrencies arouse interest from investors. Researchers have conducted studies on anomalies of cryptocurrencies. Grobys and Sapkota examined the long-term momentum effect on the cryptocurrency market [12]. Shen et al. studied on weekly momentum effect [3]. Moreover, Nguyen et al. focus on the short-term momentum within a week [4].

Gathering trading history data of around 2000 cryptocurrencies, this paper constructed a portfolio that combines cross-sectional and time-series momentum strategies. The trading history data is traced back to 2012 when most of the major cryptocurrencies do not exist. A set of cryptocurrencies are selected by their past performance. Agreeing with hardly significant cross-sectional momentum in the cryptocurrency market, time-series momentum is introduced to the selected cryptocurrencies set. The fast and slow factor introduced by Garg et al. is mutated to predict the trend [5]. The median strategy, which is the equal-weighted average of fast and slow factors, indicates the trend better by neutralizing the inadequate response slow factor and sensitive fast factor. A multilayer perceptron that learns the weights of factors is suggested to replace the median and arrives at higher performances.

2. Literature Survey

Investigating the strategy of buying past winners and selling past losers, Jegadeesh and Titman introduced the concept of momentum in finance in 1993 [1]. By choosing stocks based on previous 6-month returns and holding for 6 months, Jegadeesh and Titman achieved an average compounded excess return of 12.01 percent annually (6/6 momentum investment strategy). This challenges the previous agreement that future stock prices cannot be predicted by past information. Researchers are interested in improving momentum strategy or introducing their selective methods, especially when they find the classic momentum investment strategy performs miserably during the subprime crisis and the recovery period [2]. The 52-week high momentum strategy, which George and Hwang introduce first, takes a long or short position depending on the ratio of a stock's current price to its 52-week high [6].

Blitz et al. replace the total returns in the classic momentum strategy with residual stock returns to select stocks in 2009 [7]. This residual momentum approximately doubles the risk-adjusted profits of the classic strategy and disproves the risk-based explanations. Moskowitz et al. recommended time-series momentum in 2012 [8]. The time-series momentum, also referred to as "absolute momentum," represents the momentum of a single stock by its past price. Garg et al. integrate the signals from a slow strategy with a long lookback window and a fast strategy with a short lookback window [5]. The difference between both strategies is used to detect market turning points. Cheng et al. suggest a threshold of 17%, which is learned by a decision tree model, to determine when to utilize fast or slow signals [9].

Deep neural networks are thriving recently and are applied widely in multiple aspects. Lim et al. introduce a hybrid class of deep learning models called DMNs to time-series momentum [10]. Deep neural networks such as multilayer perceptron (MLP) and WaveNet are utilized in this strategy to predict trends first. Thereafter, the Sharpe ratio is optimized through a long short-term memory (LSTM). Kieran et al. take advantage of both Garg and Lim by introducing an online turning points detector to the DMN and achieves 33% higher than the standard time-series strategy on Sharpe ratio [11].

The cryptocurrency market has grown dramatically since the first cryptocurrency emerges. Thus, the cryptocurrency market draws considerable attention throughout its development. Researchers are interested in studying the traits of the cryptocurrency market and whether pheromones such as momentum still exist. Agreeing with the cryptocurrency market retaining higher efficiency, Grobys and Sapkota state that no evidence presents significant momentum payoffs in this market [12]. Grobys and Sapkota apply different momentum strategies to 143 cryptocurrencies from 2014 to 2018 and achieved negative or minor positive returns. On the other hand, Liu et al. present three factors including momentum to capture cryptocurrency returns since these factors indicate statistically significant excess returns [13].

3. Data & Methodology

Approximately 2000 cryptocurrencies are involved in this study and ranked by their market capitalization as of August 3rd, 2022, and their trading history. The cryptocurrency information, including market capitalization, and daily volume weighted average price in US dollars is retrieved from coincap.io, a free source of cryptocurrency market activity and price that collects trading data from thousands of exchanges. The historical data of daily price ranges from January 1st, 2012, when only bitcoin and Litecoin exist to August 1st, 2022.

Attribute to its "never sleep" trait, the cryptocurrency market shows dramatic metabolism. Under this circumstance, researchers are prone to conduct short-run return studies in the shorter term than that of traditional financial assets. Dobrynskaya prefers weekly frequency pricing data for validating short run momentum anomaly to monthly frequency [14]. Previous studies promoted by Shen et al. and Nguyen et al. also concentrate on weekly or less frequent.

Table 1. Phases Definition [Owner-draw]

	Fast +	Fast -
Slow +	*Bull*	Correction
Slow -	*Rebound*	Bear

In this study, a weekly frequency cross-sectional momentum strategy is integrated into a daily frequency time-series momentum strategy. Therefore, selecting the winner cryptocurrencies from the market and determining the chance to trade. As of the classic Jegadeesh and Titman methodology, the winner cryptocurrencies would be selected to construct a portfolio. In detail, the cryptocurrencies are ranked by their performance of cumulative return, and the top 30% of will be taken. Not all cryptocurrencies existed during the whole tracing period. In the very beginning, bitcoin only competes with Litecoin or even itself. The results are shown in Fig. 1, compared with an equal-weighted portfolio and a price-weighted portfolio. Consistent with earlier studies, there is no significant momentum.

$$W_{FAST,t} := \begin{cases} +1 & \text{if } r_{t-1,t} \geq 0 \\ -1 & \text{if } r_{t-1,t} < 0 \end{cases} \quad W_{SLOW,t} := \begin{cases} +1 & \text{if } r_{t-4,t} \geq 0 \\ -1 & \text{if } r_{t-4,t} < 0 \end{cases} \tag{1}$$

$$w_t(a) := (1-a)W_{slow,t} + aW_{fast,t} \tag{2}$$

Inspired by Garg et al., this study introduced a weekly time-series factor anda monthly factor as the fast and slow factors [5]. The factors are determined asshown in equation (1). According to Garg et al., the status of fast and slow factors are described as four phases as shown in Table 1. If both factors are positive, it is a strong positive signal that indicates the Bull phase, if both are negative indicates the bear phase. In both cases, the signal points in a deterministic direction. On the other hand, when the fast factor and slow factor are inconsistent, equation (2) is suggested, when the speed is 0.5, it is called "medium".

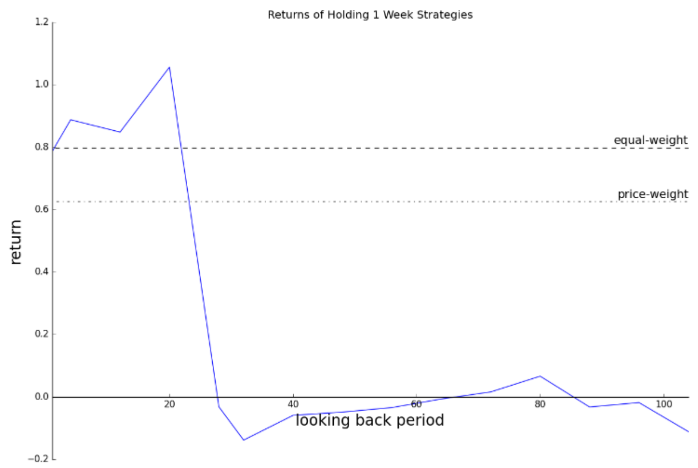

Fig. 1 Annualized Return of J/1 Strategies [Owner-draw]

4. Results & Analysis

Considering the higher volatility in the cryptocurrency market than in traditional assets, the long-run slow time-series factor and short-run fast factor are decided to be shortened. Therefore, the fast factor abstracts the trend in the past week, and the slow factor recapitulates the trend in the past month. The fast signal is more sensitive than the slow signal and thus changes direction frequently as shown in Fig. 2. The four phases are determined by the consistent or inconsistent of the fast and the slow signals, and the relative frequency is shown in Fig. 2. The chance that both signals are consistent takes over 60% parts of the total observation. The average annualized return of each phase is listed in Fig. 2. The bull and rebound appear to have high returns, the correction phase reveals few returns, and the bear phase reflects negative returns.

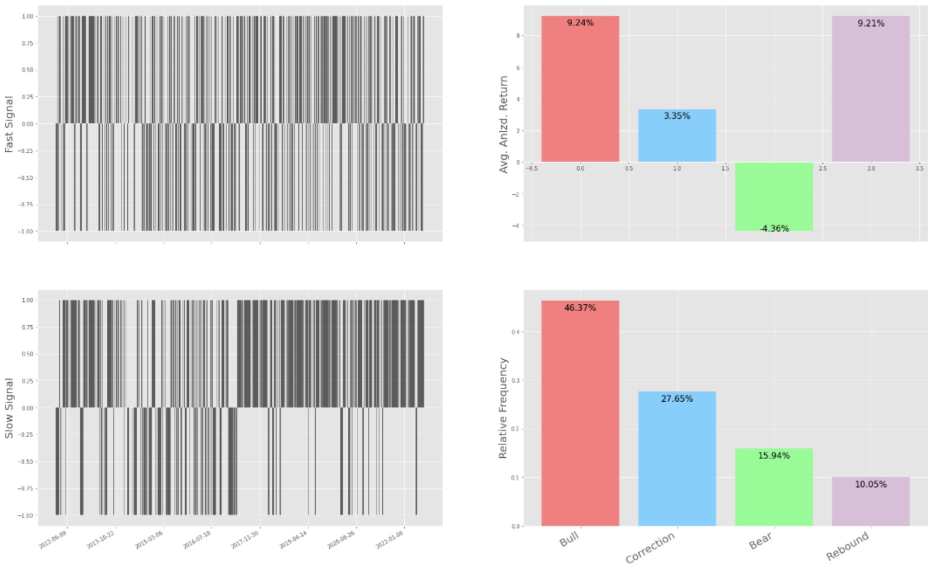

Fig. 2 Fast Slow Signals and 4 Phases [Owner-draw]

The fast, and slow signals are applied to predict time-series return trends. Moreover, the median signal, which addresses the sensitivity of the fast signal and the underreaction of the slow signal, is also adopted. As shown in Fig. 3, the median strategy could determine the trend between fast and slow signals well and outperforms strategies with only fast or slow signals. In addition, the median strategy could be viewed as an equal-weighted average of the fast and slow signals. To exploit the signal better, Cheng et al. suggest a decision tree learned threshold of 17% to determine trade based on the fast or slow signal [9].

This paper concentrates on balancing the weights of the signal from fast or slow factors and introduces a multilayer perceptron (MLP) to learn such weights from complicated and larger time-series datasets. The machine learning model is trained on data from the first 7 years and tested on data from the last 3 years. The out-of-sample performances of strategies are shown in Fig. 3, and the MLP learned weights strategy superiors equal-weighted media strategy.

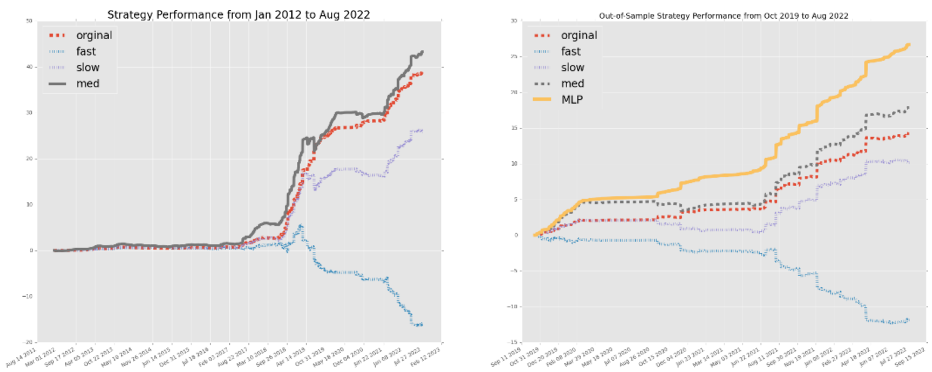

Fig. 3 Strategies Performances [Owner-draw]

5. Conclusion

The cryptocurrency market is a nascent phenomenon that emerged in the last decade, and adequate studies are launched on it. There is hardly any significant cross-sectional momentum on cryptocurrencies, which may be due to the efficiency of the cryptocurrency market. To achieve improvement from only the cross-sectional momentum strategy, an integration of cross-sectional and timeseries momentum strategies is performed on a set of approximately 2000 cryptocurrencies. This paper constructs a portfolio from winner cryptocurrencies and utilizes the time-series momentum to determine the long or short position. Furthermore, the momentum turning point suggested by Garg et al. is adopted for balancing the inadequate response slow factor and sensitive fast factor. Instead of using the equal-weighted median of fast and slow factors, this paper introduces a multilayer perceptron to learn the weights and attains better performance than the median strategy.

There is barely a consensus about categorizing cryptocurrencies into asset classes of stocks or currencies. Studies on introducing other anomalies for stocks or currencies to cryptocurrencies are promising. On the other hand, the Long Short-Term Memory (LSTM) model presents a lucrative specialty in handling time-series data and is motivated to introduce time-series momentum.

References

[1] Jegadeesh, N., Titman, S.: Returns to buying winners and selling losers: Implications for stock market efficiency. The Journal of Finance 48(1), 65–91 (1993), http://www.jstor.org/stable/2328882

[2] Singh, S., Walia, N.: Momentum investing: a systematic literature review and bibliometric analysis. Management Review Quarterly 72(1), 87–113 (Feb 2022). https://doi.org/10.1007/s11301-020-00205-6, https://doi.org/10.1007/s11301-02000205-6

[3] Shen, D., Urquhart, A., Wang, P.: A three-factor pricing model for cryptocurrencies. Fi-nance Research Letters 34, 101248 (2020)

[4] Nguyen, H., Liu, B., Parikh, N.Y.: Exploring the short-term momentum effect in the crypto-currency market. Evolutionary and Institutional Economics Review 17(2), 425–443 (2020)

[5] Garg, A., Goulding, C., Harvey, C.R., Mazzoleni, M.: Momentum turning points. Capital Markets: Asset Pricing & Valuation eJournal (2019)

[6] George, T.J., Hwang, C.Y.: The 52-week high and momentum investing. The Journal of Fi-nance 59(5), 2145–2176 (2004), http://www.jstor.org/stable/3694820

[7] David, B., Joop, H., P.E., M.M.: Residual momentum. Behavioral & Experimental Finance eJournal (2009). https://doi.org/10.1016/j.jempfin.2011.01.003

[8] Moskowitz, T.J., Ooi, Y.H., Pedersen, L.H.: Time series momentum. Journal of Financial Economics 104(2), 228–250 (May 2012), https://www.sciencedirect.com/science/article/pii/S0304405X11002613

[9] Cheng, E., Kostyuchyk, N., Lee, W., Liu, P., Ma, C.: Trending fast and slow. The Journal of Portfolio Management 48(3), 103–116 (2022)

[10] Lim, B., Zohren, S., Roberts, S.: Enhancing time-series momentum strategies using deep neural networks. The Journal of Financial Data Science 1(4), 19–38 (2019)

[11] Wood, K., Roberts, S., Zohren, S.: Slow momentum with fast reversion: A trading strategy using deep learning and changepoint detection. The Journal of Financial Data Science 4(1), 111–129 (2022). https://doi.org/10.3905/jfds.2021.1.081, https://jfds.pm-research.com/content/4/1/111

[12] Grobys, K., Sapkota, N.: Cryptocurrencies and momentum. Economics Letters 180, 6–10 (2019). https://doi.org/https://doi.org/10.1016/j.econlet.2019.03.028, https://www.sciencedirect.com/science/article/pii/S0165176519301077

[13] Liu, Y., Tsyvinski, A., Wu, X.: Common Risk Factors in Cryptocurrency. NBER Working Papers 25882, National Bureau of Economic Research, Inc (May 2019), https://ideas.repec.org/p/nbr/nberwo/25882.html

[14] Dobrynskaya, V.: Cryptocurrency momentum and reversal. Available at SSRN 3913263 (2021)