Is Momentum the Fatal Seductress in the Cryptocurrency Market?

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Abstract

The rising cryptocurrency market has drawn attention from the academia and the industry in the past decade. Investors seek ways to participate in the market through initial coin offerings, secondary market trading, and crypto derivatives. I investigate how momentum influences the returns of cryptocurrencies by forming momentum portfolios using rolling cumulative returns as a measurement of past performance. I find that unlike the momentum effects in the equity market from 1960s to late 1980s, momentum is not a strong predictor for future performance in the crypto market. This finding suggests that the crypto market may be more efficient due to its transparency and automation, thus making it harder to forecast future returns based on past performance. This evidence could help investors make better financial decisions in the highly volatile crypto market.

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Introduction

Discovering factors to optimize portfolio returns has always been an essential part of financial research and has drawn attention from both the academia and the industry. The Arbitrage Pricing Theory (APT, Ross 1976), the Capital Asset Pricing Model, the Fama-French three factor model (Fama French 1992), and the six factor model (Fama French 2015) have provided empirical researchers plenty of inspirations to document factor structures in various financial assets such as equity, bond, and currency market (Lustig, Roussanov, and Verdelhan 2011). Institutional and individual investors have taken advantage of academic research and incorporated these findings in their models to exploit profits.

In the past decade, another financial asset category is rising – the cryptocurrency market. By June 2020, the cumulative market capitalization of all crypto-related assets has reached $274 billion. There are 5609 different cryptocurrencies in the market, and the daily trading volume has reached $73 billion. Among all cryptocurrencies out in the market, Bitcoin's (BTC) dominance is 64.8% (CoinMarketCap.com) and there are many coins with various features such as Ethereum, Tether, XRP, etc. As the importance of crypto-related assets is increasing, institutional and individual investors' interests grow drastically and actively participate in the crypto market. This leaves an intriguing question for researchers and investors: what factors contribute to successful investments in the crypto market? Researchers have accumulated over 300 factors to predict stock market returns. Are there some overlapping factors which forecast the returns of both crypto assets and stocks?

This paper aims to explore the effects of momentum on the returns of crypto assets. Using rolling cumulative returns as a measure of momentum, I form 10 portfolios with portfolio 1 as losers and portfolio 10 as winners using 39 months of daily price data (from September 2015 to November 2018, collected from CoinMarketCap.com). I construct the portfolios using 1 month, 3 months, 6 months, and 9 months formation (J) and holding (K) periods. Unlike the momentum effects in the equity market, I did not find evidence to support that momentum is a predictor of crypto assets returns. In some scenarios, the losers' portfolio has the highest returns and the winners' portfolio has the lowest returns. I calculate the Sharpe ratio to take volatility/risk into consideration using three-year average 10-year treasury yield (2016-2018). There is no scenario where the winners' portfolio has the best performance. The highest Sharpe ratio portfolio in different scenarios is random, indicating no relationship with momentum. These results are statistically significant at 5% and sometimes even 1% level. Finally, the long short strategy is generally not a good way to generate profits in the crypto markets. If the formation and holding periods are sufficiently short (for example, 1 month or 3 months), buying the losers and selling the winners may potentially earn profits for investors. However, this strategy is not supported by statistical significance.

My findings suggest that the past performance is not a good predictor of the future returns in the cryptocurrency market. This could be due to the limited data availability (39 months). The results may be more accurate and convincing if I form portfolios using more than 10 years of data. Another possibility is that the crypto market is highly transparent (thanks to blockchain) and more efficient. The market is automated and eliminates unnecessary market friction. Therefore, it is more difficult to judge a cryptocurrency's future performance based on its past performance. In a more efficient market, future returns follow a pattern which is closer to random walks.

For further explorations, I use the same methodology and run my portfolio formation codes in the equity market. The results show that momentum had a strong positive correlation with portfolio returns from the 1960s to the late 1980s in the stock market, right before the Jegadeesh and Titman 1993 paper was published. However, the effects grew weaker in the past 15 years. This indicates that investors may be actively paying attention to academic research and incorporated what they learned into their investment strategies. Years of learning from investors leads to a more efficient market and some specific factors have less influence on the returns of the financial market as a whole.

In the following sections, I will cover the overview of the cryptocurrency market and its trend, revealing the data sampling process, presenting the empirical results, discussing the implications, and concluding the paper.

The Crypto Market

The cryptocurrency market is growing rapidly. Investors (either institutional or individual), fintech startups, big public firms, and established exchanges all seek ways to participate. One can get exposed to crypto assets through initial coin offerings (ICO), crypto derivatives (the Chicago Board Options Exchange and the Chicago Mercantile Exchange launched Bitcoin futures trading during the peak of the crypto bull market in December 2017. It was the milestone for the crypto industry, as a futures contract allows investors to hedge positions), and secondary market trading of cryptocurrencies. Many public firms such as Microsoft and IBM have made significant investment in blockchain and related businesses. In this paper, I focus on cryptocurrencies listed on exchanges which are available for secondary market trading.

Figure 1 shows the market dominance for the major cryptocurrencies as of November 2018. As shown below, Bitcoin dominated the market in late 2018, and now its dominance has increased to 64.8% based on CoinMarketCap.com. The top 10 cryptocurrencies occupied almost 75% of the market in late 2018. Figure 2 shows the number of cryptocurrencies available over the years. As demonstrated, there is an increasing trend of the number of crypto assets in the market over the years, suggesting an increasing importance of this asset class.

Figure 1

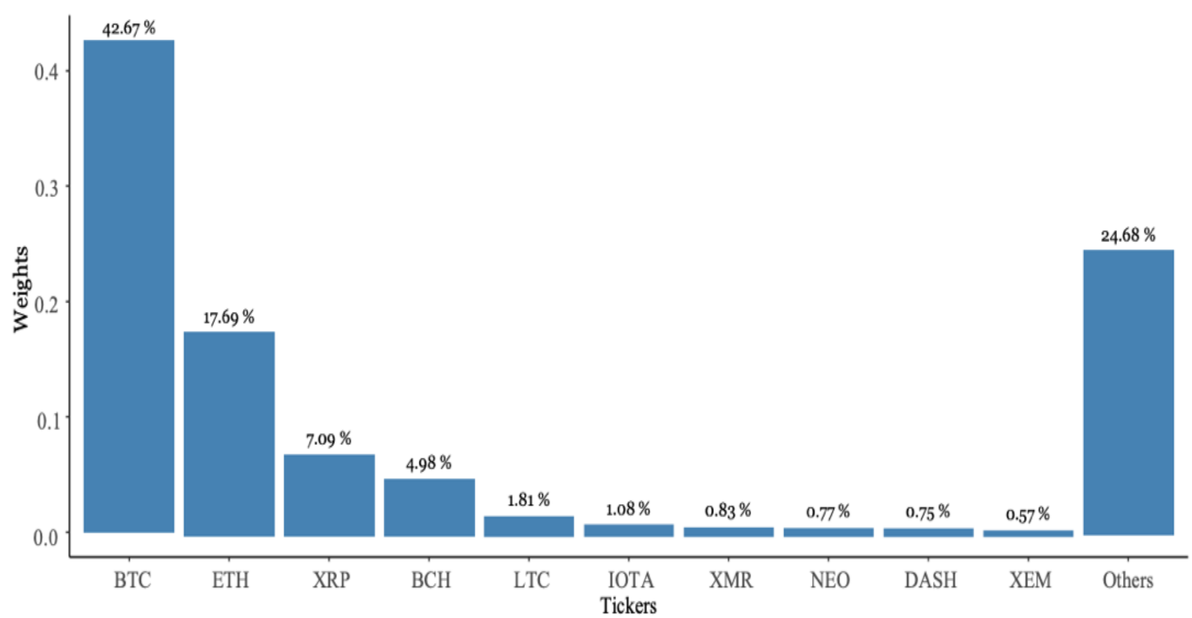
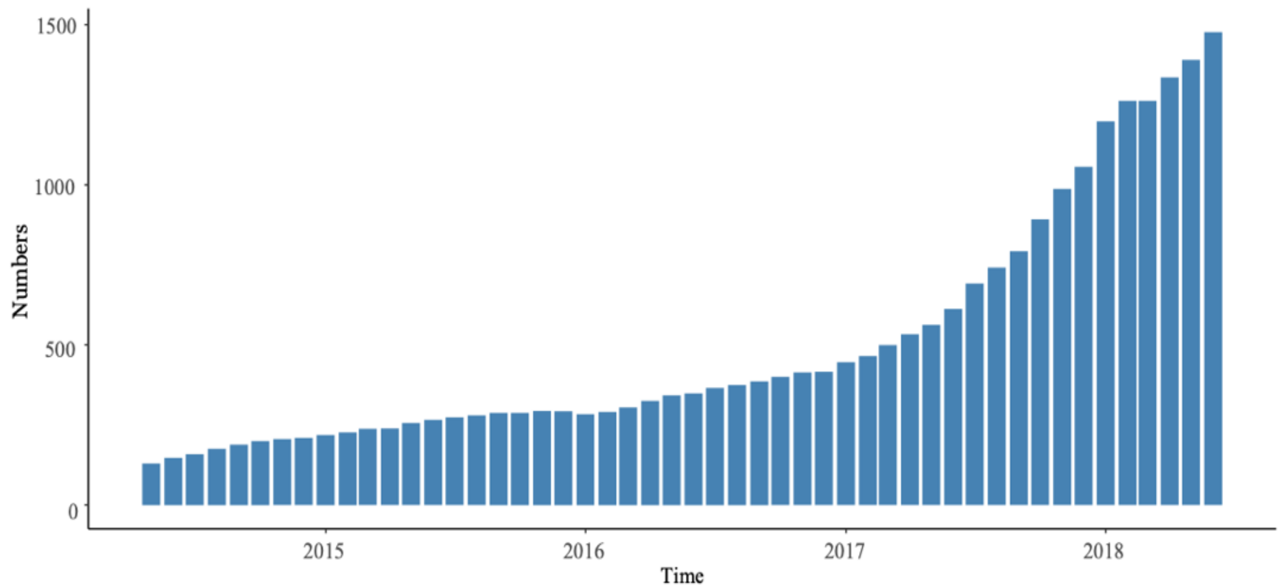


Figure 2



Data

The dataset includes 2071 cryptocurrencies, from March 2013 to November 2018, and their daily open, close, high, low price, trading volume, and market cap records. It comes from Kaggle's (Google's subsidiary) crypto market open resource. The data is originated and collected from CoinMarketCap.com. To better answer my research questions, I selected time period from September 2015 to November 2018 (39 months) and includes coins which have market capitalizations that are greater than $1 million. Small market cap coins are very volatile and too easy to be manipulated. In addition, I excluded Tether (USDT), a stablecoin which is linked to US dollars. Finally, I filtered out coins which have daily trading volume less than 100 and trading records less than 90 days. My sample selection leads to a panel of 749 crypto assets by the end of November 2018.

While applying data filtering, I noticed that many crypto assets share the same symbols but have different names. This indicates that the crypto market is not highly regulated and coins can use the same symbol to trade in the market. This leaves me the impression that sophisticated investors and coin creators could easily exploit this new and loosely regulated market and further increases my curiosity to discover if momentum has an effect on the return of crypto assets portfolios.

Empirical Results

Inspired by the momentum strategy in equity market (Jegadeesh and Titman 1993), I tested if the momentum theory works in the crypto market. Using the sample selected, I constructed 10 momentum portfolios and used rolling cumulative returns as the measure of momentum, with 1 represents the portfolio with the worst past performance (losers), and 10 represents the portfolio with the best past performance (winners). I further formed long-short portfolios by buying the winners and selling the losers. Contrary to the momentum effects in the equity market back in the 1980s, I did not find results showing that momentum is a factor which influence the returns of crypto assets. How momentum affects future returns largely depends on the portfolio formation period (J) and its holding period (K). These results are supported by a low p value and most time significant at 5% level. Below I present the empirical results and make further discussions.

As shown below in Table 1, when portfolio formation period (J) is 3 months and the holding period (K) is 3 months, portfolio 1 (losers) have the highest average monthly return and the highest volatility. The higher risks gives portfolio 1 higher returns. Different from momentum's effects in equity market, portfolio 10 does not have the highest average monthly return. If one looks solely into mean returns, winners and losers have the highest returns and risks. In addition, I use the three-year average 10-year Treasury bond yield to calculate Sharpe ratios for each portfolios. As shown below, portfolio 2 has the highest Sharpe ratio (as highlighted by light blue). Even though its return is significantly lower than the winners and losers, its low volatility makes the investment worthwhile. Winners' result is significant at a 5% level, and losers result is significant at a 1% level. The long short strategy does not work well and generate negative average returns, although the results are not significant. Finally I visualize the cumulative returns for winners and losers. As shown below, losers have consistently higher cumulative returns than winners. This phenomenon is especially strong after September 2017. The long short cumulative returns only turn positive after the second quarter of 2018, as shown in the figure. The portfolio statistics tell a story which is irrelevant to momentum.

Table 1

Portfolio Returns, J = 3 months, K = 3 months				
Momentum	Count	Mean	Std	Sharpe Ratios
1	35	0.825	1.711	0.469
2	35	0.371	0.693	0.501
3	35	0.293	0.662	0.406
4	35	0.308	0.698	0.408
5	35	0.491	1.095	0.426
6	35	0.440	0.984	0.423
7	35	0.382	0.865	0.415
8	35	0.432	0.900	0.453
9	35	0.626	1.650	0.365
10	35	0.728	1.688	0.417

Table 2

Momentum	Mean	t-stat	p-value
Winners	0.728	2.550	0.015
Losers	0.825	2.854	0.007
Long_short	-0.098	-0.596	0.555

Figure 3

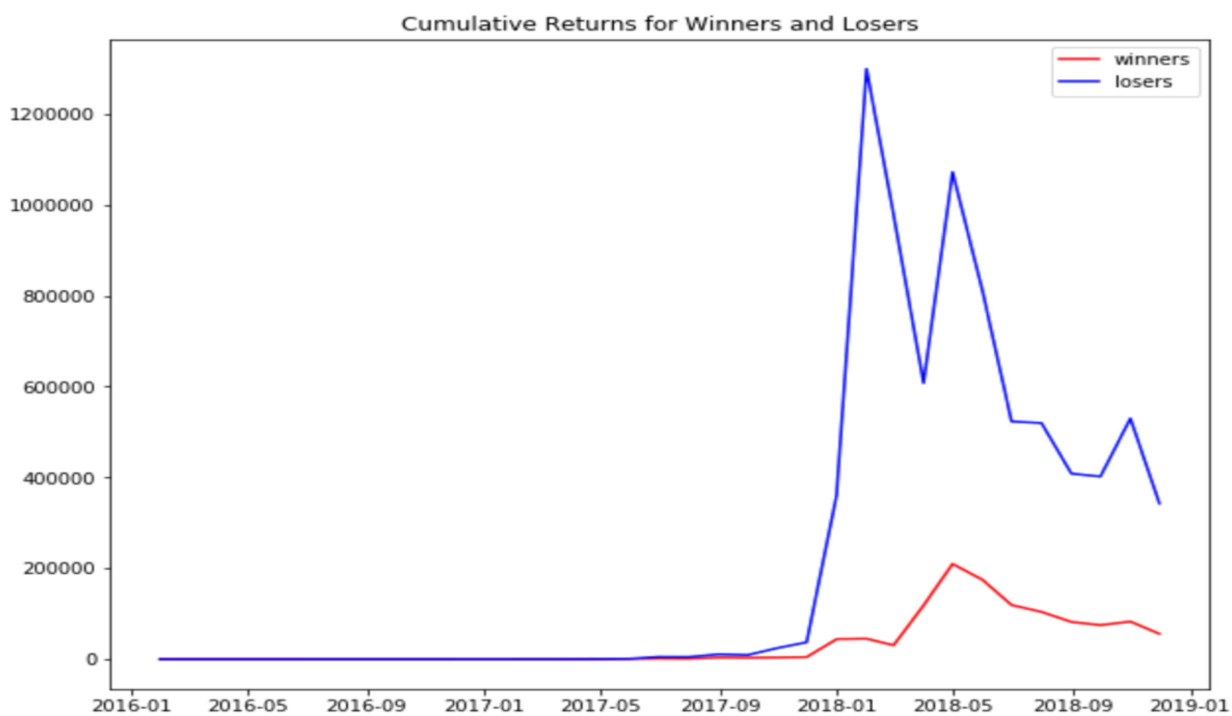


Figure 4

I present the results for formation period as 6 months and holding period as 6 months. Table 3 seems to tell the momentum story as the returns of losers are much lower than the returns of the winners. However, the highest return belongs to portfolio 7, and portfolio 1 has the highest Sharpe ratio (due to its low volatility/risk). These results are significant at a 5% level. Momentum is still not a stable predictor in this scenario after careful scrutiny.

Table 3

Portfolio Returns, J = 6 months, K = 6 months				
Momentum	Count	Mean	Std	Sharpe Ratios
1	32	0.491	0.860	0.543
2	32	0.518	1.067	0.463
3	32	0.466	1.132	0.391
4	32	0.374	0.865	0.405
5	32	0.350	0.780	0.418
6	32	0.406	0.951	0.402
7	32	0.657	1.770	0.358
8	32	0.531	1.085	0.468
9	32	0.603	1.206	0.480
10	32	0.615	1.502	0.394

Table 4

Momentum	Mean	t-stat	p-value
Winners	0.615	2.316	0.027
Losers	0.491	3.225	0.003
Long_short	0.124	0.649	0.521

Table 5 shows a scenario where both formation and holding period are 9 months. Losers have higher returns than winners, again contrary what the momentum effect will predict. Portfolio 7 has the highest average return and portfolio 8 has the highest Sharpe ratio. These results are supported by low p-value and above 2 t-statistics. This scenario again suggests that momentum does not have significant effects on crypto assets portfolio returns. The long short strategy does not work well in the crypto market. The high standard deviation in all scenarios indicates that the returns of crypto assets are highly volatile and risky.

Table 5

Portfolio Returns, J = 9 months, K = 9 months				
Momentum	Count	Mean	Std	Sharpe Ratios
1	29	0.575	1.137	0.485
2	29	0.517	0.995	0.495
3	29	0.511	1.018	0.479
4	29	0.498	1.002	0.473
5	29	0.579	1.499	0.370
6	29	0.569	1.220	0.447
7	29	0.645	1.188	0.523
8	29	0.576	0.999	0.552
9	29	0.553	1.068	0.496
10	29	0.482	1.154	0.397

Table 6

Momentum	Mean	t-stat	p-value
Winners	0.482	2.248	0.033
Losers	0.575	2.726	0.011
Long_short	-0.094	-0.454	0.653

Since 39 months is a relatively short period, I also checked the results if both formation and holding period are 1 months. The statistics are consistent with the above findings with a more noticeable difference for returns of winners and losers, as shown in Table 7. The long short strategy works terribly here. The reversed short long strategy may work better in the crypto assets when the formation and holding periods are short. Investors may have a better chance to make profits by buying losers and selling winners in this scenario when they deal with cryptocurrencies. However, this strategy is not backed by statistical significance, with a high p-value and low t-statistics. Therefore, investors should be extremely cautious exercising this strategy when it comes to crypto assets due to their highly volatile and risky nature.

Table 7 *J=1, K=1*

Momentum	Mean	t-stat	p-value
Winners	0.435	2.151	0.038
Losers	0.744	2.862	0.007
Long_short	-0.309	-1.291	0.205

Conclusion

In this paper, I investigate the effects of momentum on the returns of crypto assets using 39 months of daily price data comprised of currencies listed on exchanges. The results suggest that contrary to its effect in the equity market from the 1960s to the late 1980s, momentum is not a strong predictor on cryptocurrencies' returns. The past performance is not enough to forecast future performance. When the formation period and holding period is sufficiently short (for example, 1 months), investors could potentially exploit profits by buying losers and selling winners, although this strategy is not backed up by statistical significance.

The results may be due to the limited data availability - 39 months is a relatively short period. The crypto market is also highly automated and transparent, thanks to the blockchain technology. This may increase the efficiency of the crypto market and reduce market friction. In a more efficient market, it is difficult to judge future returns based on past returns since returns tend to follow of pattern of random walks. Therefore, momentum does not work well in this kind of market to predict future returns.

These findings are beneficial to investors who seek to participate in this newly rising market. Understanding the role of momentum in this specific asset category is essential for investors to make sound financial decisions. The study also shows that the financial market is rather complicated and different asset groups are governed by different forces or factors. The crypto market is highly volatile and risky, as shown by its high standard deviation. This opens the doors for more sophisticated financial instruments to help investors to hedge risks. The crypto market returns may be controlled by idiosyncratic noises which do not play significant roles in traditional financial asset categories such as equity and bond. Is momentum the fatal seductress in crypto market like Cleopatra's effects on Julia Caesar and Mark Anthony? You have the answer now.

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