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Momentum/Contrarian Strategy and Volatility of Cryptocurrencies

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Abbreviations

AIC	Akaike information criterion
BIC	Bayesian Information Criterion
BTC	Bitcoin
LTC	Litecoin
DASH	Dash
DGB	Digibyte
DOGE	Dogecoin
ETH	Ethereum
VTC	Vertcoin
XMR	Monero

Abstract

Momentum strategy together with contrarian strategy are proved to be efficient in a wide range of financial assets. The cryptocurrency market has emerged quickly so far, therefore it is attracting to explore whether these investment strategies are also profitable in cryptocurrencies. Based on the daily data, the finding of cross-sectional momentum/contrarian strategy is that, the contrarian strategies perform much better than every momentum strategy listed in this research in aggregate 4.2 years from 2014 to 2018. But from a perspective of individual year, it is hard to clarify which one of the two performs better. As for the time series continuation and reversal, the momentum strategies have significant superior performance of a bit longer observing and holding time from one week to one month. The volatility check of eight cryptocurrencies and cryptocurrency index denotes the best fitted model of EGARCH (1, 1), but GARCH (1, 1) is still the most applicable for the factor study. Finally, the macroeconomic factors do not have profound influence on volatilities of cryptocurrencies.

Keywords: Cryptocurrency, Momentum Strategy, Contrarian Strategy, ARCH Family Model, Alternative Investment

1. Introduction

Bitcoin is the first cryptocurrency that uses a technology of blockchain. Blockchain is an "open, distributed ledger" that can record transactions without central recordkeeping (Iansiti and Lakhani, 2017). Since the launch of Bitcoin in 2009 by Satoshi Nakamoto, there are many cryptocurrencies created by this technology while adopting different algorithms. Currently, there are 1890 cryptocurrencies trading on the market as in Aug. 2018 (see CoinMarketCap). The market cap of cryptocurrencies has skyrocketed from zero to a peak value of 813.87 billion US dollars in a few years, which has attracted lots of spotlights.

Cryptocurrencies are designed to be digital alternatives to the government-controlled fiat money. “Fiat money” is a kind of currency that is legal tender without any physical commodity backed by (Cermak, 2017). Since the collapse of the Bretton Woods Agreement in 1971, all major economies adopt the fiat system, including the US dollar. Similarly, the cryptocurrencies are also not backed by any physical commodities. They may not be endorsed by the government. Instead, most of the cryptocurrencies are controlled by a decentralized network with more transparent rules. This endorses the cryptocurrency the value of the decentralization from some governments where regulations are not transparent and are likely to induce huge inflations by issuing a bulk of fiats. Thus, its value not only lies on the transaction facilitation, but also on the its independence and transparence.

However, just like Albert Einstein says, “Technological progress is like an axe in the hands of a criminal.” The convenience of transactions also facilitates the money laundering for illicit activities. Besides, since the technology of blockchain is open, which is already adopted for creating numerous kinds of cryptocurrencies, the store value of cryptocurrencies may vanish if other cryptocurrencies with similar or better function continually spring up. It can also be noticed that some other cryptocurrencies are developing fast with higher returns as compared to that of Bitcoin and some of the later comers may have higher quality because they were improved based on Bitcoin (Gandal and Halaburda, 2016). But still, Bitcoin has a dominant market share of more than 50% now. Since Bitcoin is the innovator and it appears to be the most accepted one, the network effect[1] would be substantial.

Cermak (2017) argues that the investable cryptocurrency market is still too small as compared with other alternatives like gold. According to a leading financial expert,

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1. Network effect: the value of a product or service increases when the number of

users increases (Shapiro and Varian, 1999). For example, a social APP is more valuable if there are more users.

hedge fund CEO Dan Morehead in an interview with Bloomberg TV in 27th April 2018, the cryptocurrency market cap has a ten-year potential to reach an amount of 40 trillion USD and he already put his huge investment in the cryptocurrency market. There are also many suspicions about the value of cryptocurrencies. Some people hold the opinion that, it is just a perfect bubble. For example, the Nobel Prize-winning economist Robert Shiller says that cryptocurrency is “more of a psychological experiment than a serious investment”. Stefan Hofrichter, Allianz’s head of global economics and strategy, even says that “the intrinsic value of cryptocurrency must be zero.” The debate over whether the cryptocurrencies are of value or just bubbles is keeping hot, and it seems that there would be no clear answer before the time gives out the truth.

This finance research would not explore how much intrinsic value the cryptocurrencies are of, or whether the use of cryptocurrencies is immoral because they can be easily used for money laundering. Instead, this study is designed to inspect the investment aspect of cryptocurrencies. The analyses in cryptocurrencies are exciting and innovative. Firstly, it is an entirely new market where plenty number of players are competing (Gandal and Halaburda, 2016) and lots of opportunities show up. Secondly, data on these digital currencies are transparent, inerrant and non-missing over time, which makes the results more precise. And lastly, it is attractive to test whether the investment strategies from traditional assets have universe effects that can also work in an entirely different market.

One of the most investigated investment strategies in financial field is the momentum strategy. Momentum strategy means holding the assets that have superior past returns while shorting the assets that have lousy past performance. Its profitability has been widely proved in not only the traditional assets like equity but also alternatives like currency (Menkhoff et al., 2012; Rohrbach, Silvan and Joerg, 2017) and commodity futures (Qian, Andrew, and Subhash, 2007). Furthermore, Moskowitz, Ooi and Pedersen (2012) pool these financial assets in a diversified portfolio and find significant cross-sectional momentum profits.

While mentioning the momentum strategy, a discussion of contrarian strategy is indispensable. A contrarian strategy is just the reverse action of momentum strategy. It involves holding the assets that performed poorly in the past and selling the assets that have superior previous returns instead. This strategy is also generally confirmed to be efficient in equity markets worldwide (Schiereck , De Bondt and Weer, 1999; Kodjovi and Oumar, 2003; Kang, Liu and Ni, 2002).

Therefore, it would be quite attracting to see if these investment strategies are also effective in the entirely new cryptocurrency. Here comes the research question in this paper:

How efficient do the momentum and contrarian strategies work in cryptocurrency market and how can they be better applied by looking at the volatility of cryptocurrencies?

The effectiveness of a momentum strategy together with the contrarian strategy in cryptocurrencies will be discussed, which will be split into the cross-sectional momentum/contrarian strategy for the top ten cryptocurrencies in the very beginning on 29-06-2014 and time series momentum strategy for eight cryptocurrencies whose data are detailed and easy to be obtained, from the website of Coin Metrics.

In equity market, while the cross-sectional momentum strategy works for a medium term of 3-12 months (Jagadeesh and Titman, 1993)., the contrarian strategy is efficient in the short-term period of a month (Lehmann, 1990) and long-term of 3-5 years (DeBondt and Thaler, 1985). Therefore, an assumption that the contrarian strategy performs better in the "short run" could therefore be proposed. This idea is developed as the first hypothesis as follows:

Hypothesis 1: The long-only cross-sectional contrarian strategy is efficient in the short run.

Thereafter, the time series momentum and contrarian strategies for several individual cryptocurrencies will also be studied in this research. A plenty of paper have confirm the profitability of time-series momentum and contrarian strategies which would be discussed later. Here comes the second null hypothesis:

Hypothesis 2: The time-series contrarian strategy or momentum strategy for individual cryptocurrencies is not profitable.

A better understanding of the variance for cryptocurrencies is helpful, which would not only assistant the applying of momentum and contrarian strategy, but also a preparation for finding any factors that may influence the volatility and thus give a better prediction of variance for the investment strategies. The variances of cryptocurrencies are essentially high. Go back to the market cap of cryptocurrencies. The current market capitalization shown on the website of CoinMarketCap is around 216 billion USD, a significant drop from its peak value 813.37 billion USD. It can also be seen from the time's line graph in Figure-1 that the daily volatility is also quite large. The essentially high volatility may be due to the reason that the digital assets are entirely different from other financial assets and indeed no one can really determine the intrinsic value based on the technology, "brand value" or find some intrinsic variables that can be quantized.

For better prediction of variances in cryptocurrencies, this research would be also designed to explore the patterns of variance for cryptocurrencies by a set of ARCH family models for heteroscedastic variance. In total twelve variance models will be tested one by one for eight cryptocurrencies in sample. This careful study of the variances in cryptocurrencies is in a hope that the findings of the most fitted variance model may be extend to the variance estimation of other cryptocurrencies, i.e., external validity. Even the GARCH (1, 1) model is generally the most applied in financial assets (Chris Brook, 2014; Cermak, 2017), however, considering the unique characteristics of these digital product, the variance estimation may differ a lot from traditional financial assets or other alternatives. Therefore, the third hypothesis is constructed as follows:

Hypothesis 3: GARCH (1, 1) model can still be one of the most suitable variance models for cryptocurrencies.

Furthermore, because some cryptocurrencies are mostly traded in some significant economies, the macroeconomic factors of these economies may unavoidably have impacts on the prices of cryptocurrencies. Such research has already been done by Cermak (2017) for Bitcoin. The volatility may be predictable by macroeconomic factors like the equity markets' performance, the price of gold, treasury bond interest rates or even the exchange rates of specific big economies that involves large exchange volume of cryptocurrencies. As is also claimed by Cermak (2017), most of Bitcoin transaction is done in China, therefore, the economic fluctuation of China may have impact on the volatility. Besides, the shock even has a lasting impact. For example, the People's Bank of China forbidden Chinese banks to transact Bitcoin for preventing money laundering in December of 2013 included more than 13% of the price drop in Bitcoin, causing the highest volatility of Bitcoin so far. Therefore, a study of these macroeconomic factors' relationship with cryptocurrencies can give a better prediction of volatilities in the cryptocurrencies.

Cermak's study is only limited to one cryptocurrency bitcoin. To get an overall understanding of the relationship between macroeconomic factors and the variance for cryptocurrencies, this research will add value by extending a similar study to eight cryptocurrencies. Besides, the cryptocurrency index CCI30 will be checked by this regression to explore the influence of those factors on variance of the general cryptocurrency market since CCI30 can be regarded as a market proxy which includes up to 30 cryptocurrencies. There may be some multilinearly problems, because these macroeconomic factors usually correlated with each other. However, Cermak (2017) indicates that in such study the problem of multicollinearity does not matter because the research is designed to analyze the "larger macroeconomic picture", instead of the individual macroeconomic factors.

Therefore, the fourth hypothesis can be proposed as follows:

Hypothesis 4: Macroeconomic factors have little influence on the cryptocurrency volatility.

Apart from the macroeconomic factors mentioned above, the "microeconomic factors" of cryptocurrencies are also supposed to have effect on the volatility. For example, the "inflation rate", the increased rate of exchange volume. Besides, these additional variables can make a control of the regression for macroeconomic factors better.

Based on the hypotheses above, this research will split into four sections. The first part is a check of the cross-sectional momentum strategy and contrarian strategy in the cryptocurrency market. The second part is for the time-series momentum strategy, together with the contrarian strategy. The third part of this research, the volatility estimation, will be introduced to assistant and finish the regression in the second part. Lastly, the forth part aims to explore macroeconomic factors and some microeconomic factors that may influence the volatility of cryptocurrencies.

Literature Review

There are numerous studies of momentum and contrarian strategies in both traditional financial assets like stocks and other alternatives like commodity futures.

Jadadeesh and Titman (1993) first come up with a strategy that formatting the portfolios based on stocks' previous J-months' performance and then holds them for K months, where J,K∈{1,3,6,9,12}. They find that these cross-sectional past losers have significant positive returns for holding periods of 3-to 12-month. However, the profits gained by the first-year vanish in the following period of two years. Later, Jadadeesh and Titman (2002) confirm their findings in 1993 by spotting a continuation of momentum profits in the 1990s that these significant abnormal returns are not generated by data snooping.

Rouwenhorst (1998) conclude that the international equity markets have the continuation of returns for medium-term. For a time-span from 1980 to 1995, medium-term winner in portfolios that are internationally diversified outperform the losers by more than one percent after an adjustment of risk. Kang, Liu and Ni (2002) found statistically significant medium-term price persistence in Chinese equity market. Fama and French (2012) examine the stock exchanges of four major economies including North America, Europe, Japan and Asia Pacific, and find the continuation in stock prices over medium-term period in every economy under this research except for Japan.

The studies of momentum strategies above are all for stock market. Indeed, is also profitable for other financial assets. Shen, Szakmary and Sharma (2007) show that the momentum strategies for commodity futures market are highly profitable for holding periods of no longer than nine months. The returns are still positive even transaction fees are subsumed. Further, they also denote that the momentum profits finally reverse when holding periods are longer. Miffre and Rallis (2007) tests the short-term momentum in commodity futures including agricultural futures (coffee, wheat, milk etc.), mental futures (gold 100 oz, aluminum, copper etc.) etc., and find that there are 13 short-term momentum strategies that have an average annual return of 9.38%.

Moskowitz, Ooi and Pedersen (2012) apply a diversified portfolio (equity index, currency, bond futures, and commodity) of time series momentum strategies generate tremendous abnormal returns with low systematic risk, even perform the best when the market is extreme.

Contrarian strategy can be seen just as a reversal of momentum strategy. It is also in support of many pieces of researches. De Bondt and Thaler (1985) examine the stocks listed in NYSE and find that the past losers have significant superior performance over the past winners in the long run.

Jegadeesh (1990) find highly significant first-order monthly serial correlation of stocks during the time span of 1934-1987, which implies that the contrarian strategy also works of t top decile the short-term (one month here). The excess returns of past losers of the top decile as compared to the past winners of top decile is 2%. Lehmann (1990) investigates the stocks in NYSE and find that the “losers” of previous week have positive returns of 1.05% in the following week while the “winners” of previous week have negative returns of -0.45%, which show that the contrarian strategy is efficient in the short-term period (one week) while the momentum strategy induces loses.

The contrarian strategies are found to be profitable not only in the US market, but also in stock markets of other countries. For example, to avoid data mining, Schiereck, De Bondt and Weber (1999) study all the major German enterprises listed on the Frankfurt Stock Exchange and find out that the results are quite similar with that in

NYSE. Hameed and Ting (2000) check weekly returns of stocks in Malaysian stock exchange and find contrarian in stock prices in the following one- to four-week but the profits vanish when transaction fees reach 1%. Lee, Chan and Faff (2003) show that both the equal-weighted strategy and a newly adopted value-weighted strategy in Australian stock market generate significant contrarian profits for the short-term weekly period. Assoe and Sy (2003) confirm the validation of short-term contrarian strategy by investigating the monthly return in Canadian stock market, but if transaction costs are subsumed, the economical profitability disappear.

Kang et al. (2002) also confirm the short-term contrarian profits apart from the medium-term momentum efficiency in Chinese stock market that mentioned above. Forner and Marhuenda (2003) find that the 5-year long-term contrarian strategy is profitable, whereas the 12-month momentum strategy generate abnormal returns. Generally, the short-term and long-term reversals are the most commonly situation in stock markets all over the world; while the continuations are usually seen in the medium-term periods.

As for the reason of contrarian, De Bondt and Thaler (1985) claim that this reversal is because that the prices usually fluctuate around their intrinsic value. That is, the past losers will not continue to deviate from the inherent value too much, the prices will be drag back by well-informed investors that these “losers” start to win. Also, Barberis et al. (1997) indicate another possible explanation that some stocks with continuous past growing are prone to be overpriced because investors fail to notice that few of the can always keep an upward trend. Thus, the growing stocks may be overpriced.

Jegadeesh and Titman (2018) indicate that lots of papers prove the significant abnormal returns by adopting short-term contrarian strategies. However, owing to a higher fee occurred for the intensive short-term strategies, the success may be due to short-term price pressure or illiquidity.

Indeed, the transaction fees of these financial assets are not negatable and some stock especially the small ones often suffer from illiquidity. For the cryptocurrency, the two-way transaction fee ranges from 0.045% to 0.2% (see fees schedule of Binacne), which is relatively small as compared to an approx. of 1% to 2% for stocks. Besides, Therefore, the reversal may not occur in the cryptocurrency market.

Besides, even the success of short-term and long-term period has been approved in stock exchanges in a wild range. The study in commodity futures by Miffre and Rallis (2007) show that none of the long-term contrarian none of the long-term contrarian strategy is profitable. Therefore, it is also very likely that the contrarian strategy is not profitable in cryptocurrencies. However, Hameed and Ting (2000) indicate that, the intensively traded stocks are more profitable as compared with illiquid stocks. As the exchange of cryptocurrencies are quite frequent, it is also possible that the contrarian strategy has pronounced performance in this volatile market.

Fortunately, there are also some papers about the momentum and contrarian strategies in cryptocurrencies. Stefan Hubrich (2017) provides the first study of momentum, value and carry based factor in cryptocurrencies. He indicates that the longitudinal (time series) momentum strategy is quite profitable while the cross-sectional momentum effect is weaker. Hanlin Yang (2018) finds that cryptocurrencies have weak price reversal as compared to equity market.

Cermak (2017) indicates that a currency "serves as a medium of exchange, a unit of account and a store of value." Bitcoin is theoretically a good medium of exchange by facilitating exchanges of money without "unreasonable fees" charged by intermediaries. However, it is more regarded as an investment rather than currency because it has not yet been accepted by sufficient merchandises. Cermak (2017) finds that Bitcoin's high volatility is the biggest obstacle to be a currency. Since the variancecovariance of Bitcoin returns may be volatile during shocks, the conventional models of measuring volatility, like standard deviation or moving average deviation, cannot capture this relationship in variances of a different time. Considering this, the GARCH model seems to be a better selection. Cermak (2017) his factors research of volatility on the general accepted GARCH (1, 1) model.

Chu, Nadaraijah and Osterrieder (2017) explore twelve GARCH type models like SGARCH, GJRGARCH, TGARCH and conclude that the GJRGARCH and IGARCH models have the best fits. Their model selection is based on maximum likelihood. Because some of the models are not nested, they also use other criteria for discrimination, for example, AIC, BIC, CAIC, AICc (the corrected Akaike Information Criteria) and HQC. For the IGARCH fitting, however, they indicate that it may be a spuriously good estimate if there is any structural change in data. Thus, further research is suggested to check possible fundamental change.

Hansen and Lunde (2005) compare 330 ARCH-type models and find no evidence of that other more sophisticated models outperform the GARCH (1, 1) model in their research of DM-USD exchange rate, but GARCH (1, 1) is inferior to models that corporate leverage effects. The models are also estimated by maximum likelihood for an in-sample test, while the evaluation of out-of-sample forecasting is based on MSE (Mean Squared Errors), QLIKE and MAE (Mean Average Errors).

Dyhrberg (2016) inspect the volatility of Bitcoin, gold and US dollar by using GARCH models. Based on the research of Tully and Lucey (2007), the explanatory variables are selected as follows: “Federal funds rate, USD-EUR exchange rate, USD-GBP exchange rate, the gold bullion USD/troy ounce rate (Gold Cash), the CMX gold futures 100-ounce rate in USD (Gold future) and the Financial Times Stock Exchange Index (FTSE Index).” The estimations are based on a variance equation of GARCH (1, 1) with the mean equation of AR(1) or AR(2).

The first model is GARCH (1, 1) with AR(1) process. In the mean equation regression, the federal funds rate t-1, have positive coefficient at the 1% significance level. He explains that, when the federal funds rate increases and therefore the US dollar appreciates, the import will increase as well as online purchase. However, according to Cermark (2017), the cryptocurrencies merely involve daily transactions because of their high volatilities. Thus, the explanation of the positive effect of the federal funds rate on Bitcoin returns in Dyhrberg's work is still arguable. Dyhrberg (2016) also conclude that regional/country-specific factors are present because of the significant difference between the coefficients of USD-EUR exchange rate-1 and the USD-GBP exchange rate-1. Therefore, Bitcoin can offer effective hedging against the US dollar.

In the variance equation regression of the first model, he finds that the coefficient of the federal funds rate-1 is negative 6.801 at the 1% significance level, which means that an increase the federal funds rate is correlated with a decrease in the Bitcoin volatility. This interesting trait may endorse Bitcoin an additional risk management capability, which is similar with gold as he cites to Capie, Mills and Wood (2005). Apart from this, he says the traits of Bitcoin's volatility clustering and a high level are also similar to gold.

The second model of their research is the exponential GARCH (1, 1) model with a mean equation of AR(2). It can measure how sensitive the Bitcoin's reaction to the right or bad news. The finding shows that good or bad news has no asymmetric effect on the volatilities, which is also similar to gold, as is cited to Hammoudeh and Yuan (2008). Because both the Bitcoin and gold have no asymmetry to positive and negative shocks, they can be used to hedge market risks. Besides, because bitcoin has no significant effect of leverage, it can be an excellent hedge tool if the investors anticipate an adverse shock.

Data and Methodology

Part I Cross-sectional Momentum Strategy and Contrarian Strategy

Like studying the momentum strategy of stocks by looking at the performance of the component companies in stock indexes (for example, S&P 500), it is ideal to examine the components in a cryptocurrencies index.

There are indeed some cryptocurrencies indexes. For example, the Cryptocurrency Index (CRIX) is a market-value-weighted cryptocurrency index which consists of 20 cryptocurrencies now. The index is a good proxy of the crypto market, however, since the cryptocurrencies are quite volatile, this index is designed to reallocate its members per three months by three criteria (average trading volume, average traded coins, AIC/BIC) to ensure that the index represents the market well. Such rebalances are quite useful in presenting the volatile young market, however, by this method, the index will only contain the very successful ones that have high trading volumes and market caps, which is very likely to cause a survivorship bias that distort the result to be looked better.

Other cryptocurrency indexes like Crypto Currency Index 30 (CCI30), which consists of 30 top cryptocurrencies in market capitalization, is also rebalanced its components every quarter. Bitcoin always takes the fixed weight 35% of the whole index and the rest top 29 is balanced by the square root of the market cap. CRYPTO20 is a cryptocurrency index designed for the use of investment, which is rebalanced weekly. All these crypto indexes are created to rebalance very often, according to their market cap and exchange volume, or even according to their investment value (CRYPTO20), therefore, it is not appropriate to study the cryptocurrencies in theses crypto indexes in this research of momentum strategy because of the possibility of causing a severe survivorship bias.

Directly examining the whole market is neither appropriate because there are currently 1855 different sorts of cryptocurrencies available in the market as is shown on the website of CoinMarketCap (18th Aug. 2018). Merely choosing top 10 cryptocurrencies today will also suffer from some distortion. It is because the top 10 today are undoubtedly the winners in the past among this market. Therefore, we would like to select a fixed ten cryptocurrencies which are of long history, to investigate the cross-sectional momentum and contrarian strategy.

The website of CoinMarketCap offers historical snapshots back to earliest 28th April 2013, on which day only seven cryptocurrencies are available. The next possible day is 5th May 2013, on which day ten cryptocurrencies are listed there in total, but the data of Devcoin are not available since 23rd Nov. 2017. The current price and market cap change of Devcoin can be found on the website of CoinGecko, but the trading volume is zero. Since the execution of momentum strategy will not be applied to the non-active cryptocurrencies, it is nonsense to include such cryptocurrencies in this research. On the day of 29th June 2014, the top 10 cryptocurrencies have non-zero trading volume every day until now. These top 10 in very early time may not be successful enough later (for instance, failed to have high volume and high market cap after that) to be incorporated in any crypto index. Therefore, this research will adopt this method to avoid some distortion due to not checking the whole market.

These top 10 cryptos on the day of 29-04-2014 are as follows.

Name	Symbol	Release	Rank on 29-04-2014	Rank today
Bitcoin	BTC	2009	1	1
Litecoin	LTC	2011	2	7
Nxt	NXT	2013	3	91
Dash	DASH	2014	4	14
Ripple	XRP	2013	5	151
Peercoin	PPC	2012	6	153
Dogecoin	DOGE	2013	7	32
Namecoin	NMC	2011	8	188
BlackCoin	BLK	2014	9	473
Bytecoin	BCN	2014	10	28

This research will prob into long-only momentum strategy and long-only contrarian strategy. A long-only cross-sectional momentum strategy involves holding the assets which used to have highest returns before (winners), without any shorting of assets that have lowest returns before. While a short-only cross-sectional contrarian strategy is holding the assets that used to have lowest returns before (losers), also without any shorting actions. Take an example of a simple day-to-day long-only cross-sectional momentum strategy. According to the momentum strategy, investors hold the cryptocurrencies that have the highest returns in the previous day (winner portfolio). In the end of the day, the winner portfolio will be rebalanced based on the return of all cryptocurrencies today, then invest in the cryptos that have the highest returns today in the expectation that the crypto will continue to have relative high return tomorrow, and that cycle repeats. The strategy in this research is designed to be an equal-weighted method, i.e., every time, the amount of money for purchasing is equal. We assume the value to be one US dollar.

In much other research (Fama and French, 2015), the stocks that have good returns ranked top decile are winners, while the bottom decile are losers. In this research, the winner will also be the cryptocurrency having the top decile returns during the observing period. There are ten kinds of cryptocurrencies studied in each period. Therefore, only the best one will be selected by the criterion of top decile. Similarly, the one with the worst performance during every observing period will be assigned as the loser.

Apart from the most straightforward day-to-day strategy above, there are other strategies that of different observing time and participating time. For the stock market, the momentum/contrarian strategies are usually based on the form of weeks, months and even annuals. Since the cryptocurrencies are quite volatile, the time span of strategies will be formed based on one day, three days, one week, half month (15 days) and one month (30 days). The following table shows different strategies for momentum and contrarian, where x denotes the observing days and y indicates the strategy of corresponding participating days (buying or shorting).

In addition, the annual of the more interested momentum/ contrarian strategies (x=1, y=1), (x=3, y=3), (x=7, y=7), (x=15, y=15) and (x=30, y=30) in each year from 2014 to 2018 will be drawn in line graphs, which will give a better comparison of the performance of different strategies horizontally, and a better comparison of the performance in each year vertically.

Generally, the profitability of momentum or contrarian strategy will be check by incorporating the risk-free rate to generate the excess returns. Since the market of cryptocurrency is opened all the time, while the risk-free rates are not available during weekends, the real excess returns of cryptos against the risk-free rate during the weekend cannot be calculated. Besides, the risk-free rate of the US government 10-year treasury bond does not fluctuate a lot. Therefore, a direct comparison between the profits of the investment strategy and the risk-free rate can be drawn. Thus, this research will calculate the return of cryptos directly.

By definition, the daily return of a certain cryptocurrency is the increased price divided by the price of the previous day. Since $x \sim \ln(1+x)$ when x is very small ($0 \leq x \ll 1$), the daily return can be proxied by $r_t = \ln(Price_t) - \ln(Price_{t-1})$

(1.1)

It is because $r_t \sim \ln(1 + r_t) = \ln\left[1 + \frac{Price_t - Price_{t-1}}{Price_{t-1}}\right] = \ln(Price_t) - \ln(Price_{t-1})$

A big advantage of taking the logarithm form to present the return is log-normality, which is will be explained in the second part. Log-normality is very helpful in the time series analyses of momentum/contrarian strategy. To make the results of this research integral, this cross-sectional part would also adopt the log return.

Take the purchasing date as time t, then the cumulated log return of an observing period of x days is calculated as$\mathrm{r}_{x,t} = r_{t-1} + r_{t-2} + \cdots + r_{t-x}$

(1.2)

Similarly, the cumulated log returns of a participating period of y days is calculated as:

$\mathrm{r}_{y,t} = r_t + r_{t-1} + \cdots + r_{t-y+1}$

(1.3)

By doing this, the returns of the observing period of multiple days can be seen and thus as the criteria for sorting out the winners and losers.

Lastly, the annual return of x observing days and y participating days is

$$\mathrm{R}_y = \sum_{t=x+1}^{t=n-y} \frac{lnacr_{y,t}}{y} \quad ,$$

Where n is the total number of days in a sample. (1.4)

Because this cross-sectional momentum/contrarian strategy involves bubble sort, the coding work will be operated in C programming.

Part II: Time-series Momentum Strategy and Contrarian Strategy

Firstly, the daily price of specific cryptocurrencies needs to be collected. From the website of Coin Metrics (see https://coinmetrics.io/data-downloads/), data of core cryptocurrencies can be downloaded directly by one click. The cryptocurrencies that to be checked include Bitcoin (BTC), Litecoin (LTC), Dash (DASH), Digibite (DGB), Dogecoin (DOGE), Ethereum (ETH), Vertcoin (VTC), Monero (XMR). All these eight cryptocurrencies have high liquidity (high daily exchange volume) as well as relatively longer history (except for ETH which has transaction record since Aug. 7th, 2015) among the cryptocurrencies in the dataset called core sample. Because Ethereum is entirely representative in the cryptocurrencies regarding its technology, it is also included in this research despite its short history. The summary of these cryptocurrencies is shown as follows. Moreover, the time's line graphs of these cryptocurrencies are shown in Figure-1.

The second hypothesis assumes that the momentum/contrarian strategy does not have effect on the cryptocurrency market. Three different methods will be taken to test this hypothesis in the following:

1 Basic Regressions of Adjusted Return

Moskowitz, Ooi and Pedersen (2012) use the form of the return divided by the previous h period’s standard deviation, which is shown as

$$\frac{r_t}{\sigma_{t-1}} = \alpha + \beta\left(\frac{r_{t-h}}{\sigma_{t-h-1}}\right) + \varepsilon_t \tag{2.1}$$

They argue that because the differences in variance of these different assets are quite significant, they divide all excess returns by their variance to make them on the same scale.

This operation is beneficial in inspecting the performance of these volatile cryptocurrencies. Higher returns often involve higher volatility, the volatilities of each cryptocurrency vary a lot not only between the different cryptos horizontally but also from period to period, as can be seen from the time series line graph in Figure-1. Therefore, an adjustment for the returns based on the volatility (a proxy of risk) is handy for evaluating the investment in this volatile market.

However, this research will adopt a regression a bit differently. Indeed, equation (2.1) can give a straightforward prediction of the volatility-adjusted returns based on previous h-th period's data. They use this regression because they only need to consider the vast volatility differences between assets rather than the time series volatility. It is because the volatilities are entirely different from one kind of assets to another kind of assets; while the volatilities of an individual asset are more stable over time within the asset itself. In this research, it is known that the volatility of cryptos not only differ from their peers (cross-sectional comparison) but differ a lot from day to day (time series comparison). I.e., the current volatility may change a lot from the previous period's volatility (see Figure-1), it is likely that time-varying volatility is not correlated with the previous one; or the correlation is weak. Therefore, if the standard deviation of the previous period is applied, the "adjusted" return will not be precise enough, which may induce no findings from research. Therefore, the current period's standard deviation will be taken as the denominator rather than that of the one of the previous periods. Also, by doing this, the risk of cryptocurrency can be controlled, which gives a better concept of the investment value in this volatile market.

The regression function in this research is:

$$\frac{r_{y,t}}{\sigma_{y,t}} = \alpha + \beta\left(\frac{r_{x,t-1}}{\sigma_{x,t-1}}\right) + \varepsilon_t \ ,$$

where y denotes the participating period, and x denotes the observing days (2.2)

There is two difference as compared with the regression (2.1) of Moskowitz et al. One difference is the denominator, as is mentioned above. The other is that the cumulative returns of three days, one week, half month (15 days) and one month (30 days) will also be regressed, rather than of sole one day (as is one month in their research). In total five representative strategies (x=1, y=1), (x=3, y=3), (x=7, y=7), (x=15, y=15) and (x=30, y=30) will be analyzed via this regression.

If the coefficient β is significantly positive, then it implies a continuation or trend of the "volatility-adjusted" return (momentum strategy holds); if a significant negative sign of the coefficient shows, then it shows a reversal (contrarian strategy holds). By doing such regression on several approaches, we could conclude whether the null hypothesis that time-series contrarian strategy or momentum strategy hold for only cryptocurrencies holds.

While before the regression, there are two preparations.

First preparation: Logarithm form of return

A significant advantage of taking the logarithm form to present the return is log-normality. According to the histograms of the eight cryptocurrencies, the daily prices are skewed to the right. After the log normality process, the returns rt=ln(1+r) present a normal distribution, which is a crucial assumption for determining the best OLS regression.

Second preparation: Stationary

Non-stationary data can behave as trends, cycles or random walks, or the combination of these three. A regression on non-stationary data may cause spurious results, and therefore the understanding and forecasting may be wrong. In this research, the stationarity of rt and rt/σt needs to be checked carefully. For a determination of whether the returns of cryptocurrencies are stationary, the augmented Dickey-Fuller tests will be done in STATA.

In Figure 7 (see Appendix), the time's line graph of the daily returns of the eight cryptocurrencies are presented. There is no trend, so only the test for a unit root

The equation is $\Delta y_t = \delta \Delta y_{t-1} + \Delta \mu_t$

If δ=0, there is a unit root. It is because, if the data are stationary, the current dependent variable is a significant predictor of the dependent variable of the next period. Therefore, δ should be negative rather than zero.

Apart from the return, volatility is also required for operating the regression (2.2). Since volatilities are unobservable, a proxy is needed. The discussion of volatility estimation will be concentrated in Part III. Also, the prediction of returns based on (2.2) is also possible by finding a fitted volatility model such as GARCH or TARCH for these cryptocurrencies, which will also be discussed further in Part III.

Part II-2 *Sign Regression*

Similarly, a sign regression which consists of the categorical variable that denotes whether the previous return is positive, zero or negative. This method is also inspired by Tobias et al. (2010) in their research of time-series momentum. Their regression function is shown as follows:

$$\frac{r_t}{\sigma_{t-1}} = \alpha + \beta sign\left(\frac{r_{t-h}}{\sigma_{t-h-1}}\right) + \varepsilon_t$$

As is claimed above, the current standard deviation will be chosen in this research rather than the standard deviation of the previous period. The sign regression is shown as follows:

$$\frac{r_{y,t}}{\sigma_{y,t}} = \alpha + \beta sign\left(\frac{r_{x,t-1}}{\sigma_{x,t-1}}\right) + \varepsilon_t \tag{2.4}$$

The factor $sign\left(\frac{r_{x,t-1}}{\sigma_{x,t-1}}\right)$ is valued 1 if the adjusted return at time *(t-1)* is positive (as well as the return of the (t-1) th period, because the standard deviation is never negative); the sign factor will be assigned -1 if the adjusted return $\frac{r_{t-h}}{\sigma_{t-h-1}}$ is negative; 0 if the adjusted return $\frac{r_{t-h}}{\sigma_{t-h-1}}$ is zero.

If the coefficient of the sign is significantly positive, then the momentum strategy performs better than the contrarian strategy. Since a positive sign presents a previous positive return, if the coefficient of the factor sign is positive, the last positive return has a positive impact on current return, or the previous negative return has n negative impact on current yield, i.e., momentum strategy holds. On the contrary, if the coefficient of the sign is significantly negative, the contrarian strategy may be a good choice.

Part III-3 Historical Profitability of Momentum and Contrarian Strategies

The profitability of both time-series momentum strategy and contrarian strategy will be inspected by looking at the arithmetical average daily return during the holding or shorting period. Both the long-short and long-only investment strategy will be under inspection. Besides, both the momentum and contrarian strategy will have five different groups of observing time and investing time. Therefore, in total, there are 20 different kinds of investment strategy in this part. They are as follows:

Momentum Strategy		Contrarian Strategy	
Long-Short	Long-only	Long-Short	Long-only
x=1, y=1	x=1, y=1	x=1, y=1	x=1, y=1
x=3, y=3	x=3, y=3	x=3, y=3	x=3, y=3
x=7, y=7	x=7, y=7	x=7, y=7	x=7, y=7
x=15, y=15	x=15, y=15	x=15, y=15	x=15, y=15
x=30, y=30	x=30, y=30	x=30, y=30	x=30, y=30

The arithmetical average of lnar together with its 95% confidence interval will be shown in a table. Besides, to give a better understanding of the effectiveness of the investment strategies, the annualized return will be calculated as: average return of ry times 365/y, i.e., Annualized_ry=lnary* (365/y)

Note that r denotes the logarithm form of return in this time series part, while R in the cross-sectional part denotes the return that measured by the increased price divided by the previous price. They can be transformed to each other: rt=ln(1+Rt).

Part III: Volatility determination

The determination of volatility needs to be clarified since the time-series momentum strategy above will adopt a volatility-adjustment for the returns. It is known to all that the volatility of financial assets is a curtail part of financial studies, which can give a better risk control and portfolio management. Especially, the cryptocurrencies suffer from massive volatility in price. Thus, it is quite meaningful to inspect and predict the volatility in this financial market.

Volatility is unobserved; thus, a proxy is needed to present the volatility. There are (at least) four methods of estimating volatilities. One method is taking the square of returns as the proxies of volatility. According to Chris Brook (2014), there are ample of evidence that this proxy presents poorly: even if it is a reasonable estimate on average, while for the individual days, the proxy deviates a lot from the actual. Therefore, it is not suitable for high-frequency data.

This estimation of variance is: $\sigma_t^2 = r_t^2$ (3.1)

Another method is called the range estimator of volatility. It can be generated by taking the logarithm of the ratio of the highest price to the lowest price, which can be shown as follows (Chris Brooks, 2014):

$$\sigma_t^2 = \log(\frac{high_t}{low_t}) \qquad (3.2)$$

Andersen and Bollerslev (1998) proposed a method that is adding up the intra-daily data for the daily volatility. For instance, adding up all the squared hourly returns of a day to generate daily volatility. It would be quite applicable in this research since the estimation of the volatility of, for example, three-days' return of cryptocurrencies, can be directly calculated by adding up the squared return of these days, which can be presented as:

$$\sigma_{x,t}^2 = \sum_{i=t-x}^{i=t} r_i^2 \qquad (3.3)$$

The fourth method is the use of time series models. Chris Brook (2014) proposes that there is also lots of evidence that, the adoption of volatility estimated by more sophisticated time series models would generate more precise valuations of option assets (Akgiray, 1989; Chu and Freund, 1996). Generally, the GARCH (1, 1) model is proved to be one of the most applicable for proxying the volatility in the field of applied finance (Cermak, 2017). However, considering the unique traits of cryptocurrencies (such as technological/digital based, high daily volatility) that may induce a different performance of cryptocurrencies than other traditional financial assets, it is better to have a look at different volatility models.

The ARCH family models will go through the eight cryptocurrencies used in Part II time-series momentum strategy. Besides, the cryptocurrency index will also be checked aiming to probe into the volatility performance of the crypto market. Here CCI30 is selected because of two reasons. One is that since Bitcoin usually dominances massive portion in the whole cryptocurrency market (currently 53%), the design of fixed 35% portion for Bitcoin in CCI30 gives more presence of other cryptocurrencies rather than CRIX. Besides, CCI30 contains 30 cryptocurrencies rather than 20 of that in CRIX. Therefore, CCI30 would be more diversified.

Part III-1 Conditional Mean equation

To start with, a best fitting conditional mean equation should be determined because the variance is based on the function of mean.

The D-F tests for the stationary check which is already mentioned in Part II show that the daily returns of cryptocurrencies are all stationary in this research. Therefore, the conditional mean equations must be an AR, ARMA when analyzing the returns' volatility in the financial field. Then, he adopts the first-order-autoregression AR (1). In this research of cryptocurrencies, again, since the cryptocurrency is an entirely different new asset in the market, an exploration of the fitted ARMA models are also necessary. The graphs of autocorrelation function and partial correlation function of each of the eight cryptocurrencies will be checked preliminary, then a more precise inspection based on the value of BIC will be executed to get the most fitted mean equation model. BIC means Bayesian Information Criterion, which is proposed by Gideon E. Schwarz in 1978. This criterion bases partially on the likelihood function but it introduces a penalty of incorporating too many parameters to avoid overfitting.

After the best fitted mean equations are determined, the volatility equations can be explored based on the estimated residuals in the mean equation. First of all, whether the volatility is of homoscedasticity or heteroscedasticity needs to be clarified:

Homoscedasticity vs. Heteroscedasticity

In Figure 1, the time's line graph of the daily returns and eight cryptocurrencies together with the index CCI30 are presented. From these graphs, a preliminary conclusion of the heteroscedasticities can be drawn by observing the clustering. However, the quantitative tests would also be needed for accuracy. The extension version of the Breusch-Pagan test can give an insight on whether there is heteroscedasticity in a linear regression model. It assumes that if the variance does not depend on the independent variables, then the variance that proxied by the square of residuals cannot be determined by the independent variables, which can be expressed as follows:

$$\hat{u}^2 = \gamma_0 + \gamma_1 x + v$$

The null hypothesis that $\gamma_1 = 0$ implies the variance cannot be determined by the independent variable, i.e., the variance is of homoscedasticity. It can be tested right after the linear mean equation regression in STATA.

If homoscedasticity does not hold, the heteroscedasticity ARCH family models will be tested in this research. The heteroscedasticity volatility models that are going to be tested in this research are presented as follows, together with some discussion (Chris Brook, 2014):

1) ARCH model:

$$\sigma_t^2 = a_0 + a_1 u_{t-1}^2 + a_2 u_{t-1}^2 + \cdots + a_q u_{t-q}^2 \quad u_t \sim N(0, \sigma_t^2)$$

ARCH stands for AutoRegressive Conditionally Heteroscedastic. It describes the current variance as a function of the previous periods' residuals of the mean regression. The ARCH model of variance can be seen as an AR (Autoregressive) model of mean.

The introduce of the squared past residuals can better describe the time series variance for volatility clustering. However, ARCH models have rarely been applied in the past, since:

The determination of the number of lags needs a likelihood ratio test, and the number of lags may be quite large.

Constraints of non-negative for coefficients: because the squared lagged residuals are never negative, all the coefficients of the ARCH model need to be non-negative to ensure the positive variance estimates. This constraint of coefficients is sufficient for non-negative variance estimates but not necessary.

2) GARCH model:

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} \alpha_1 u_{t-1}^2 + \sum_{j=1}^{p} \beta_1 \sigma_{t-j}^2$$

GARCH stands for General AutoRegressive Conditionally Heteroscedastic. It is usually used in estimating the volatility of returns of bonds and stocks by financial institutions, to assistant their risk management, hedging, asset management and portfolio constructions.

Generally, GARCH (1, 1) model can incorporate enough volatility clustering in financial data. A higher order of GARCH model is rare (Chris Brook, 2014).

One of the drawbacks of GARCH model is that, if the variance is non-stationary ($\alpha+\beta>=1$), For a stationary GARCH model, the estimates of conditional variance will converge upon the long-term average value, while for a non-stationary GARCH model ($\alpha+\beta=1$), the converge will not happen and for the GARCH ($\alpha+\beta>1$), the estimates of variance will be approaching to infinity as the forecast further.

Secondly, the basic GARCH model cannot reflect leverage effects. A negative shock is prone to rise the volatility by more than the same magnitude positive shock does.

Finally, there is no direct feedback between the variance and the mean equation.

3) GARCH-AR

$$y_t = \mu + \delta(y_{t-1} - \mu) + u_t, u_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} \alpha_1 u_{t-1}^2 + \sum_{j=1}^{p} \beta_1 \sigma_{t-j}^2$$

Above is the example of GARCH(1, 1)-AR(1) model. It endorses more impact from past residuals on the mean equation.

4) GARCH-ARMA

$$y_t = \mu + \delta(y_{t-1} - \mu) + \theta u_{t-1} + u_t, u_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q} \alpha_1 u_{t-1}^2 + \sum_{j=1}^{p} \beta_1 \sigma_{t-j}^2$$

Above is the example of GARCH(1, 1)-ARMA(1, 1) model. The only difference from the GARCH-AR model is that the previous residuals are allowed to add back to the mean equation directly.

5) EGARCH

EGARCH model is the exponential GARCH model which was proposed by Nelson in 1991. It can be expressed as follows:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}]$$

The advantages of the GARCH model are that:

(i) Asymmetries are allowed: if the relationship between the residuals and volatilities are negative, then γ will be negative. The introduction of asymmetry is cardinal because the financial returns often have asymmetric payoff characteristics. That is to say, “the upside potential is greater than the downside risk” (McKoan and Ning, 2011).

EGARCH model is one of the two popular models that incorporate the leverage effect. (ii) The variance can still be positive even if the parameters are negative. i.e., there is no need to impose any non-negative requirements on the parameters.

6) TARCH

$$\sigma_t^\delta = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^\delta \, I(\varepsilon_{t-i} < 0)$$

where δ=1 as in Zakoian (1991) or δ=2 as in Glosten et al. (1993)

TARCH stands for the Threshold ARCH model. It divides the distribution of residuals into discrete intervals and then estimates a linear function of standard deviation (δ=1) or variance (δ=2). It is assumed that low volatility of residual is followed by another low volatility for a prolonged period.

7) GJR-ARCH

The GJR model was proposed by Glosten, Jagannathan, and Runkle in 1993. By adding a term that reflects possible asymmetries to the pure ARCH model, the volatility can be better proxied than the pure ARCH model when there is an asymmetry of returns. The GJR model is the other one of the popular models that incorporate the leverage effect.

8) GJR-GARCH

Similarly, by simply adding a term that reflects possible asymmetries, the GJR-GARCH model can be generated from the pure GARCH model. It is given as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 + \beta \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1}$$

$$I_{t-1} = 1 \; if \; \varepsilon_{t-1} < 0$$

$$= 0 \; otherwise$$

Similar to GJR-ARCH model, the GJR-GARCH is able to incorporate asymmetry effect on the volatility from the previous residuals.

9) NARCH

The NGARCH model is a Nonlinear Asymmetric ARCH model. More explanation see NGARCH model below.

10) NGARCH

The NGARCH model is a Nonlinear Asymmetric GARCH model.

$\sigma_t^2 = \omega + \alpha(\epsilon_{t-1} - \theta\sigma_{t-1})^2 + \beta\sigma_{t-1}^2$ where $\alpha \geq 0, \beta \geq 0, \omega > 0 \; and \; \alpha(1+\theta^2) + \beta < 1$

If the parameter θ is positive, it will magnify the squared factor of (ϵ_(t-1)-θσ_(t-1)) when the residuals are negative. Therefore, it can reflect a “leverage effect” that a negative return increases the future variance by a more considerable amount than the positive returns of the same magnitude.

The primary criterion is the log likelihood, with the assistance of another criteria AIC and BIC.

11) ARCH-in-mean

$$\gamma_t = \mu + \delta\sigma_{t-1} + u_t, u_t \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$$

Investors are assumed to be rewarded for taking a higher risk by gaining a higher return. Therefore, the GARCH-in-mean model that incorporate the historical standard deviations into the mean regression model can reflect this concept. Since GARCH models are more applicable than ARCH model, it is generally more efficient to estimate a GARCH-in-mean model.

If δ is significantly positive, the increase in volatility drives up the return. Therefore, a positive δ is represented as a risk premium.

12) GARCH-in-mean

Example:

$$y_t = \gamma_0 + \gamma_1 x_t + \gamma_2 g(\sigma_t^2) + \epsilon_t$$

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \alpha_1 \epsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_1 \sigma_{t-1}^2$$

$$\epsilon_t | \Phi_{t-1} \sim N(0, \sigma_t^2)$$

This model has additional variables of previous residuals in the mean equation as compared with the GARCH-AR model discussed above.

Part IV: Microeconomic and Macroeconomic factors that influence the volatility of cryptocurrencies.

Microeconomic factors of the individual cryptocurrency for their own

The daily data of the eight cryptocurrencies are derived from the website of Coin Metrics. The information of cryptocurrencies (such as the daily price, market capitalization, daily generated coins) as follows:

Daily Price: close price (12:00 am of the day) of one cryptocurrency, measured in US dollars.

Market Cap: The total market value of the cryptocurrency, measured in US dollars

Daily Generated Coins: units of cryptocurrency successfully mined on that day.

Exchange Volume: daily transaction of the cryptocurrencies, measured in US dollars.

Active Address: "the number of unique sending and receiving addresses participating in transactions on the given day" (Coin Metrics). The address is a term of cryptocurrency, and it can be compared like a bank account that store the cryptocurrencies. In every transaction, the address will be activated, and therefore, this variable can be taken as a proxy for transaction frequency. It is a bit different from exchange volume measured in US dollar. The transaction frequency implies the popularity of the cryptocurrency to some degree (more people participant).

Based on the data above, the microeconomic factors are constructed as follows:

r_{t-1} (or L.r_t)

Daily return of cryptocurrency, which is proxied by the logarithm of a daily price at time t minus the logarithm of a daily price at the time (t-1)

$\mathrm{D.vol}_{t-1}$ (or LD.vol_t)

The increased exchange volume rate at time (t-1). It is measured by:

$\ln(\text{ExchangeVolume})_{t-1}-\ln(\text{ExchangeVolume})_{t-2}$

$\mathrm{inflation}_{t-1}$ (or L.$inflation_t$)

The inflation rate of cryptocurrency at time (t-1). It is measured by:

$(DailyGeneratedCoins_{t-1} \times DailyPrice_{t-1})/MarketCap_{t-1}$

Just like the pricing of currency, the inflation rate is an essential factor that influences the value. Cryptocurrencies are designed to facilitate the trading, playing a role as the exchange medium and suffer from inflation that designed in the protocol. The short-term high inflation rate implies higher supply, while the supply together with demand can influence the prices. The change in supply in previous period may have some influence on the volatility today.

$\mathrm{D.lnactadd}_{t-1}$ (or $\mathrm{LD.lnactadd}_t$)

The active address presents the daily transaction frequency of cryptocurrency. An increase rate of transaction frequency previously may have impact on

Macroeconomic factors of the specific economy

Apart from these "microeconomic factors," macroeconomic factors may also influence the cryptocurrency volatilities. Cermak (2017) adds some macroeconomic explanatory variables to variance equations, like the federal rates, the currency exchange rates, and the treasury bond rates of main Bitcoin trading regions, to check whether Bitcoin is the real decentralized "currency" that exempt from specific countries'/regions' economic fluctuation. Inspired by his work, this research also adds some explanatory variables.

The data of macroeconomic factors are directly downloaded from the website of the Economic Research Division of Federal Reserve Bank of St. Louis, including:

Overnight interest rates of USD, EUR, and CNY;

One-year Treasury bond rates of the US, Germany, and China;

The daily exchange rate of EUR/USD and CNY/USD;

Daily S&P 500 stock index, daily MSCI Europe stock index, daily Shanghai Stock Index.

The variables that will be included in the volatility regression are as follows:

$\mathrm{D.USDovnt}_{t-1}$ (or $\mathrm{LD.USDovnt}_t$)

$\mathrm{D.EURovnt}_{t-1}$ (or $\mathrm{LD.EURovnt}_t$)

$\mathrm{D.CNYovnt}_{t-1}$ (or $\mathrm{LD.EURovnt}_t$)

The increased interest rate of USD/EUR/CNY overnight interest at the time (t-1) respectively. It is measured by the logarithm of USD/EUR/CNY overnight interest rate at the time (t-1) minus the logarithm of the overnight interest rate of the same currency at the time (t-2), which can be expressed as ln(USDovntt-1)-ln(USDovntt-2)

The overnight interest rates are applied here aiming to explore the relationship between the volatility of cryptocurrencies and the main country's/region's short-term economic fluctuations.

D.USD1y$_{t-1}$ (or LD.USD1y$_{t}$)

D.EUR1y$_{t-1}$ (or LD.EUR1y$_{t}$)

D.CNY1y$_{t-1}$ (or LD.EUR1y$_{t}$)

Similarly, they present the increased interest rate of USD/EUR/CNY overnight interest at the time (t-1). The 1-year treasury bond rates are applied here aiming to explore the relationship between the volatility of cryptocurrencies and the main country's/region's medium-term economic fluctuations.

D.EURUSD$_{t-1}$ (or LD.EURUSD$_{t}$)

D.CNY USD$_{t-1}$ (or LD.CNYUSD$_{t}$)

They present the increased daily exchange rate EUR/USD and CNY/USD at the time (t-1). The raw data are also retrieved from the website of the Federal Reserve Bank of St. Louis. A change in the exchange rate between two economies is assumed to be associated with a change in the macroeconomic environment of them. Therefore, this research also adds in the factors of changes in exchange rates for the three specific regions.

D.SP500$_{t-1}$ (or LD.SP500$_{t}$)

D.MSCIEU$_{t-1}$ (or LD.MSCIEU$_{t}$)

D.SSH$_{t-1}$ (or LD.SSH$_{t}$)

The increased rate of representative equity indexes in the US, EU, and China: daily S&P 500 stock index, daily MSCI Europe index, and daily Shanghai Stock Exchange Composite Index proxy the stock market performance as well as the macroeconomic environment.

Results

Part I: Cross-sectional momentum and contrarian strategy

General comparison of momentum and contrarian strategies

As is shown in Table-2, all the momentum strategies suffer from a loss even the transaction fees and risk-free rate are not incorporated. It reaches the lowest of -6.07% daily log return and -2214% annually.

While the long-only contrarian strategies (see Table-3) perform quite well. All the strategies listed are profitable, which ranges from an annual log return of 63% to 1618%. The returns are extraordinarily high when the observing days are short and participating days are long. We find that, except for the strategy (x=33, y=1), the return of every strategy of x=1 dominant x=3, strategies of x=3 dominants x=7, and so forth from x=7 to x=30. It may be due to the volatility of this immature market, which makes the cumulative return of more extended period less predictable, and therefore the shorter observing days can give rise to a higher yield of the contrarian strategy.

It can also be noticed that, when the participating days are longer, the return is higher, keeping the observing days fixed. It may not be a result the boom of this market these years because we can also see from Table-2 that the longer participating days cause a more significant loss for the momentum strategy, keeping the observing days constant. A weak explanation is that the longer participating days enlarge the influence. However, if the assumption that the shorter observing days are more predictable because of the volatility of this immature market holds, the longer participating days would induce a vanish of the advantage of taking this strategy.

The log returns above are all excluded of any transaction fees and risk-free rate. Now a consideration of rough costs for these transactions will be made as follows.

The risk-free rate proxied by the overnight US dollar LIBOR interest rate keep an approximate increasing trend from around 0.08% to 1.93% and never go beyond 2% yearly. Therefore, the maximum daily risk-free rate will never go beyond 0.0054% during this period. Indeed, since the risk-free interest rate during these years stayed at a very low level if see from a perspective of long history. Thus, a setting of 2% yearly risk-free rate is not conservative but can also give a better reference for the future investment.

As for the transaction fees, according to the fee schedule of one of the most significant crypto exchange Binance, the maker will be charged a transaction fee ranges from 0.015% to 0.1% of the transaction value, and the taker will be charged a transaction cost ranges from 0.03% to 0.1% of the transaction value. If the worst scenario that the winner/loser changed every time for the (x=1, y=1) long-only strategy, the daily transaction fee for long-short will range from 0.2% to 0.045% according to the fee schedule. A table of transaction fees of the most expensive fee schedule for every long-only strategy in the worst scenario (every time the winner/loser changes) is shown in Table-4.

Since all the gross returns of the momentum strategies are negative, an exploration of the net returns is not meaningful because the net returns will be all negative. The fees in Table-4 denotes the highest transaction costs (the winner changes every time and the most expensive fee adopted). Therefore, the net return of the contrarian strategy based on this fee schedule and a high risk-free rate of 2% as mentioned before, would be quite conservative. The net log daily returns of the long-only contrarian strategies are presented in Table-5. The annual net log return is again based on the log daily net return. It can be noticed that, except for the contrarian strategies of x=15, y=1 and x=30, y=1, all these long-only contrarian strategies are still profitable even under this restricted setting of transaction costs and risk-free rate.

From the analyses above, the first null hypothesis that the short-term cross-sectional contrarian strategies are profitable cannot be rejected. Indeed, the cross-sectional momentum strategies adopted in the sample of this research suffer from huge loss. On the contrary, the contrarian strategies are quite profitable, especially for a shorter observing period.

Vertical comparison of momentum and contrarian strategies by years

Note that the time span of the data is from 29-06-2014 to 18-08-2018. Thus, the result in 2014 and 2018 cannot represent the full year's performance. Figure-6 exhibits both the annual log return of specific long-only momentum strategies and long-only contrarian strategies by years.

In Figure-6(a), it is evident that the trend of all strategy from year to year is at the same pace and the return of the same strategy differs from year to year. In 2017, all the momentum returns are positively high, while in 2018, all the momentum returns are extremely negative. Generally, these momentum strategies are around or below the horizontal axis where the 0% gross return is presented. The profits of shorter run momentum strategies remain the lowest ones even seen from the separate years.

For the contrarian strategies shown in Figure-6(b), except for the starting year 2014, the performance of most strategy is stable above a gross annual log return of 50%. The low return in2014 maybe because of its beginning stage. The walk trend of these strategies is not so similar to that of the momentum strategies above. The contrarian strategy of (x=1, y=1) performs remarkably well the very year from 2015 until now.

Figure-7(a) presents the annual returns of all momentum strategies (in blue) and that of all contrarian strategies (in orange) as compared with the S&P 500 yearly return; Figure-7(b) exhibits the with the annual return as compared with the cryptocurrency index CCI30. It can be seen from Figure-7(a) that, most of the momentum and the contrarian strategy in cryptocurrencies perform better than the stock market. However, it may be due to the enormous return of cryptocurrencies in these years. As compared with a “passive” investment strategy proxied by the benchmark CCI30 (Figure-7b), the cryptocurrency index which includes the top 30 cryptocurrencies seems to perform better, where the return in year 2017 is quite notable. It is most likely that, the CCI30 only take the “real-time” top 30 cryptocurrencies (actually it is rebalanced per three months), while the sample selected for this research is based on the top 10 long ago, which are deemed to not perform so well as the “real-time” excellent ones. Indeed, the CCI30 cannot be seen as a real passive benchmark, it rebalances the components in every three months according to the market cap.

While go back to the comparison of the momentum and contrarian strategy, it can be seen that, in 2014 and 2017 the momentum strategies outperform the contrarian strategies while in the rest of the time the contrarian strategy performs much better. Therefore, this tangle that results from seeing the strategies in the perspective of individual years make the answer of whether the momentum or contrarian strategies are better more ambiguous. However, still, the shorter-run contrarian strategies are the best in both the first section general check or the second section yearly check in this cross-sectional part.

Part II: Time-series momentum strategy

The result of basic regression and the sign regression will be discussed together since they are intuitively similar.

Recall that the basic regression $\frac{r_{y,t}}{\sigma_{y,t}} = \alpha + \beta\left(\frac{r_{x,t-x}}{\sigma_{x,t-x}}\right) + \varepsilon_t,$

and the sign regression $\frac{r_t}{\sigma_t} = \alpha + \beta sign\left(\frac{r_{t-x}}{\sigma_{t-x}}\right) + \varepsilon_t.$

The overall results for the basic regression and sign regression are shown in Table-8 listed by strategy period (see Appendix). As it is obvious that the coefficients of both basic regression and sign regression are all negative for the very short-term strategy of (x=1, y=1). Among which two out of eight cryptocurrencies have significant negative coefficients of both basic and sign regression; another two out of eight have significant coefficients of both regressions at the least 10% significance level. This result means that the short run contrarian strategy of (x=1, y=1) is efficient.

For the groups (x=7, y=7), (x=15, y=15) and (x=30, y=30), the coefficients of both regressions are all positive for all cryptocurrencies. All these coefficients of the sign regressions for all strategies are all significant at the 1% significance level, which denotes an uninterrupted continuation of the adjusted returns. That is to say; the momentum strategy is quite pronounced for these relatively "longer" time span of x and y.

The rest one is the group (x=3, y=3). The coefficients of the two regressions do not exhibit a clear pattern, but the positive ones are more than the negative ones. Therefore, the group (x=3, y=3) may be a transition stage that the profitable strategies change from contrarian to momentum.

The third method of testing the efficiency of time series momentum and contrarian strategy is looking at the historical return of adopting the corresponding strategies.

Since the return of long-short contrarian strategy of individual cryptocurrency is precisely the opposite of the return of the long-short momentum strategy, only the long-short momentum strategy will be displayed here. TableSet-9 (see Appendix) shows the profitability of the long-short momentum, long-only momentum and long-only contrarian strategy marked out by every group. The term "equal-wtd. ave." in the column of table denotes the equal-weighted average return of these eight cryptocurrencies.

As is shown in the table, the relatively "longer" time span groups {(x=7, y=7), (x=15, y=15) and (x=30, y=30)}, the return of long-only momentum are all positive at the 5% significance level. The returns of long-short momentum strategies are also positive at the 5% significance level except for XMR of (x=7, y=7) group, where the return is also positive but not significant at the 5% significance level. The daily log return excluded the insignificant XMR long-short momentum for (x=7, y=7) ranges from 2.56% to 21.30%, which is quite large even considering the transaction fees in Table-4. For long-short strategies, the highest theoretical transaction fees are two times the similar long-only strategies in Table-4, assume the transaction of shorting does not call for extra fees. Even if considerate the highest theoretical transaction fees {0.058% for (x=7, y=7), 0.026% for (x=15, y=15) and 0.014% for (x=30, y=30) strategy groups} that will never be reached, these momentum strategies are still of huge profits.

The finding of momentum efficiency for "longer" time span groups {(x=7, y=7), (x=15, y=15) and (x=30, y=30)} is corresponding with the results of the analyses of the two regressions above.

While for the group (x=1, y=1), almost all returns are insignificant positive at the 5% significance level. Among which, two out of the ten long-short momentum and one out of the ten long-only contrarian exhibit insignificant negative returns. There are no significant findings can be drawn from the analysis of this group.

Group (x=3, y=3) is exciting. Almost all the long-short and long-only momentum strategies have positive returns at the 5% significance level except for three insignificant positive ones. However, the gains of long-only contrarian strategies are all insignificant, and three out of ten cryptos have positive daily log return for contrarian strategies. Therefore, group (x=3, y=3) can also be seen as a transaction stage that the momentum starts to be stably profitable.

Part III: Volatility Model

By the assistance of the graphs of autocorrelations function and partial autocorrelations function shown in FigureSet-10, and then determined by the BIC criterion, findings of the mean equation for the cryptos and CCI30 are that all of them have the best fitted model for the raw daily return of $r_t = \alpha + \varepsilon_t$.

The null hypothesis of homoscedastic variances in the eight cryptocurrencies and CCI30 are firmly rejected by the Breusch-Pagan tests after the mean regressions. Based on that, the result of volatility equation checks for them is shown in Table-11.

From the table, it can be found that EGARCH (1, 1) is the only top three most fitted models for every cryptocurrency and CCI30. Besides, it is the best model for Bitcoin, Dash, DOGE and the market index CCI30.

The most fitted model for each cryptocurrency according to the criteria is shown as follows:

BTC: EGARCH (1, 1)

LTC: NARCH (1, 1)

DASH: EGARCH (1, 1)

DGB: TARCH (1, 1)

DOGE: EGARCH (1, 1)

ETH: GARCH (1, 1) ARMA (1, 1)

VTC: GJR-GARCH (1, 1)

XMR: NGARCH (1, 1)

CCI30: EGARCH (1, 1)

In aggregate, the EGARCH model perform the best in the research of these eight cryptocurrencies together with the cryptocurrency index CCI30. The GARCH (1, 1) models are no longer the most proper ones among the cryptocurrencies that checked. These findings may be able to extend to other out-of-sample cryptocurrencies. The exogenous validity requires further researches in more cryptocurrencies.

Part IV: Factors that influence the volatility

Region-Specific Macroeconomic

While applying the best fitted model EGARCH (1, 1) for the factor analyses of these cryptocurrencies, it encounters flat log likelihoods, i.e., STATA cannot find upward direction to determine the parameters of the variance regressions. The same outcome applied to another candidate fitted model TARCH. Therefore, the Part IV research cannot be done if stick to EGARCH (1, 1) or TARCH (1, 1). Then look back to the basic GARCH (1, 1) model. It can be seen from Table-11 that, the BIC criteria of GARCH (1, 1) also ranks top 4 for eight out of the nine assets (cryptos& CCI30). Thus, GARCH (1, 1) model is still a reasonable choice in this research of influential factors for volatility.

Table-12 lists the regressions of all the cryptocurrencies and CCI30, taking in all the microeconomic factors and macroeconomic factors.

As is can be seen, the coefficients of l.archt (the residual from mean equation ut-1) are positive significant for all cryptos and CCI30 at the 1% significance level, which
As it can be seen, the region-specific macroeconomic factors for the US, EU and China like the exchange rates, stock market indexes, overnight interest rates, one-year treasury bonds, seem to have little impact on the volatility of cryptocurrencies, which is different from the findings of Cermak (2017) for Bitcoin volatilities.

As is expected, the coefficients of D.lngoldt-1 (the increasing rate in gold prices of last period) are positively correlated with the volatility for all cryptos. Gold is regarded as an ideal hedge, so its price increases when the economy is suffered from an adverse shock. Moreover, the shock is likely also to continue to increase the current volatility of cryptos prices.

Among all these region-specific macroeconomic factors, the LD.lnSP500 which denotes the increased rate in last period is positively significant that the 5% significance level. The coefficients of LD.lnSP500 are positive in seven cryptos and CCI30; the only negative one is even not significant at the 10% level. Therefore, the increased rate of last period in the US stock market may be positively correlated with the volatility of cryptos today.

Surprisingly, the return of the last period, the change rate in exchange volume in the previous period, the inflation rate of cryptocurrencies and active address previously, are significantly correlated with the volatility. While the signs of coefficients are different from cryptocurrency to cryptocurrency, all the increases in the active address are positively correlated with the increase of current volatility, among which, those of DGB ETH and VTC are significant at the 1% significance level. It may denote that an increase in popularity/activeness of the previous day is correlated with an increase in today's volatility.

The macroeconomic factors of the specific region seem to have little impact on the volatility of Bitcoin, which deviates from the outcome of Cermak (2017). It may because the data in this research are more recent, as the time passing, these cryptocurrencies especially Bitcoin have been more decentralized.

Discussion

The long-only cross-sectional contrarian strategies of observing period and participating period from one day up to one month are all profitable, especially for a very short-term period. The short-term reversal in cryptocurrency seems to be in accordance with that in equity. The profitability is pronounced that even the most expensive transaction fees are subsumed, the cross-sectional contrarian strategies still yield positive returns. While the cross-sectional momentum strategies are all suffered from losses, it seems that the contrarian strategies perform better. However, if seen from year to year, the tremendous advantage of the contrarian strategy over the momentum strategy seems vanishes, because the momentum strategy outperforms the contrarian strategy in both 2014 and 2017. While the time span of these data is only from 29-06-2017 to 18-08-2018.

The time series analyses of individual cryptocurrencies highlight the efficiency of "longer-term" period momentum strategies. So called "longer-term" is that the observing period and participating period are above one week, an until the longest period one month, which reaches the up constraint in the checking period of this research. Because the definition of short-term, medium term or long term for cryptocurrencies may differ a lot from that in stock market, such period of one week to one month may just like the "medium term" in stock market, and probably that a check of longer term period would see a reversal rather than continuation, just like the contrarian starts to be efficient in the long-term for stocks. Therefore, further research is suggested to adopt a period of longer term that excess one month to see if momentum strategy still holds.

The short-term time series contrarian strategies of (x=1, y=1) are likely to be profitable because the coefficient of both basic regressions and sign regressions are all negative, but only four of the eight are significant.

Since the volatility-adjusted time series momentum strategies are strongly significant for all cryptocurrencies, the estimation and prediction of the dominator standard deviation would be essentially important. In the section of finding the most fitted ARCH family models for these cryptocurrencies' pattern of volatility, EGARCH models have the most excellent performance. However, when other factors are taken into the EGARCH model, most of the regressions cannot be generated because the flat likelihood is encountered, in other words, the parameters of EGARCH model cannot be defined. Same situation applies to TARCH model. While the pure GARCH model still perform well, the study of influential factors adopts the GARCH as the variance regression model. And the regressions show that the macroeconomic factors of major trading economies have mere impact on cryptocurrencies' volatility.

Conclusion

This research aims to examine the efficiency of the momentum strategy and contrarian strategy in the interesting and young market of cryptocurrencies. The findings are attracting however, this research should not consider to be a recommendation of investment in cryptocurrencies as the asset class. It is just interesting to explore the efficiency of the investment strategies together with volatility performance in this entirely different market.

There are some shortcomings of this research. The transaction fees adopted here is the most expensive schedule for the worst scenario. Since the transaction fees are low for cryptocurrencies, this proxying of real transaction fees does not largely affect the profitability of these strategies. However, for more precision, further research is suggested to include a transaction cost function of the sign that if the previous return is negative, the sign assigned -1, and today's transaction cost will be equal to (-sign*0.3%) in most expensive schedule and (-sign&0.045%) in the cheapest schedule) for momentum strategy. By doing this, the real historical returns of these investment strategies can be worked out.

Lastly, the 12 ARCH family models under test in this research are still not the full set of ARCH family models. For example, ARCH model with non-normal errors may also be applicable because the returns are quite leptokurtotic, which means that large positive or negative returns happen more intensively than expect if returns are actually normally distributed. Further research can not only be improved by testing more cryptocurrencies, but also more variance models to come up with a better understanding of this young market.

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Appendix

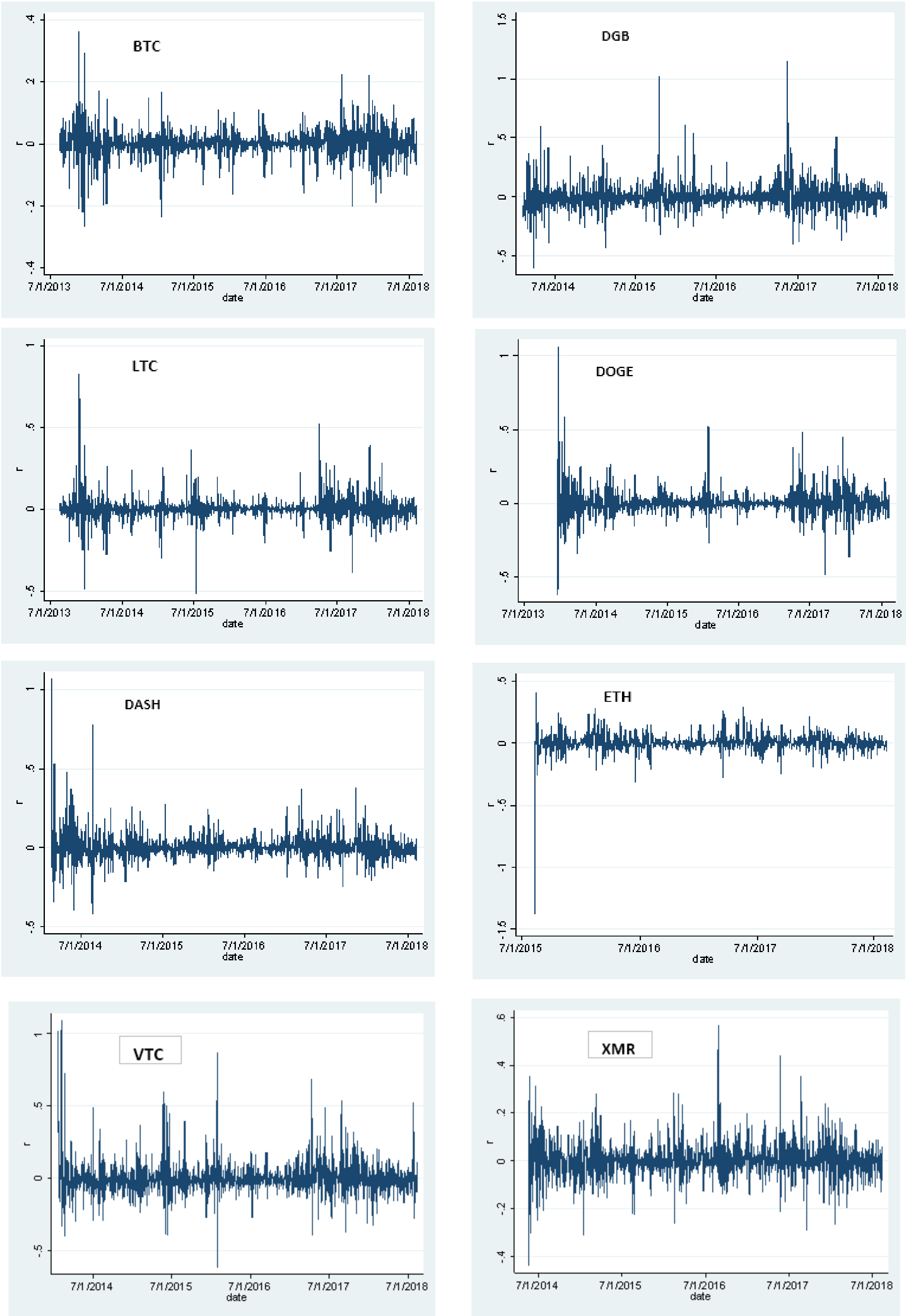

BTC
DGB
LTC
DOGE
DASH
ETH
VTC
XMR
r
date
7/1/2013
7/1/2014
7/1/2015
7/1/2016
7/1/2017
7/1/2018

Figure-1

long-only momentum (daily log return)		Observing days				
		1	3	7	15	30
Participating days	1	-0.61%	-0.36%	-0.26%	-0.16%	-0.02%
	3	-4.10%	-1.87%	-0.81%	-0.24%	-0.11%
	7	-5.44%	-2.87%	-1.17%	-0.44%	-0.19%
	15	-6.00%	-3.00%	-1.30%	-0.39%	-0.22%
	30	-6.07%	-3.25%	-1.70%	-0.69%	-0.38%

long-only momentum (annual log return)		Observing days				
		1	3	7	15	30
Participating days	1	-222%	-130%	-94%	-59%	-6%
	3	-1498%	-684%	-297%	-89%	-39%
	7	-1984%	-1047%	-428%	-161%	-68%
	15	-2190%	-1094%	-474%	-144%	-80%
	30	-2214%	-1188%	-621%	-252%	-139%

Table-2

long-only contrarian (daily log return)		Observing days				
		1	3	7	15	30
Participating days	1	0.71%	0.25%	0.29%	0.20%	0.17%
	3	3.31%	1.48%	0.70%	0.41%	0.32%
	7	3.24%	1.68%	0.75%	0.38%	0.33%
	15	3.92%	1.68%	0.84%	0.47%	0.31%
	30	4.43%	2.46%	1.23%	0.61%	0.47%

long-only contrarian (annual log return)		Observing days				
		1	3	7	15	30
Participating days	1	259%	90%	106%	73%	63%
	3	1209%	539%	254%	151%	115%
	7	1181%	612%	272%	140%	120%
	15	1432%	612%	305%	173%	112%
	30	1618%	897%	449%	222%	171%

Table-3

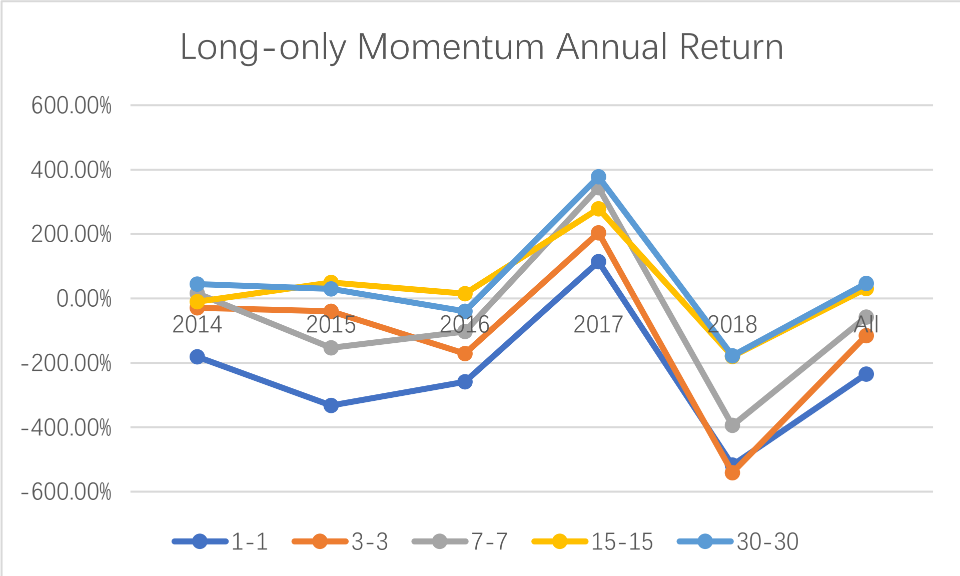
highest transaction fee for the worst scenario		Observing days				
		1	3	7	15	30
Participating days	1	0.200%	0.200%	0.200%	0.200%	0.200%
	3	0.067%	0.067%	0.067%	0.067%	0.067%
	7	0.029%	0.029%	0.029%	0.029%	0.029%
	15	0.013%	0.013%	0.013%	0.013%	0.013%
	30	0.007%	0.007%	0.007%	0.007%	0.007%

Table-4

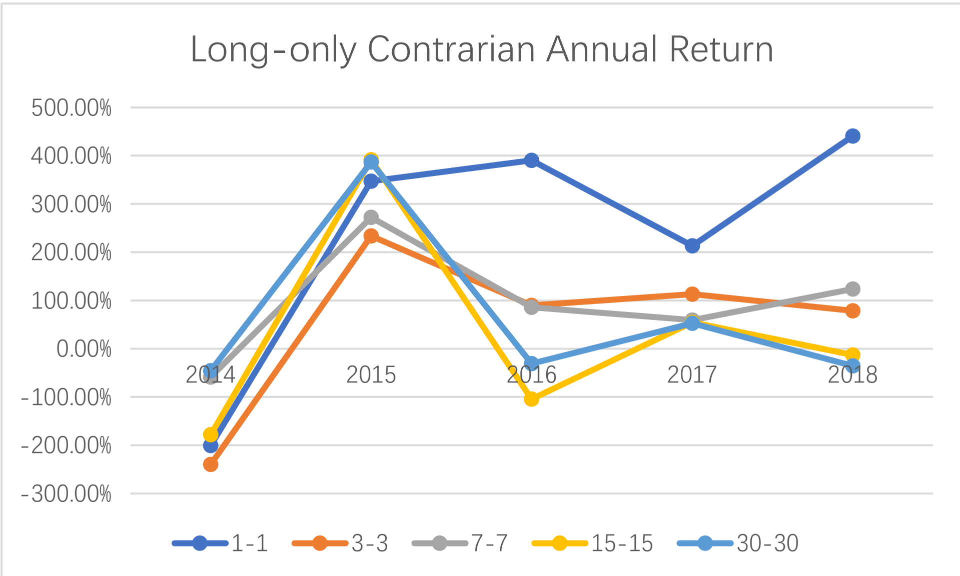
long-only contrarian (daily log return)		Observing days				
		1	3	7	15	30
Paticipating days	1	0.50%	0.04%	0.08%	-0.01%	-0.03%
	3	3.24%	1.40%	0.62%	0.34%	0.24%
	7	3.20%	1.64%	0.71%	0.35%	0.30%
	15	3.91%	1.66%	0.82%	0.46%	0.29%
	30	4.42%	2.45%	1.22%	0.60%	0.46%

long-only contrarian (annual log return)		Observing days				
		1	3	7	15	30
Paticipating days	1	184%	15%	31%	-2%	-12%
	3	1183%	512%	228%	124%	89%
	7	1169%	600%	260%	128%	108%
	15	1426%	605%	298%	166%	105%
	30	1613%	893%	444%	218%	167%

Table-5

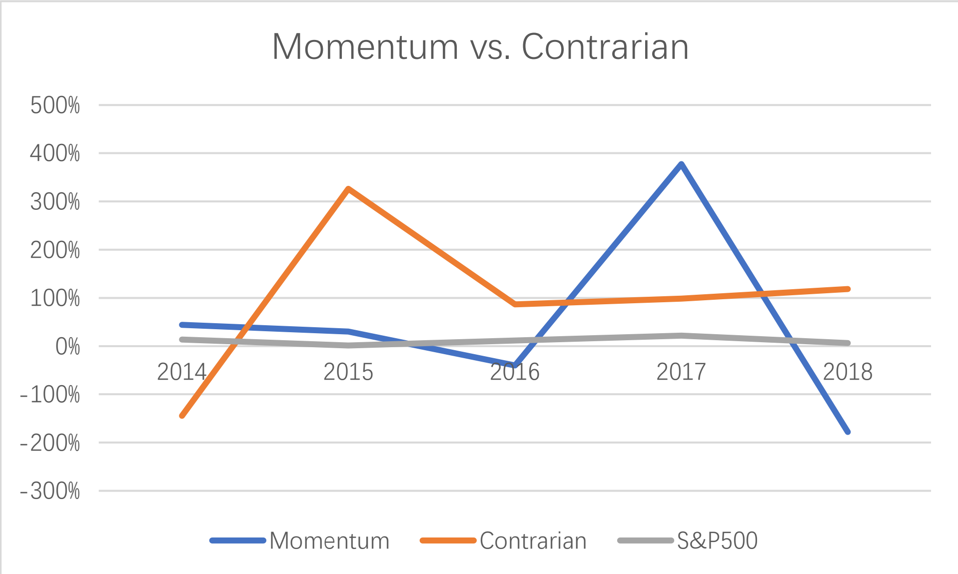

Long-only Momentum Annual Return
600.00%
400.00%
200.00%
0.00%
-200.00%
-400.00%
-600.00%
2014
2015
2016
2017
2018
All
1-1
3-3
7-7
15-15
30-30

(a)


Long-only Contrarian Annual Return
500.00%
400.00%
300.00%
200.00%
100.00%
0.00%
-100.00%
-200.00%
-300.00%
2014
2015
2016
2017
2018
1-1
3-3
7-7
15-15
30-30

(b)

Figure-6



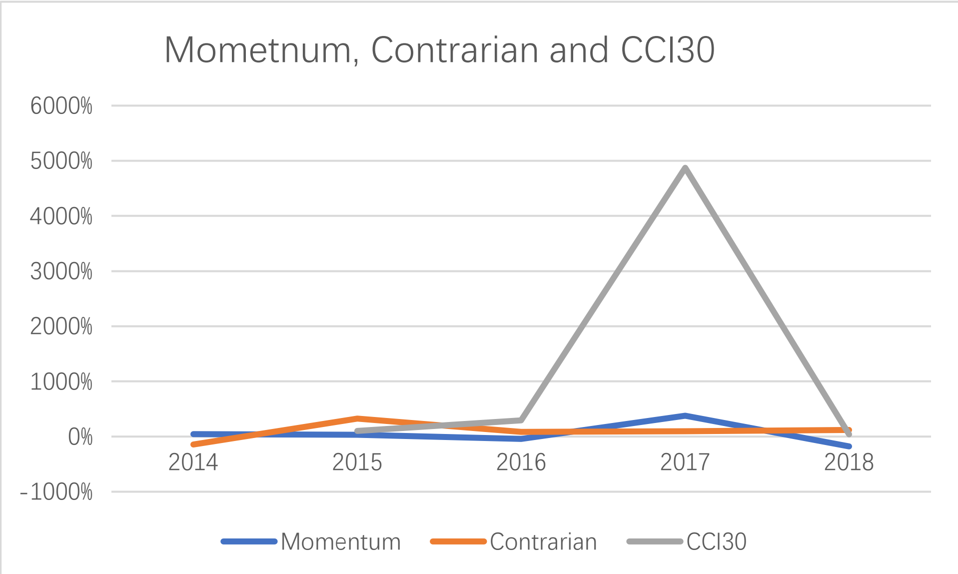


Figure-7

1-1	basic regression			
cryptocurrency	coef.		cons.	
BTC	-0.94%		9.47%	***
LTC	-6.73%	***	-3.72%	
DASH	-2.54%		-4.95%	**
DGB	-5.41%	**	-9.36%	***
DOGE	-8.49%	***	-10.30%	***
ETH	-1.86%		-1.13%	
VTC	-3.61%		-10.87%	***

1-1	sign regression			
cryptocurrency	coef.		cons.	
BTC	-0.90%		9.51%	***
LTC	-6.59%	***	-3.58%	
DASH	-2.92%		-5.33%	**
DGB	-4.71%	*	-8.66%	***
DOGE	-7.76%	***	-9.57%	***
ETH	-1.84%		-1.84%	
VTC	-3.76%		-11.03%	***

XMR	-4.26%	*	-2.72%	

XMR	-4.51%	*	-2.97%	

3-3	basic regression			
cryptocurrency	coef.		cons.	
BTC	1.55%		15.71%	***
LTC	-7.23%	***	-3.74%	*
DASH	3.03%		-5.52%	**
DGB	-1.23%		-11.34%	***
DOGE	2.23%		-12.81%	***
ETH	6.65%	**	3.27%	
VTC	2.42%		-17.16%	***
XMR	-0.54%		-3.13%	

3-3	sign regression			
cryptocurrency	coef.		cons.	
BTC	51.68%	***	9.59%	***
LTC	44.56%	***	-2.26%	
DASH	50.70%	***	-2.97%	
DGB	50.69%	***	-7.23%	***
DOGE	46.74%	***	-8.20%	***
ETH	50.20%	***	0.99%	
VTC	50.12%	***	-9.45%	***
XMR	49.76%	***	-2.05%	

7-7	basic regression			
cryptocurrency	coef.		cons.	
BTC	10.37%	***	18.13%	***
LTC	0.06%		-4.38%	**
DASH	5.67%	**	-1.73%	
DGB	1.32%		-10.15%	***
DOGE	1.90%		-15.10%	***
ETH	6.50%	**	9.94%	***
VTC	6.33%	**	-19.96%	***
XMR	2.05%		-0.24%	

7-7	sign regression			
cryptocurrency	coef.		cons.	
BTC	71.91%	***	12.17%	***
LTC	63.52%	***	-2.91%	*
DASH	69.61%	***	-0.56%	
DGB	66.73%	***	-5.65%	***
DOGE	66.17%	***	-6.70%	***
ETH	76.28%	***	6.15%	***
VTC	67.31%	***	-10.11%	***
XMR	71.08%	***	1.20%	

15-15	basic regression			
cryptocurrency	coef.		cons.	
BTC	24.81%	***	19.52%	***
LTC	21.56%	***	-2.63%	
DASH	28.38%	***	4.77%	**
DGB	16.82%	***	-5.97%	**
DOGE	23.19%	***	-10.86%	***
ETH	36.12%	***	13.95%	***
VTC	18.46%	***	-19.72%	***
XMR	13.54%	***	2.41%	

15-15	sign regression			
cryptocurrency	coef.		cons.	
BTC	76.98%	***	16.12%	***
LTC	61.88%	***	-1.45%	
DASH	70.45%	***	3.05%	*
DGB	65.19%	***	-3.20%	*
DOGE	63.70%	***	-5.31%	***
ETH	82.19%	***	13.49%	***
VTC	70.76%	***	-10.83%	***
XMR	71.54%	***	-1.40%	

30-30	basic regression			
cryptocurrency	coef.		cons.	
BTC	9.26%	***	41.11%	***
LTC	7.67%	***	-9.62%	***
DASH	10.25%	***	17.66%	***
DGB	0.88%		-12.22%	***
DOGE	4.62%	*	-27.46%	***
ETH	11.48%	***	45.55%	***
VTC	8.61%	***	-35.41%	***

30-30	sign regression			
cryptocurrency	coef.		cons.	
BTC	117.47%	***	26.46%	***
LTC	93.36%	***	-5.94%	**
DASH	111.00%	***	9.09%	***
DGB	83.07%	***	-6.93%	***
DOGE	101.06%	***	-11.36%	***
ETH	131.52%	***	25.88%	***
VTC	98.38%	***	-22.65%	***

XMR	9.29%	***	5.51%	XMR	103.44%	***	-1.38%

Table-8

(x=1, y=1)

1-1 long-short momentum	daily log return	95% confidence interval		annualized log return
BTC	0.04%	-0.16%	0.25%	16.29%
LTC	0.06%	-0.25%	0.38%	23.23%
DASH	0.06%	-0.34%	0.45%	20.12%
DGB	0.15%	-0.37%	0.67%	55.06%
DOGE	0.24%	-0.16%	0.64%	0.20%
ETH	0.30%	-0.18%	0.77%	107.86%
VTC	-0.09%	-0.65%	0.47%	-32.82%
XMR	-0.02%	-0.40%	0.37%	-6.75%
equal-wtd. ave.	0.09%			22.90%

1-1 long-only momentum	daily log return	95% confidence interval		annualized log return
BTC	0.25%	-0.02%	0.52%	90.44%
LTC	0.23%	-0.24%	0.71%	85.52%
DASH	0.48%	-0.07%	1.04%	176.25%
DGB	0.35%	-0.45%	1.14%	126.63%
DOGE	0.34%	-0.30%	0.99%	0.20%
ETH	0.74%	0.40%	1.52%	269.58%
VTC	0.07%	-0.83%	0.96%	23.80%
XMR	0.23%	-0.34%	0.79%	82.35%
equal-wtd. ave.	0.34%			106.85%

1-1 long-only contrarian	daily log return	95% confidence interval		annualized log return
BTC	0.20%	-0.11%	0.51%	73.49%
LTC	0.11%	-0.31%	0.54%	40.72%
DASH	0.35%	-0.20%	0.90%	126.42%
DGB	0.03%	-0.65%	0.71%	10.19%
DOGE	-0.15%	-0.63%	0.34%	0.20%
ETH	0.15%	-0.40%	0.69%	53.55%
VTC	0.22%	-0.50%	0.94%	79.34%
XMR	0.25%	-0.27%	0.78%	92.90%
equal-wtd. ave.	0.14%			59.60%

(x=3, y=3)

3-3 long-short momentum	daily log return	95% confidence interval		annualized log return
BTC	0.65%	0.30%	1.00%	237.43%
LTC	1.11%	0.55%	1.67%	404.00%
DASH	0.92%	0.24%	1.59%	334.00%
DGB	1.15%	0.23%	2.06%	418.44%
DOGE	1.12%	0.39%	1.84%	0.20%
ETH	0.65%	-0.18%	1.49%	238.72%
VTC	0.80%	-0.20%	1.80%	290.59%
XMR	1.18%	0.52%	1.85%	431.65%
equal-wtd. ave.	0.95%			294.38%

3-3 long-only momentum	daily log return	95% confidence interval		annualized log return
BTC	1.18%	0.71%	1.65%	429.36%
LTC	1.66%	0.75%	2.58%	607.52%
DASH	2.25%	1.16%	3.34%	820.76%
DGB	1.84%	0.30%	3.39%	673.01%
DOGE	1.61%	0.30%	2.93%	0.20%
ETH	2.01%	0.71%	3.31%	734.54%
VTC	1.31%	-0.45%	3.08%	478.93%
XMR	2.01%	0.97%	3.06%	735.34%
equal-wtd. ave.	1.74%			559.96%

3-3 long-only contrarian	daily log return	95% confidence interval		annualized log return
BTC	0.03%	-0.49%	0.55%	11.07%
LTC	-0.57%	-1.23%	0.09%	-207.23%
DASH	0.30%	-0.53%	1.13%	110.24%
DGB	-0.55%	-1.61%	0.51%	-202.45%
DOGE	-0.72%	-1.49%	0.05%	0.20%
ETH	0.86%	-0.14%	1.86%	313.58%
VTC	-0.42%	-1.57%	0.74%	-152.49%
XMR	-0.37%	-1.20%	0.45%	-136.16%
equal-wtd. ave.	-0.18%			-32.90%

(x=7, y=7)

7-7 long-short momentum	daily log return	95% confidence interval		annualized log return
BTC	1.37%	0.82%	1.92%	501.30%
LTC	1.69%	0.80%	2.58%	616.47%
DASH	1.84%	0.83%	2.85%	671.05%

DGB	1.71%	0.28%	3.13%	622.88%
DOGE	2.29%	1.25%	3.33%	0.20%
ETH	1.86%	0.67%	3.05%	679.71%
VTC	2.18%	0.65%	3.72%	796.82%
XMR	0.82%	-0.21%	1.85%	299.74%
equal-wtd. ave.	1.72%			523.52%

7-7 long-only momentum	daily log return	95% confidence interval		annualized log return
BTC	2.63%	1.84%	3.43%	960.48%
LTC	2.95%	1.44%	4.47%	1078.30%
DASH	4.47%	2.87%	6.06%	1630.65%
DGB	3.28%	0.82%	5.74%	1197.02%
DOGE	3.50%	1.65%	5.34%	0.20%
ETH	5.17%	3.46%	6.88%	1888.69%
VTC	3.23%	0.40%	6.06%	1180.29%
XMR	2.56%	0.98%	4.13%	933.21%
equal-wtd. ave.	3.47%			1108.60%

7-7 long-only contrarian	daily log return	95% confidence interval		annualized log return
BTC	0.25%	-0.47%	0.98%	92.22%
LTC	-0.46%	-1.41%	0.49%	-167.90%
DASH	0.75%	-0.47%	1.98%	274.40%
DGB	-0.35%	-1.94%	1.24%	-127.93%
DOGE	-1.35%	-2.51%	-0.19%	0.20%
ETH	1.99%	0.43%	3.56%	727.96%
VTC	-1.41%	-3.07%	0.25%	-515.75%
XMR	0.86%	-0.47%	2.19%	314.19%
equal-wtd. ave.	0.04%			74.67%

(x=15, y=15)

15-15 long-short momentum	daily log return	95% confidence interval		annualized log return
BTC	3.77%	2.90%	4.64%	1376.29%
LTC	5.15%	3.79%	6.50%	1878.27%
DASH	7.21%	5.73%	8.68%	2630.26%
DGB	5.59%	3.48%	7.69%	2038.54%
DOGE	3.25%	1.71%	4.78%	0.20%
ETH	10.07%	8.33%	11.80%	3673.92%
VTC	7.59%	5.32%	9.85%	2768.74%
XMR	3.17%	1.60%	4.74%	1155.99%

equal-wtd. ave.	5.72%			1940.28%

15-15 long-only momentum	daily log return	95% confidence interval		annualized log return
BTC	6.33%	5.06%	7.60%	2310.68%
LTC	8.11%	5.69%	10.53%	2960.51%
DASH	11.64%	9.37%	13.91%	4249.32%
DGB	9.94%	6.14%	13.73%	3627.49%
DOGE	5.66%	3.04%	8.28%	0.20%
ETH	16.12%	13.61%	18.63%	5884.24%
VTC	10.20%	5.97%	14.44%	3724.76%
XMR	6.64%	4.24%	9.03%	2421.91%
equal-wtd. ave.	9.33%			3147.39%

15-15 long-only contrarian	daily log return	95% confidence interval		annualized log return
BTC	-0.37%	-1.43%	0.69%	-135.23%
LTC	-2.32%	-3.61%	-1.04%	-847.51%
DASH	-2.09%	-3.83%	-0.35%	-761.77%
DGB	-1.81%	-3.93%	0.31%	-660.96%
DOGE	-1.42%	-3.25%	0.40%	0.20%
ETH	-2.33%	-4.45%	-0.21%	-850.66%
VTC	-5.68%	-8.09%	-3.28%	-2074.99%
XMR	0.83%	-1.08%	2.74%	302.75%
equal-wtd. ave.	-1.90%			-628.52%

(x=30, y=30)

30-30 long-short momentum	daily log return	95% confidence interval		annualized log return
BTC	4.60%	3.20%	6.00%	1679.93%
LTC	4.91%	2.78%	7.04%	1791.78%
DASH	4.21%	1.75%	6.67%	1535.90%
DGB	3.54%	0.17%	6.92%	1293.47%
DOGE	8.64%	6.33%	10.96%	0.20%
ETH	8.98%	5.91%	12.04%	3277.11%
VTC	7.82%	4.47%	11.18%	2856.00%
XMR	4.77%	2.43%	7.10%	1739.79%
equal-wtd. ave.	5.93%			1771.77%

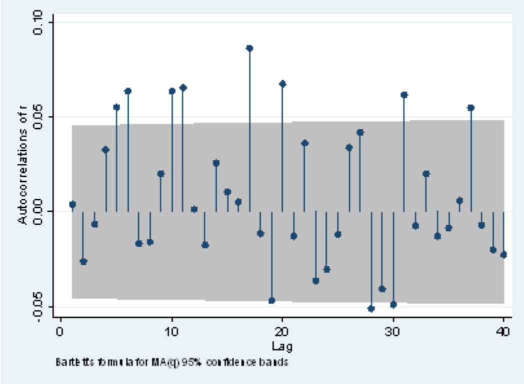
30-30 long-only momentum	daily log return	95% confidence interval		annualized log return
BTC	9.80%	7.79%	11.82%	3578.30%

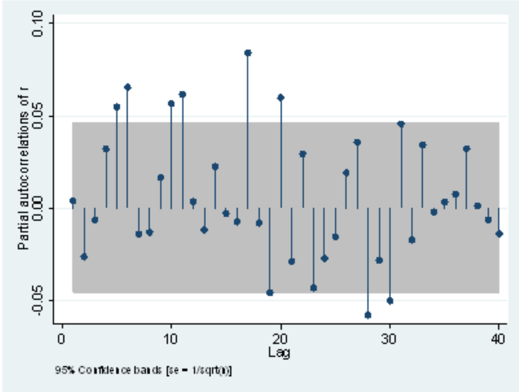
LTC	10.95%	7.46%	14.44%	3997.40%
DASH	13.32%	9.88%	16.75%	4860.72%
DGB	12.62%	6.38%	18.86%	4607.56%
DOGE	14.30%	9.79%	18.82%	0.20%
ETH	21.30%	17.00%	25.59%	7773.52%
VTC	9.20%	3.83%	14.57%	3357.79%
XMR	11.77%	8.56%	14.99%	4297.82%
equal-wtd. ave.	12.91%			4059.16%

30-30 long-only contrarian	daily log return	95% confidence interval		annualized log return
BTC	2.69%	0.99%	4.38%	980.85%
LTC	0.73%	-1.75%	3.21%	266.48%
DASH	7.11%	3.79%	10.44%	2595.78%
DGB	4.20%	1.00%	7.41%	1534.15%
DOGE	-4.36%	-6.52%	-2.19%	0.20%
ETH	9.19%	5.62%	12.75%	3353.02%
VTC	-6.80%	-11.08%	-2.51%	-2480.47%
XMR	3.74%	0.45%	7.03%	1365.04%
equal-wtd. ave.	2.06%			951.88%

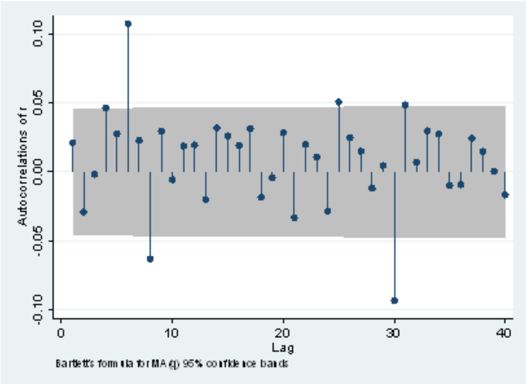
TabelSet-9

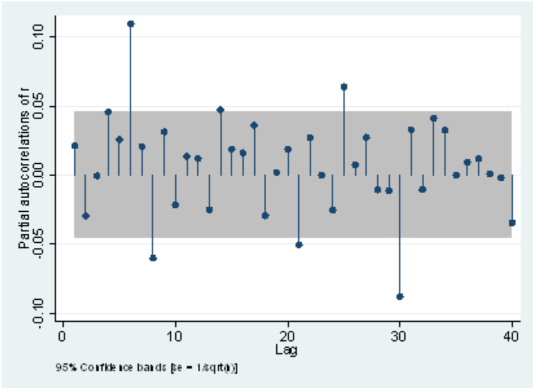
BTC



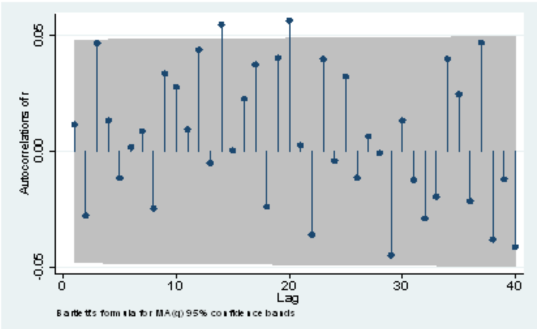


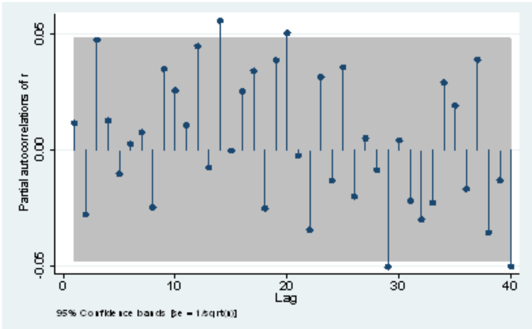
LTC



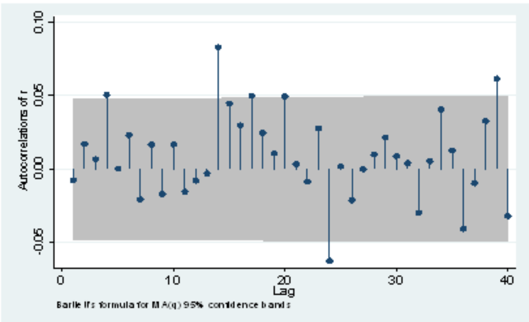


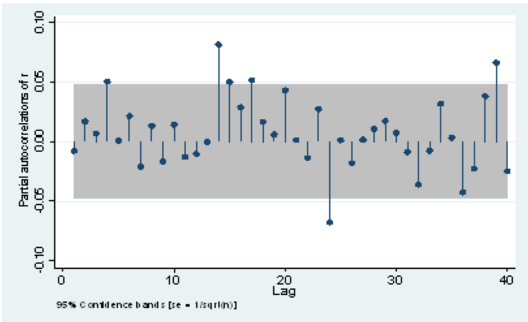
DASH



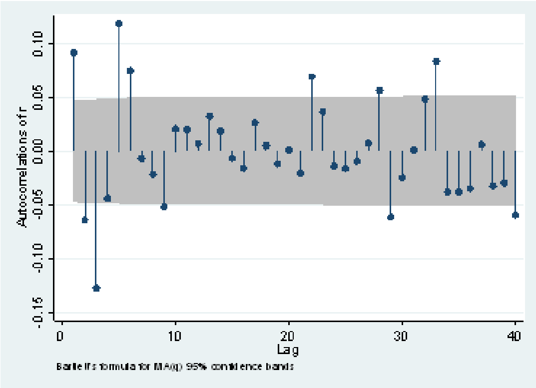


DGB

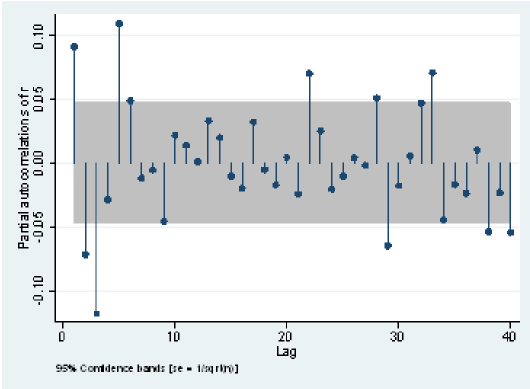




DOGE

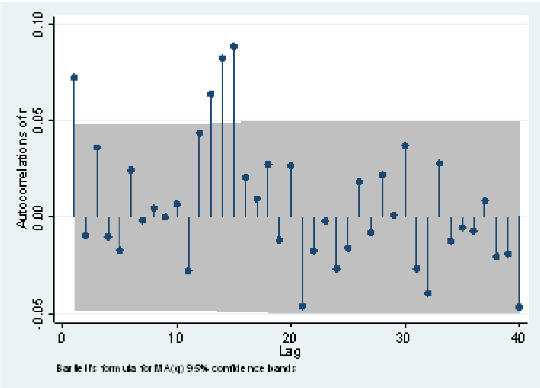


Autocorrelations of r
0.10
0.05
0.00
-0.05
-0.10
-0.15
0
10
20
30
40
Lag
Bartlett's formula for MA(q) 95% confidence bands

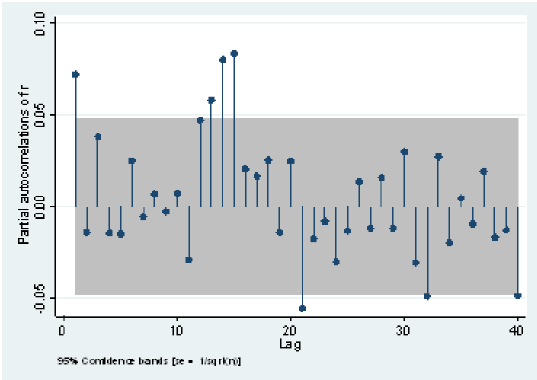


Partial autocorrelations of r
0.10
0.05
0.00
-0.05
-0.10
0
10
20
30
40
Lag
95% Confidence bands [se = 1/sqrt(n)]

VTC

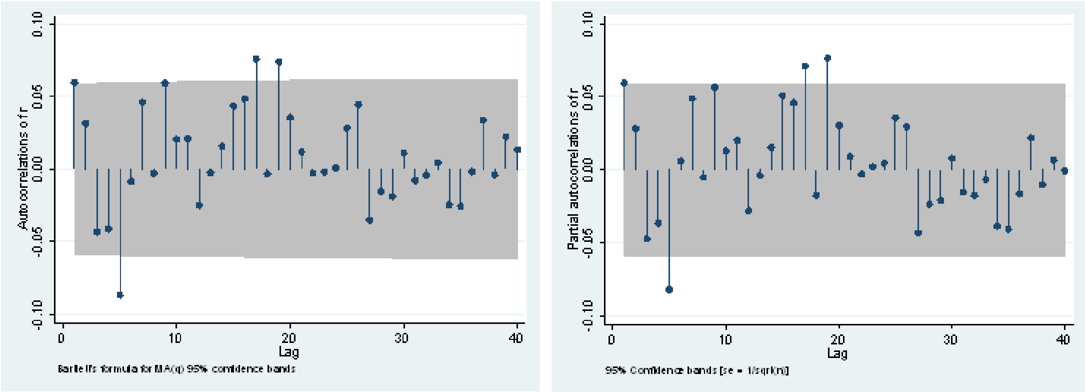


Autocorrelations of r
0.10
0.05
0.00
-0.05
0
10
20
30
40
Lag
Bartlett's formula for MA(q) 95% confidence bands

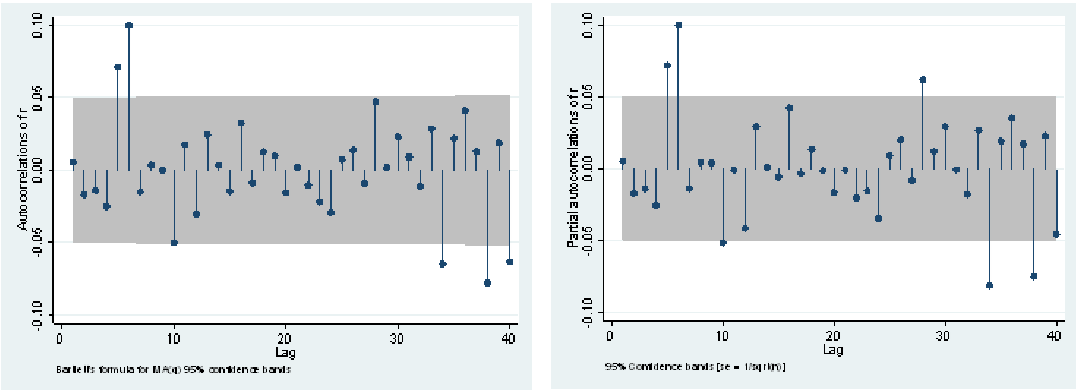


Partial autocorrelations of r
0.10
0.05
0.00
-0.05
0
10
20
30
40
Lag
95% Confidence bands [se = 1/sqrt(n)]

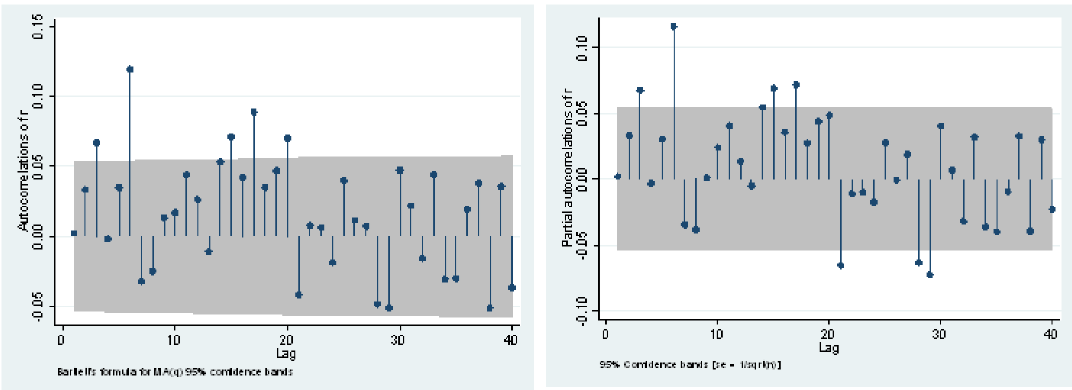
ETH



XMR



CCI30



FigureSet-10

	BTC			LTC		
	Likelihood	*AIC*	*BIC*	*Likelihood*	*AIC*	*BIC*
ARCH(1)	3229.3	-6452.6	-6436.0	2487.8	-4969.6	-4953.0
GARCH(1, 1)	3439.8	**-6871.5**	**-6849.5**	2637.0	-5266.1	-5244.0
GARCH (1, 1) AR(1)	3440.7	-6871.4	-6843.9	2638.7	-5267.4	-5239.9
GARCH (1, 1) ARMA(1, 1)	**3441.3**	-6870.5	-6837.5	2639.7	-5267.5	-5234.4
EGARCH (1, 1)	**3452.0**	**-6894.0**	**-6866.4**	**2648.5**	**-5287.0**	**-5259.5**
TARCH (1, 1)	**3447.5**	**-6885.1**	**-6857.5**	**2653.6**	**-5297.3**	**-5269.7**
GJR-ARCH (1, 1)	3229.8	-6451.5	-6429.5	2492.7	-4977.4	-4955.3
GJR-GARCH (1, 1)	**3441.0**	**-6871.9**	**-6844.4**	**2647.7**	**-5285.4**	**-5257.8**
NARCH (1, 1)	3230.2	-6452.4	-6430.4	2497.3	-4986.6	-4964.6
NGARCH (1, 1)	3440.4	-6870.8	-6843.2	**2656.6**	**-5303.3**	**-5275.7**
ARCH-in-mean (1, 1)	3249.7	6491.5	-6469.4	2499.0	-4990.0	-4968.0
GARCH-in-mean (1, 1)	3440.5	6870.9	-6843.4	2637.8	-5265.6	-5238.0

	DASH			DGB		
	Likelihood	*AIC*	*BIC*	*Likelihood*	*AIC*	*BIC*
ARCH(1)	2066.7	-4127.3	-4111.1	1381.7	-2757.4	-2741.2
GARCH(1, 1)	2201.6	**-4395.2**	**-4373.6**	1508.4	-3008.9	**-2987.2**
GARCH (1, 1) AR(1)	**2203.0**	**-4396.0**	**-4369.0**	1511.2	-3012.3	-2985.3
GARCH (1, 1) ARMA(1, 1)	**2203.0**	-4394.0	-4361.6	1511.2	-3010.4	-2978.0
EGARCH (1, 1)	**2205.4**	**-4400.8**	**-4373.8**	**1530.4**	**-3050.8**	**-3023.7**
TARCH (1, 1)	2201.8	-4393.6	-4366.6	**1531.5**	**-3053.0**	**-3026.0**
GJR-ARCH (1, 1)	2066.9	-4125.7	-4104.1	1382.7	-2757.3	-2735.7
GJR-GARCH (1, 1)	2202.2	-4394.5	-4367.5	**1514.2**	**-3018.3**	-2991.3
NARCH (1, 1)	2065.2	-4122.4	-4100.8	1384.9	-2761.7	-2740.1
NGARCH (1, 1)	2202.8	-4395.6	-4368.6	**1521.5**	**-3033.1**	**-3006.0**
ARCH-in-mean (1, 1)	2082.6	-4157.2	-4135.6	1381.7	2755.4	-2733.8
GARCH-in-mean (1, 1)	**2202.9**	**4395.9**	**-4368.9**	1508.5	-3007.0	-2979.9

	DOGE			ETH		
	Likelihood	*AIC*	*BIC*	*Likelihood*	*AIC*	*BIC*
ARCH(1)	2177.2	-4348.5	-4332.2	1219.0	-2432.1	-2417.0
GARCH(1, 1)	2441.4	-4874.8	**-4853.1**	1340.0	-2672.0	**-2652.0**
GARCH (1, 1) AR(1)	**2443.0**	**-4876.0**	**-4848.8**	**1341.2**	**-2672.3**	-2647.3
GARCH (1, 1) ARMA(1, 1)	**2445.9**	**-4879.7**	-4847.1	**1470.7**	**-2929.4**	**-2899.4**
EGARCH (1, 1)	**2454.8**	**-4899.5**	**-4872.3**	1243.3	-2476.5	-2451.5
TARCH (1, 1)	**2453.5**	**-4896.9**	**-4869.7**	**1362.4**	**-2714.8**	**-2689.7**
GJR-ARCH (1, 1)	2185.7	-4363.5	-4341.7	1219.2	-2430.4	-2410.4
GJR-GARCH (1, 1)	2442.0	-4874.0	-4846.8	**1345.6**	**-2681.1**	**-2656.1**
NARCH (1, 1)	2176.5	-4345.1	-4323.3	1219.5	-2431.0	-2410.9
NGARCH (1, 1)	2441.6	-4873.2	-4846.0	1335.9	-2661.8	-2636.8

ARCH-in-mean (1, 1)	2177.6	-4347.1	-4325.4	1232.4	-2456.9	-2436.9
GARCH-in-mean (1, 1)	2441.4	4872.9	-4845.7	1340.2	-2670.5	-2645.5

	VTC			XMR		
	Likelihood	*AIC*	*BIC*	*Likelihood*	*AIC*	*BIC*
ARCH(1)	1438.5	-2871.0	-2854.8	1833.9	-3661.7	-3645.6
GARCH(1, 1)	1501.9	**-2995.8**	**-2974.1**	1896.8	-3785.6	-3764.2
GARCH (1, 1) AR(1)	1502.6	-2995.2	-2968.1	1897.1	-3784.2	-3757.5
GARCH (1, 1) ARMA(1, 1)	**1502.8**	-2993.5	-2961.0	1897.0	-3781.9	-3749.9
EGARCH (1, 1)	**1504.5**	**-2999.0**	**-2971.8**	**1905.6**	**-3801.3**	**-3774.6**
TARCH (1, 1)	N/A	N/A	N/A	**1905.7**	**-3801.4**	**-3774.7**
GJR-ARCH (1, 1)	1444.8	-2881.7	-2860.0	1837.3	-3666.6	-3645.2
GJR-GARCH (1, 1)	**1508.4**	**-3006.7**	**-2979.6**	**1908.8**	**-3807.7**	**-3781.0**
NARCH (1, 1)	1438.3	-2868.6	-2846.9	1835.2	-3662.4	-3641.0
NGARCH (1, 1)	**1505.7**	**-3001.4**	**-2974.3**	**1914.6**	**-3819.3**	**-3792.6**
ARCH-in-mean (1, 1)	1440.0	-2871.9	-2850.3	1836.9	-3665.8	-3644.4
GARCH-in-mean (1, 1)	1502.0	-2994.1	-2967.0	1897.0	-3784.0	-3757.3

	CCI30		
	Likelihood	*AIC*	*BIC*
ARCH(1)	2407.3	-4808.5	-4792.9
GARCH(1, 1)	2565.3	-5122.7	**-5101.9**
GARCH (1, 1) AR(1)	2566.2	-5122.3	-5096.4
GARCH (1, 1) ARMA(1, 1)	**2567.7**	**-5123.4**	-5092.3
EGARCH (1, 1)	**2576.3**	**-5142.6**	**-5116.7**
TARCH (1, 1)	**2573.5**	**-5137.1**	**-5111.1**
GJR-ARCH (1, 1)	2411.9	-4815.7	-4795.0
GJR-GARCH (1, 1)	2565.3	-5120.7	-5094.8
NARCH (1, 1)	2409.4	-4810.8	-4790.1
NGARCH (1, 1)	2566.0	-5122.0	-5096.1
ARCH-in-mean (1, 1)	2410.7	-4813.3	-4792.6
GARCH-in-mean (1, 1)	**2566.6**	**-5123.2**	**-5097.3**

Table-11

	BTC	LTC	DASH	DGB	DOGE	ETH	VTC	XMR	CCI30
r L1.	9.18% **	7.65% ***	-13.75% ***	-6.55% *	0.39%	11.68% ***	0.39%	0.53%	19.17% ***
lnvol LD.	-0.81% ***	3.08% ***	3.10% ***	5.89% ***	2.21% ***	1.03% *	2.21% ***	2.40% ***	
lnactadd LD.	1.29%	3.37% **	2.00%	4.69% *	1.67%	8.39% ***	1.67%	1.83% *	
inflation D1.	-4508.00%	-77.34%	-180.96%	299.27% ***	2483.52% **	47536.75% **	2483.52% **	-1527.67% ***	
lnCNY LD.	93.79%	-15.21%	-63.14%	32.19%	-69.16%	207.35% **	-69.16%	31.55%	72.77%
lnEUR LD.	-274.30%	-549.45%	32.35%	-67.99%	1.26%	-21.26%	1.26%	-15.47%	-8.79%
lnSP500 LD.	14.46%	52.44%	63.36% **	17.73%	35.06%	79.05% **	35.06%	-12.19%	31.35%
lnMSCIEU LD.	-7.01%	-20.18%	-0.59%	-17.27%	10.80%	-50.86%	10.80%	15.45%	-5.46%
lnSSH LD.	-1.89%	-10.82%		13.16%	-11.60%	9.64%	-11.60%	4.83%	3.98%
USDovnt LD.	-1.73%	-3.84%		16.78% *	-0.10%	-7.36%	-0.10%	1.91%	0.19%
USD1y LD.	306.36%	654.86%	0.41%	-5.14%	-5.54%	8.16%	-5.54%	0.76%	-10.26%
CNYovnt LD.	-1.72%	0.49%	-3.72%	-1.76%	-3.23%	-3.54%	-3.23%	0.83%	4.95%
CNY1y LD.	5.26%	-6.38%	3.27%	14.65%	-4.78%	9.55%	-4.78%	25.66%	-9.41%
EURovnt LD.	3.05%	3.41%	6.47%	1.36%	-2.08%	4.34%	-2.08%	-0.03%	-1.18%
EUR1y LD.	-34.68%	-52.99%	-59.43%	-76.85%	-78.32%	22.12%	-78.32%	27.62%	-167.48% ***
lngold LD.	32.67% *	13.42%	12.55%	48.69%	13.58%	45.45%	13.58%	56.92%	-11.80%
_cons	-0.03%	-0.18%	0.17%	-0.04%	-0.23%	0.06%	-0.23%	0.13%	-0.01%
ARCH arch L1.	25.72% ***	7.60% ***	64.43% ***	67.23% ***	22.11% ***	42.77% ***	22.11% ***	24.62% ***	64.65% ***
garch L1.	13.31%	146.21% ***	8.61%	6.05%	89.54% ***	10.72%	89.54% ***	6.01%	-4.11%
_cons	0.11% ***	-0.22%	0.21% ***	0.43% ***	-0.06%	0.24% ***	-0.06%	0.39% ***	0.09% ***

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