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Low-volatility strategies for highly liquid cryptocurrencies

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ABSTRACT

Managing extreme price fluctuations in cryptocurrency markets are of central importance for investors in this market segment. Using a sample of highly liquid cryptocurrencies from January 2017 to June 2021, this paper proposes a dynamic investment strategy that selects cryptocurrencies based on their historical volatility and is complemented by a simple stop-loss rule. Our results reveal that investing in highly concentrated low volatility cryptocurrency portfolios with six to twelve months volatility look-back and holding period generate statistically significant excess returns. By including a simple stop-loss rule, the downside risk of cryptocurrency portfolios is reduced markedly, and the Sharpe ratios are improved significantly.

1. Introduction

Cryptocurrency (CC) markets are once more at the market participants' focus of attention. Since the market capitalization of the first decentralized digital currency, Bitcoin, exceeded the USD 1 trillion threshold for the first time, the CC market became too large to ignore even in the eyes of institutional investors. However, previous episodes of CC price surges were typically followed by excessive selloffs and volatility, i.e., daily CC price drops of up to 40% (Chaim and Laurini (2018)). Therefore, passive long-only investments even in highly diversified CC portfolios might lead to substantial drawdowns.[1] In this paper, we propose a concentrated dynamic low volatility investment strategy that selects CCs based on their historical volatility and is complemented by a simple stop-loss rule.

In recent years, literature on CC returns and trading strategies grew significantly. The early literature on CC prices investigates the efficiency and predictability and presents that CC prices are either inefficient or weakly efficient (Tiwari et al. (2018) and Wei (2018)). Focusing on the momentum strategies in CC markets, Grobys and Sapkota (2019) and Tzouvanas et al. (2020) show that these are profitable only in the short term. Building on this, the CC portfolios have also been examined in a mean-variance framework (Brauneis and Mestel (2019), Liu (2019), and Platanakis et al. (2018)) with the main finding that equal-weighted CC portfolios outperform mean-variance optimized portfolios.

The volatility of the CCs received enhanced attention over time, too. Baur and Dimpfl (2018) document asymmetric volatility effects in CC returns while Jiang et al. (2018), and Phillip et al. (2019) present long memory in CC volatilities. Bouri et al. (2019) show that the trading volume of Litecoin, NEM, and Dash include information for volatility prediction. Katsiampa (2019) reveal interdependencies in the volatility of larger CCs. Bialkowski (2020) study industry stop-loss rules for CC investments and showed that such risk management rules help reduce the risk of investment in CCs. In a recent paper, Burggraf and Rudolf (2021) study the low volatility anomaly of 1000 CC from 2013 to 2019 with the main conclusion that CC market returns are efficient. However, they state

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[1] There are limited hedging possibilities in CC markets using standard financial instruments. For example, in the UK, FCA banned the sale of CC-derivatives to retail consumers on 9.10.2020.

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that the efficiency of the market change with an increasing number of investors entering the CC market in recent years. This potentially leads to low volatility premia.

Testing a broad range of different trading strategies, Liu (2021) document that CCs with a large market capitalization are, in general, much more liquid than the smaller coins, and trading strategies based on a highly liquid sample might present different results. Indeed, small CCs are not traded on many exchanges, are illiquid, and there is a risk of them going out of rotation. Despite the recent interest in low volatility anomaly in CC markets, low volatility strategies applied to highly liquid CCs have not been analyzed to date. Even more, the impact of stop-losses has not been considered in the context of low volatility strategies. Our paper contributes to the investment strategy literature for CC markets by testing a low-volatility strategy utilizing a sample of liquid CCs. We study the long and short strategy returns, maximum drawdowns, and Sharpe ratios of highly concentrated low volatility CC portfolios and scrutinize stop-losses impact. Our results show that low volatility CC portfolios generate statistically significant excess returns without and with applying a stop-loss rule. Meanwhile, the inclusion of the stop-loss rule increases the Sharpe ratios of the long-only portfolios where the stop-loss threshold Sharpe ratio relation takes a hump-shape.

2. Data and empirical strategy

For our empirical strategy, we downloaded daily CC prices from January 1, 2017, to June 30, 2021, from CoinMarketCap.[2] We select CCs that had a market capitalization of at least USD 1 bn as of January 1, 2017, to include the most traded CCs in our analysis and to alleviate concerns around the survivorship bias in the sample. Within this group, we choose CCs that have started trading latest on January 1, 2016, to be able to test strategies with a backward-looking window of up to one year. Our final sample consists of 35 CCs. We calculate logarithmic first differences of CC returns. The corresponding summary statistics for CC returns are presented in the appendix.

We build equal-weighted low-volatility CC portfolios by ranking the CCs based on their historical volatility from smallest to the largest. Following previous literature, where typically up to 25% of the investment universe is used to construct low volatility portfolios (Baker et al. (2011), Walkshausl (2013)), we select up to ten CCs with the lowest volatility for the long portfolio and the corresponding number of CCs with the highest volatility for the short portfolio. We test the performance of our strategy by selecting different historical periods (J) to calculate the volatility ("volatility look-back"), and holding periods (K) and present results for J, K= 1, 3, 6, and 12 months separately.[3] We re-balance the portfolios at the end of each holding period. For re-balancing, we implement a trading cost of 0.175% and a bid-ask spread of 0.5% in each strategy[4].

Finally, we test the stop-loss level as in Equation 1.

$$\textit{Stop loss rule} = \begin{cases} \textit{Stay invested} & \textit{if } \sum_{d=1}^{n} R_{i,d} \leq \overline{S} \\ \textit{Sell} & \textit{if } \sum_{d=1}^{n} R_{i,d} > \overline{S} \end{cases} \tag{1}$$

where $R_{i,d}$ refers to the cumulative return for CC i at day d in a month with n days. $\overline{S}$ is the stop loss threshold for cumulative return. In our setting, if the stop-loss threshold is breached by any of the CC in the portfolio, the CC that breaches the threshold is sold for that month and reinvested in the consecutive month taking into account the transaction costs for selling and re-buying as specified above.

3. Empirical results

Table 1 presents average monthly returns for long and short portfolios for various look-back windows and investment horizons without the stop-loss. For the sake of brevity, we present portfolios that include 3, 5, 7, or 9 CCs, but results for other strategies are available upon request. In columns are the look-back periods for historical volatility calculation, and in rows are the investment horizons.

The main takeaway from Table 1 is that long portfolios which invest in low volatility CCs generate significantly positive returns, whereas short portfolios which invest in high volatility CCs do not. A longer look-back of six or twelve months to compute historical volatility persistently generates statistically significant positive returns. Rebalancing frequency seems to be associated with lower returns and lower statistical significance. Put differently, the highest average returns are achieved if investors have a twelve-month volatility look-back and stay invested twelve months both for long-only and long-short portfolios. Portfolios with a larger number of CCs do not achieve higher monthly returns than portfolios with smaller CCs. Probably the extreme volatility of smaller tokens and the high correlation between low volatility CCs hamper the diversification benefits of a larger number of portfolio constituents. By investing and trading an exclusively small circle of CCs, investors, while being able to build diversified enough portfolios, avoid excessive price movements of the more volatile smaller tokens.

[2] https://coinmarketcap.com/coins/.

[3] See Moskowitz, Ooi, and Pedersen (2012) and Alexander, Korovilas, and Kapraun (2016) for a similar selection of parameters and associated representation.

[4] Trading cost refers to the average of maker and taker Fee at Hitbtc, one of the leading European CCs trading platforms and the spread the conservative estimate suggested by Liu et al. (2021).

Table 1
Strategies without stop loss

		Panel A: 3 CCs				Panel B: 5 CCs			
		1	3	6	12	1	3	6	12
	Long	0.054	0.074*	0.045	0.07*	0.047	0.072*	0.044	0.065*
		(1.25)	(1.63)	(1.09)	(1.52)	(1.06)	(1.60)	(1.24)	(1.59)
1	Short	-0.04	-0.03	-0.058	-0.051	-0.048	-0.031	-0.042	-0.051
		-(0.57)	-(0.46)	-(0.97)	-(0.88)	-(0.80)	-(0.59)	-(0.46)q	-(0.27)
	Long-Short	0.04	0.051	0.002	0.035	0.033	0.045*	0.011	0.033
		(0.68)	(0.98)	(0.04)	(0.73)	(0.78)	(1.42)	(0.78)	(1.13)
	Long	0.064	0.06*	0.059*	0.08**	0.059	0.067*	0.055*	0.07*
		(1.30)	(1.34)	(1.47)	(1.74)	(1.26)	(1.45)	(1.43)	(1.68)
3	Short	-0.022	-0.049	-0.052q	-0.048	-0.033	-0.05	-0.056	-0.06
		-(0.36)	-(0.77)	-(0.88)	-(0.77)	-(0.61)	-(0.94)	-(0.46)	-(0.51)
	Long-Short	0.071*	0.015	0.021	0.05	0.048*	0.025	0.019	0.028
		(1.48)	(0.35)	(0.55)	(0.99)	(1.55)	(0.83)	(1.02)	(1.24)
	Long	0.051	0.075*	0.077**	0.086**	0.052	0.072*	0.07*	0.075*
		(1.07)	(1.52)	(1.78)	(1.74)	(1.13)	(1.58)	(1.64)	(1.66)
6	Short	-0.048	-0.043	-0.067	-0.039	-0.052	-0.05	-0.061	-0.062
		-(0.78)	-(0.73)	-(1.11)	-(0.71)	-(0.93)	-(0.95)	-(0.49)	-(0.49)
	Long-Short	0.019	0.052	0.025	0.063*	0.013	0.038	0.04	0.031
		(0.48)	(1.14)	(0.56)	(1.54)	(0.41)	(1.29)	(1.06)	(1.11)
	Long	0.066*	0.075*	0.069*	0.097**	0.058	0.07*	0.069*	0.087**
		(1.39)	(1.50)	(1.55)	(1.93)	(1.25)	(1.55)	(1.49)	(1.90)
12	Short	-0.071	-0.039	-0.05	-0.024	-0.067	-0.042	-0.055	-0.049
		-(1.26)	-(0.74)	-(1.02)	-(0.45)	-(1.30)	-(0.83)	-(0.59)	-(0.38)
	Long-Short	0.011	0.055	0.033	0.088**	0.004	0.044*	0.044**	0.056**
		(0.30)	(1.29)	(1.04)	(2.37)	(0.16)	(1.49)	(1.70)	(1.91)

		Panel C: 7 CCs				Panel D: 9 CCs			
		1	3	6	12	1	3	6	12
	Long	0.059	0.065*	0.047	0.065*	0.057	0.055	0.051	0.06*
		(1.25)	(1.47)	(1.10)	(1.51)	(1.25)	(1.25)	(1.15)	(1.38)
1	Short	-0.06	-0.03	-0.046	-0.039	-0.059	-0.024	-0.042	-0.039
		-(1.01)	-(0.62)	-(0.94)	-(0.77)	-(1.05)	-(0.48)	-(0.85)	-(0.78)
	Long-Short	0.02	0.042*	0.017	0.047*	0.02	0.041*	0.031*	0.041**
		(0.57)	(1.51)	(0.66)	(1.62)	(0.66)	(1.65)	(1.35)	(1.80)
	Long	0.07*	0.075*	0.061*	0.067*	0.074*	0.062*	0.051	0.062*
		(1.51)	(1.67)	(1.39)	(1.55)	(1.55)	(1.44)	(1.15)	(1.43)
3	Short	-0.035	-0.041	-0.053	-0.057	-0.036	-0.045	-0.049	-0.055
		-(0.67)	-(0.78)	-(1.02)	-(1.09)	-(0.72)	-(0.88)	-(0.97)	-(1.09)
	Long-Short	0.052**	0.044*	0.026	0.039*	0.053***	0.037*	0.024	0.035*
		(2.16)	(1.47)	(0.96)	(1.32)	(2.44)	(1.53)	(1.00)	(1.46)
	Long	0.053	0.076**	0.068*	0.071*	0.056	0.071*	0.061*	0.066*
		(1.17)	(1.69)	(1.50)	(1.60)	(1.24)	(1.61)	(1.33)	(1.45)
6	Short	-0.048	-0.042	-0.049	-0.064	-0.041q	-0.056	-0.05	-0.059
		-(0.91)	-(0.81)	-(0.95)	-(1.20)	-(0.84)	-(1.10)	-(0.97)	-(1.16)
	Long-Short	0.022	0.05**	0.044*	0.038*	0.032*	0.042**	0.037*	0.037*
		(0.89)	(1.79)	(1.58)	(1.35)	(1.49)	(1.96)	(1.54)	(1.56)
	Long	0.059	0.075**	0.062*	0.076**	0.06	0.071*	0.053	0.067*
		(1.25)	(1.68)	(1.34)	(1.72)	(1.28)	(1.60)	(1.12)	(1.49)
12	Short	-0.063	-0.037	-0.049	-0.054	-0.053	-0.048	-0.05	-0.053
		-(1.27)	-(0.73)	-(0.96)	-(1.03)	-(1.05)	-(0.98)	-(0.98)	-(1.04)
	Long-Short	0.013	0.055**	0.039*	0.053**	0.025	0.05**	0.029	0.045**
		(0.62)	(2.00)	(1.62)	(1.96)	(1.01)	(2.39)	(1.28)	(1.84)

This table presents the average monthly returns for the different look-back windows for volatility calculation and holding periods. In columns are the look-back periods for historical volatility calculation, and in rows are the holding periods. In parenthesis are t-statistics.

* Refers to significance at 10%.

** 5% and.

*** 1%.

A highly concentrated CC portfolio might suffer from heightened downside risk during bear markets, though. Put differently, if there are significant positive correlations between CC returns, highly concentrated CC portfolios while having considerable upside potential, might present deep setbacks in portfolio returns. To delve deeper into this aspect, we look at the portfolio maximum drawdowns (MDDs). Figure 1 presents the MDDs for all our CC strategies. The lowest MDDs are achieved when CC portfolios have a longer look-back window to calculate volatility and a longer holding period. This observation holds for all portfolios consisting of different numbers of CCs. Second, portfolios with a higher number of CCs have larger MDDs most of the time, i.e., the CCs portfolios with nine CCs have the highest MDDs, whereas with three CCs, the smallest. As MDD reflects the capital preservation potential for a

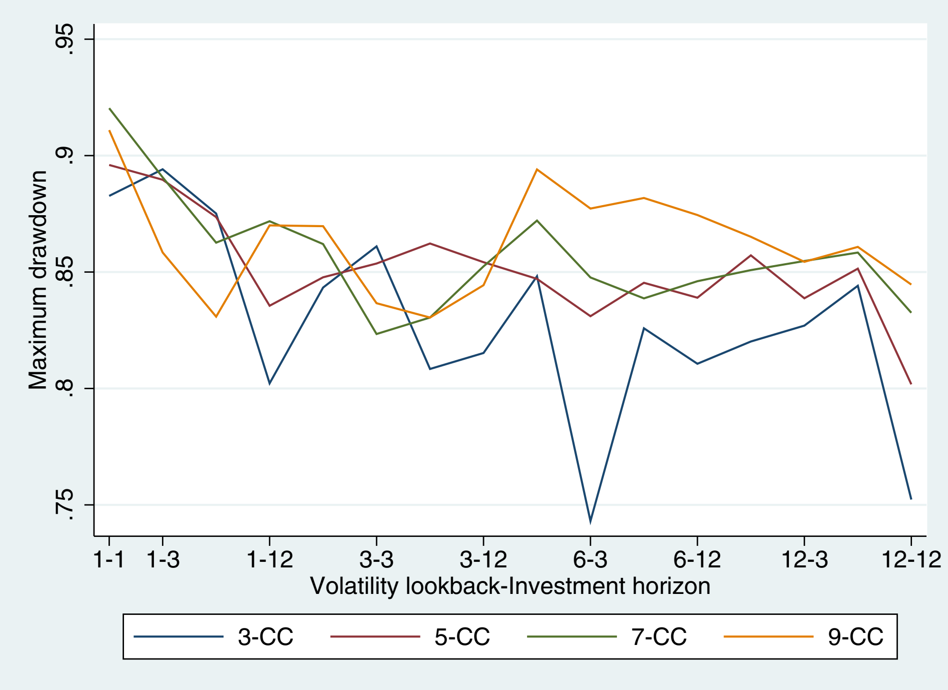

Fig. 1. Maximum drawdown for different strategies.

given strategy, it assesses the relative riskiness of one trading strategy versus another. In this vein, unlike other market segments, CC markets seem to present a lower risk if a small number of low-volatility CCs are selected for investment.

We continue with the implementation of the stop-loss to our strategy. In Figures 2 and 3 we present the Sharpe ratios of strategies for portfolios that include three and nine CCs and stop-losses of up to 25% threshold. We concentrate on longer volatility look-back windows for brevity and calculated the Sharpe ratios for different stop-loss thresholds. The Sharpe-ratios take a hump shape with

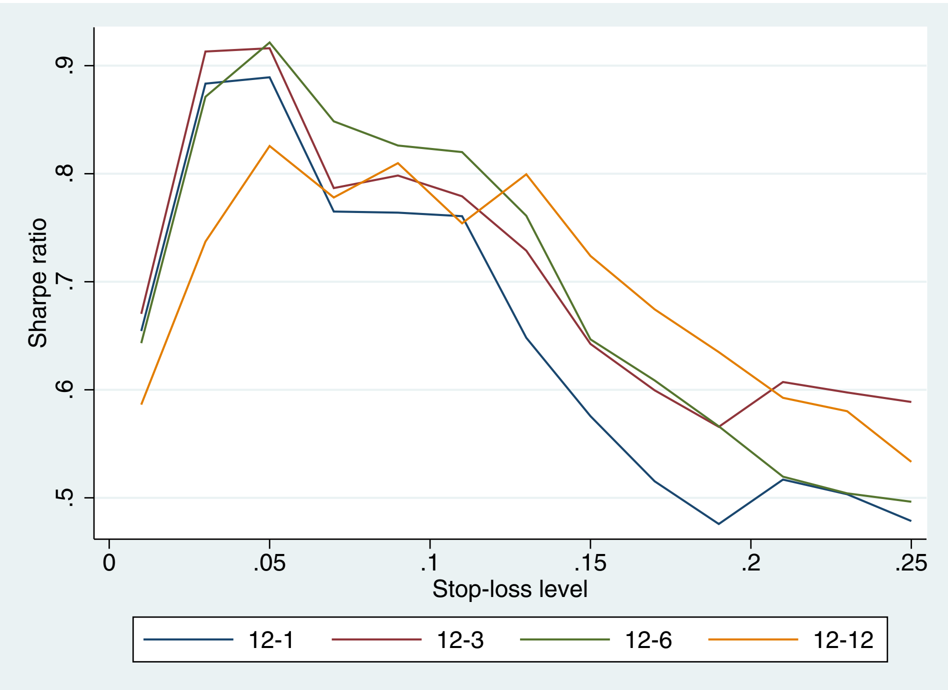

Fig. 2. Stop-loss Sharpe ratio for three CCs portfolio.

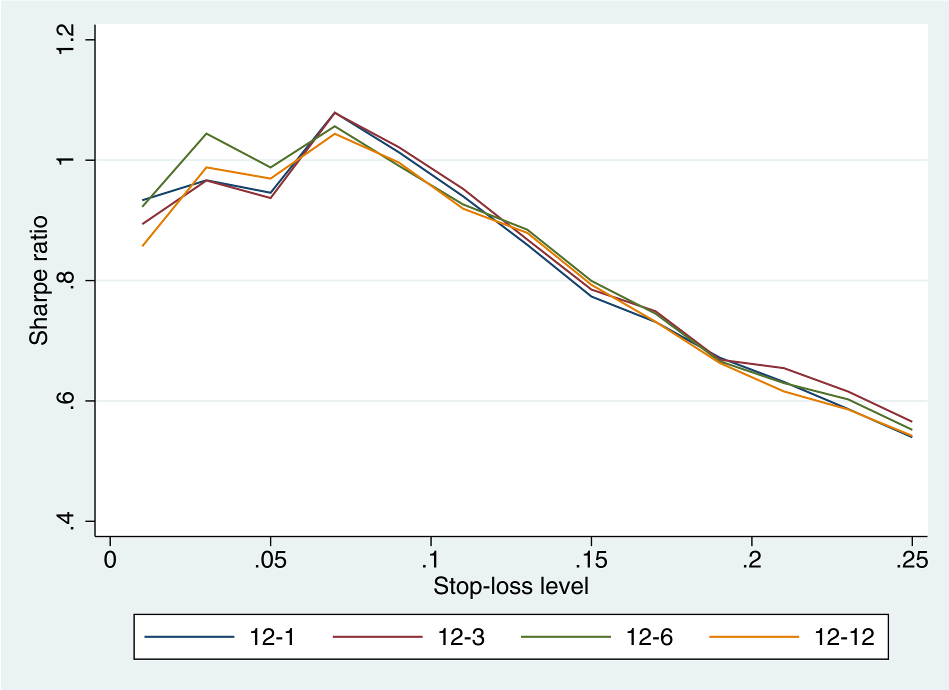

Fig. 3. Stop-loss Sharpe ratio for nine CCs portfolio.

respect to the stop-loss level. To be specific, for the portfolio with three CCs, the Sharpe ratio increases significantly up to around 5% stop-loss threshold and decreases gradually afterward. After around 10%, stop-loss becomes detrimental to the portfolio as the Sharpe ratios become smaller than a portfolio without stop-loss. For nine CCs, a similar picture is visible with a different inflection point, though. Up to around 10%, stop-loss increases the Sharpe ratio of the portfolio, and its contribution decline afterward. For both portfolios, we calculated the MDDs but not reported for brevity. Around the 5% and 15% stop-loss thresholds for three and nine CCs, MDDs came down to as low as 40% and 70%, respectively. This shows that stop-loss as a risk management approach contributes favorably to risk-return dynamics of the tested strategies.

We make several robustness checks to our findings. First, we exclude bitcoin from our sample. Second, we select different samples, such as CCs with a market cap of USD 5 bn in 2017 or a market cap of USD 10 bn in 2018. Third, we take a subset of our sample with 15 CCs. In all specifications, our main results hold.

4. Conclusion

This paper tests a low volatility portfolio strategy for CC markets. For a sample of most traded CCs, our results reveal that investing in a highly concentrated low volatility CC portfolio with a six to twelve months volatility look-back and holding period increases the investment performance significantly. Interestingly, increasing the number of CCs in the portfolio does not lower portfolio volatility. By including a simple stop-loss rule, the downside risk proxied by MDDs of CC portfolios is reduced, and the Sharpe ratios are improved markedly.

Appendix

See Table A1.

Table A1
Summary statistics

CC	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis
Bitcoin	0.07	0.05	0.24	-0.45	0.53	-0.10	2.47
Ethereum	0.10	0.08	0.38	-0.77	1.15	0.34	3.43
Xrp	0.09	-0.03	0.57	-1.11	2.22	1.50	6.19
LiteCoin	0.06	0.04	0.34	-0.55	0.97	0.44	2.78
Monero	0.05	-0.01	0.33	-0.59	1.26	1.01	4.96
Dash	0.05	-0.05	0.39	-0.65	1.04	0.77	3.15
Augur	0.03	0.04	0.35	-0.57	0.99	0.47	3.29
MaidSafeCoin	0.04	0.00	0.36	-0.51	0.83	0.34	2.18
NEM	0.07	-0.04	0.50	-0.66	1.52	1.12	3.85
Factom	0.10	-0.04	0.71	-0.70	4.40	4.15	25.56
DogeCoin	0.13	0.00	0.54	-0.76	2.07	1.74	6.68
Stellar	0.09	-0.03	0.51	-0.52	1.96	1.50	5.60
GameCredits	-0.01	-0.09	0.48	-0.83	1.35	0.84	3.63
BitShares	0.04	-0.03	0.55	-0.80	1.58	0.86	3.51
ByteCoin	0.05	0.01	0.54	-0.91	2.38	1.71	8.38
Gulden	0.00	-0.11	0.37	-0.56	1.19	1.34	4.88
EmerCoin	-0.01	-0.05	0.45	-0.91	1.12	0.36	2.96
Counterparty	0.00	-0.06	0.45	-1.22	1.61	0.73	5.65
SiaCoin	0.08	-0.02	0.54	-0.83	1.99	1.21	5.43
PeerCoin	0.03	-0.01	0.32	-0.66	0.90	0.51	3.11
Syscoin	0.05	0.01	0.50	-0.83	1.19	0.34	2.69
Namecoin	0.03	0.05	0.41	-1.31	0.99	-0.42	3.97
Pot Coin	0.00	-0.01	0.39	-0.77	1.25	0.32	3.47
Grid Coin	0.00	-0.04	0.39	-0.78	0.98	0.38	2.81
Nav Coin	0.04	0.03	0.45	-0.78	1.30	0.67	3.80
Black Coin	0.01	0.01	0.37	-0.71	1.05	0.41	3.40
Digibayt	0.10	-0.05	0.58	-0.74	2.79	2.45	10.88
Omni	0.00	-0.08	0.55	-1.21	2.28	1.39	7.15
Aeon	0.03	-0.06	0.55	-0.83	1.52	0.89	3.47
Fedora Coin	0.02	-0.16	0.86	-1.43	3.94	1.93	9.37
Nexus	0.05	-0.03	0.50	-1.06	1.38	0.67	3.83
Sib Coin	-0.03	-0.04	0.44	-1.04	0.97	-0.13	2.82
VertCoin	0.05	0.02	0.48	-0.82	1.62	0.67	3.78
Expanse	-0.02	-0.12	0.50	-0.82	1.00	0.45	2.05
MonaCoin	0.08	0.02	0.47	-0.73	1.85	1.23	5.41

This table presents the summary statistics of CC returns for the period between January-2017 and June- 2021.

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