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Author(s): Grobys, Klaus; Sapkota, Niranjan

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Cryptocurrencies and momentum

Klaus Grobys[1], Niranjan Sapkota*,[1]

Department of Accounting and Finance, University of Vaasa, Wolffintie 34, 65200 Vaasa, Finland

HIGHLIGHTS

- We explore whether momentum does exist in cryptocurrency markets.
- We find that momentum is insignificant in the 2014–2018 sample period.
- Digital currency markets seem to be more efficient than earlier studies suggest.

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ABSTRACT

Retrieving a set of 143 cryptocurrencies for a sample spanning 2014–2018, we investigate the popular momentum strategy implemented in the cryptocurrency market. Contrary to earlier studies our findings do not indicate any evidence of significant momentum payoffs, supporting the view that the cryptocurrency market is far more efficient than suggested in earlier studies.

1. Introduction

The momentum effect (Jegadeesh and Titman, 1993) has been subject to a flood of investigations. Significant momentum payoffs have been found in international equity markets (Rouwenhorst, 1997), foreign exchange markets (Menkhoff et al., 2012), and commodities (Miffre and Rallis, 2007), among others. Unlike many other anomalies, recent findings of Hou et al. (2019) indicate that momentum is persistent. In addition, Asness et al. (2013), who explore the pervasiveness of the momentum phenomenon, argue that momentum payoffs are positively co-moving across otherwise unrelated asset markets. Surprisingly, there is no study available investigating this well-known asset pricing anomaly in new digital currency markets.

Zhang et al. (2018) test the efficiency of nine different cryptocurrencies and find them all inefficient. Similarly, Al-Yahyaee et al. (2018) studied the market efficiency of Bitcoin compared to gold, stocks, and the currency market and found Bitcoin to be more inefficient than other markets. Urquhart (2016) tested the market efficiency of Bitcoin and found it inefficient over the full sample period applied, whereas a sample-split test showed Bitcoin to be efficient in the later subsample, indicating that it is developing toward market efficiency. Vidal-Tomás and Ibañez (2018) and Sensoy (2019) also argue that Bitcoin has become more efficient over time, whereas Bariviera's (2017) findings highlight Bitcoin's informational efficiency since 2014. Moreover, Nadarajah and Chu (2017) revisit Urquhart's (2016) paper and report that Bitcoin returns do satisfy the efficient market hypothesis. Furthermore, Khuntia and Pattanayak (2018) support Vidal-Tomás and Ibañez (2018) and Sensoy (2019) and argue that Bitcoin exhibits market efficiency over time, validating the adaptive market hypothesis. Other studies find that return predictability among cryptocurrencies diminishes when market liquidity is high (Wei, 2018; Brauneis and Mestel, 2018). In summary, despite the different views in the literature there currently remains no consensus over the market efficiency of cryptocurrencies.

The purpose of our paper is to investigate the existence of momentum implemented in the cryptocurrency market. We employ monthly time series data on 143 cryptocurrencies in the 2014–2018 period, and follow the literature in implementing different

* Corresponding author.
E-mail addresses: klaus.grobys@uva.fi (K. Grobys), niranjan.sapkota@uva.fi (N. Sapkota).

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Table 1
Predicted momentum returns using all available cryptocurrencies.

Strategy	Loser (L)	2	3	4	Winner (W)	W-L	(4-2)
12-1-1	24.70	19.53	47.72	19.11	42.94	18.24	−0.42
						(1.18)	(−0.09)
12-1-1[a]						0.87	−1.53
						(0.10)	(−0.52)
6-1-1	26.46	19.16	20.62	38.79	33.18	6.72	19.63
						(0.56)	(0.92)
6-1-1[a]						−6.48	2.48
						(−0.99)	(0.55)
1-0-1	38.48	23.50	18.51	18.34	32.20	−6.28	−5.17
						(−0.28)	(−0.73)
1-0-1[a]						−14.87**	−4.54
						(−2.20)	(−0.92)

** Statistically significant on a 5% level.
[a]Estimates based on trimmed data.

Table 2
Predicted momentum returns using 30 cryptocurrencies with highest market capitalization.

Strategy	Loser (L)	2	3	4	Winner (W)	W-L	(4-2)
12-1-1	32.82	27.73	12.90	10.59	41.32	8.50	−17.14*
						(0.33)	(−1.78)
12-1-1[a]						−7.84*	−5.32
						(−1.68)	(−1.17)
6-1-1	36.29	19.11	14.86	18.19	53.66	6.72	19.63
						(0.56)	(0.92)
6-1-1[a]						−6.48	2.48
						(−0.99)	(0.55)
1-0-1	53.03	14.32	16.21	23.04	13.00	−40.04	8.72
						(−1.31)	(0.99)
1-0-1[a]						−4.80	3.22
						(−0.63)	(0.91)

** Statistically significant on a 5% level.
* Statistically significant on a 10% level.
[a]Estimates based on trimmed data.

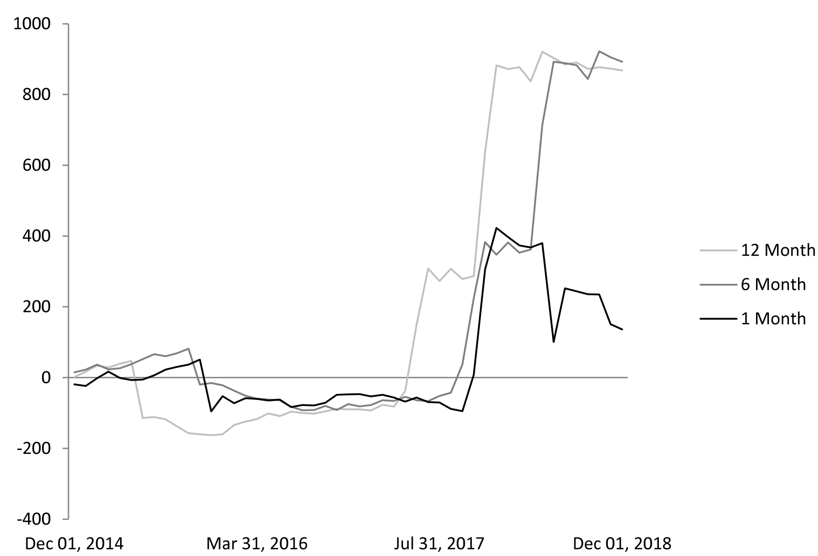

Fig. 1. Cumulative returns of time series momentum strategies.

momentum strategies. We also examine a data set consisting of 30 cryptocurrencies exhibiting the highest market capitalizations. Robustness checks help trim the data and revisit our analysis. Finally, we also implement the more recently proposed time series momentum strategies.

Our paper contributes to the wide strand of literature investigating the profitability of momentum strategies. Specifically, the analysis of the cryptocurrency market extends the findings of Menkhoff et al. (2012) on the traditional currency market. This is the first paper that explores this well-known phenomenon implemented among cryptocurrencies. Moreover, we add to the recent discussion on cryptocurrency market efficiency (Nadarajah and Chu, 2017; Zhang et al., 2018; Urquhart, 2016) by exploring a new perspective because the existence of momentum would suggest market inefficiency. While earlier literature addresses market efficiency on a single cryptocurrency level (Al-Yahyaee et al., 2018; Zhang et al., 2018; Urquhart, 2016), we employ portfolio analysis (Fama and French, 2008).

Surprisingly, contrary to earlier studies (e.g., Hou et al., 2019; Asness et al., 2013), we do not find any evidence for cross-sectional momentum in the cryptocurrency market. We also do not find any strong evidence that supports Moskowitz et al.'s

(2012) time series momentum effects. If anything, some of strategies generate rather negative payoffs.

2. Methodology

The analysis involved downloading cryptocurrency data from coinmarketcap.com.[2] Our data contain all cryptocurrencies that incorporated the *Proof-of-Work* mechanism and started trading prior to December 31, 2014. Our monthly data set is from January 1, 2014 until December 31, 2018. In total, we retrieved 143 cryptocurrencies.

Using Fama and French's (2008) portfolio approach, we sorted all cryptocurrencies by their cumulative past returns in an increasing order into quintiles. The first group (*loser*) contains the 20% of equal-weighted cryptocurrencies exhibiting the lowest cumulative returns for the period t-12–t-2, whereas the fifth group (*winner*) contains the 20% of equal-weighted cryptocurrencies exhibiting the highest cumulative returns for the same period. The portfolios are held one month ahead. This n-m-h strategy, where $n = 12$, $m = 1$, and $h = 1$ (Jegadeesh and Titman, 1993), was updated and rebalanced at the beginning of each month. In the same manner, we also investigated the 6-1-1 and 1-0-1 strategies (Jegadeesh and Titman, 1993; Jegadeesh, 1990). The zero-cost portfolios were compounded by selling the loser (group 1) and buying the winner (group 5) portfolio. We also considered a less extreme strategy that is long on group 4 and short on group 2. For each strategy, we employed only those cryptocurrencies for which data were available in the portfolio formation period. Moreover, we analyzed trimmed payoffs, which we defined as payoffs with the two most extreme returns for each series excluded.

Table 1 reflects the payoffs of the corresponding momentum strategies in percent per month using the whole sample of 143 cryptocurrencies. On average, we could invest in 89 cryptocurrencies, which is a much larger data set than usually used in studies investigating traditional currencies.[3] Table 1 reveals that none of the untrimmed momentum strategies generated statistically significant payoffs. We then excluded the returns exhibiting the largest economic magnitude, corresponding to −294.28% and 540.51% (−104.85% and 154.97%), 182.00% and 504.83% (1087.85% and 174.11%), and 1029.40% and −569.41% for the 12-1-1, 6-1-1 and 1-0-1 strategies, where we are long on group 5 (group 4) and short on group 1 (group 2).[4] After trimming, only the trimmed 1-0-1 strategy appeared to have generated significant average payoffs, and those, surprisingly, were negative.

To address the concern that the results could be driven by small cryptocurrencies that contaminate the strategies' payoff due to their potentially higher volatilities, we sorted all cryptocurrencies by their market capitalization from largest to smallest and condition our investment universe on those 30 cryptocurrencies that exhibited the highest market capitalization as of December 28, 2014.[5] To address the outlier problem, we again report in addition the payoffs where we cut off the returns exhibiting the largest economic magnitude, corresponding to 1279.45% and −412.42% (−392.44% and −256.33%), 1269.39% and 636.18% (151.05% and −111.14%), and −1591.06% and −462.25% (−108.29% and 433.50%) for the 12-1-1, 6-1-1 and 1-0-1 strategies, being long on group 5 (group 4) and short on group 1 (group 2). The results are reported in Table 2 and support our previous findings: If anything, some strategies generated insignificant negative payoffs suggesting that our results are not driven by small cryptocurrencies.

Interestingly, our results from Tables 1 and 2 also reveal that there is no linear spread in predicted returns as we move from the loser to the winner group, despite Panels A and B of Table A.3 in the Appendix revealing a clear linear spread in average formation period returns, regardless of data set used. It is possible that cross-sectional return momentum does not fully account for financial cycles. Moskowitz et al. (2012) proposed the time series momentum strategy that performs remarkably well even in different market scenarios. Hence, we estimate time series momentum (TSMOM) as defined by

$$r_{t,t+1}^{TSMOM,s} = sign\left(r_{t-K}^{s}\right) \cdot r_{t,t+1}^{s},$$

where r_{t-K}^{s} is the return of security s over the past K months and $r_{t,t+1}^{s}$ is next month's return which indicates taking a long position when the sign of the cumulative past K-month return is positive and a short position otherwise. While traditional cross-sectional momentum takes long and short positions, TSMOM evaluates momentum security-by-security and thus it is possible to short all assets, or be long all assets at the same time (Moskowitz et al., 2012). Fig. 1 illustrates the cumulative returns using $K = \{12, 6, 1\}$. The average payoffs are 17.71, 18.22 and 3.94 for $K = 12$, $K = 6$, and $K = 1$, with corresponding t-statistics of 1.65, 1.84, and 0.41 indicting that the strategies do not generate statistically significant payoffs on a common 5% level either.

Table A.1
Descriptive statistics.

Panel A. 6-1-1 strategies				
(Long-Short)	(5–1)	(5-1)[a]	(4-2)	(4-2)[a]
Mean	6.72	−6.48	19.63	2.48
Median	−5.62	−5.70	1.02	1.02
Maximum	504.83	138.35	1087.85	151.73
Minimum	−164.99	−164.99	−174.11	−110.64
Std.Dev.	87.91	47.78	154.91	32.93
Skewness	3.57	0.13	6.32	1.15
Kurtosis	21.05	6.06	44.39	11.95
Jarque–Bera	832.03	20.07	4136.28	181.37
Probability	0.00	0.00	0.00	0.00
Panel B. 12-1-1 strategies				
(Long-Short)	(5-1)	(5-1)[a]	(4-2)	(4-2)[a]
Mean	18.24	0.87	−0.42	−1.53
Median	1.07	−1.04	−2.48	−2.48
Maximum	540.51	216.87	154.97	71.90
Minimum	−196.97	−196.97	−104.85	−50.77
Std.Dev.	107.14	62.57	33.87	20.45
Skewness	2.78	0.43	1.64	1.08
Kurtosis	14.07	7.44	12.44	6.94
Jarque–Bera	306.71	39.28	199.79	38.73
Probability	0.00	0.00	0.00	0.00
Panel C. 1-0-1 strategies				
(Long-Short)	(5-1)	(5-1)[a]	(4-2)	(4-2)[a]
Mean	−6.28	−14.87	−5.17	−4.54
Median	−6.57	−6.57	−3.46	−3.46
Maximum	1029.40	113.39	174.32	75.24
Minimum	−569.41	−182.29	−218.86	−112.08
Std.Dev.	165.01	49.23	51.33	35.91
Skewness	3.70	−0.95	−0.81	−0.91
Kurtosis	30.72	5.25	9.47	5.64
Jarque–Bera	1955.39	19.91	105.59	23.56
Probability	0.00	0.00	0.00	0.00

[a]Estimates based on trimmed data.

[2] This website provides cryptocurrency data after April 28, 2013.

[3] Fig. A.1 (see Appendix) reports the number of cryptocurrencies available for investing each month over the period. The results are based on the 6-1-1 strategy; the graphs for the 12-1-1 and 1-0-1 strategies look very similar and are available upon request.

[4] The corresponding descriptive statistics are provided in Panels A–C of Table A.1 in the Appendix.

[5] See Table A.2 in the Appendix.

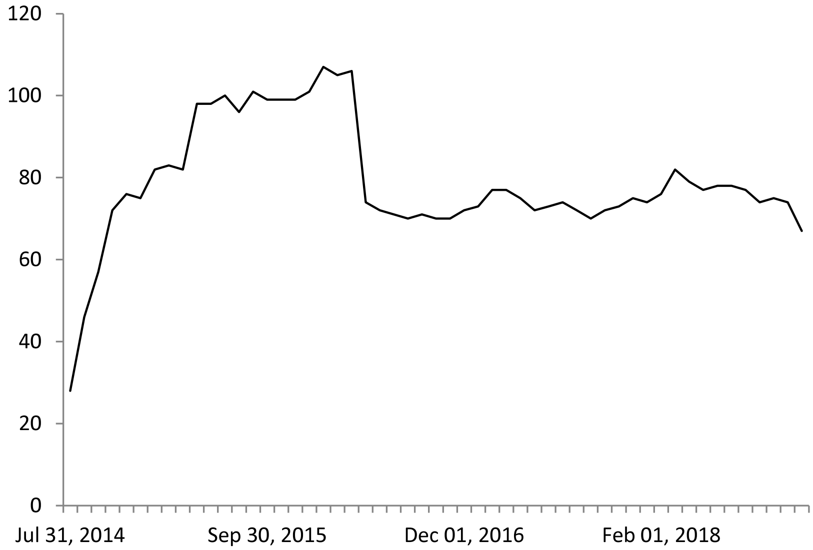

Fig. A.1. Available cryptocurrencies for investing.

Table A.2
Top 30 cryptocurrencies.

RANK	Cryptocurrency	Symbol	Market capitalization[a]
1	Bitcoin	BTC	4333395591
2	Paycoin	XPY	151955176
3	Litecoin	LTC	95993588
4	Stellar	XLM	20620132
5	Dogecoin	DOGE	17877560
6	Peercoin	PPC	12955668
7	Namecoin	NMC	7634718
8	Bytecoin	BCN	1328203
9	Quark	QRK	1241473
10	Feathercoin	FTC	1045563
11	Reddcoin	RDD	867751
12	Primecoin	XPM	795821
13	iXcoin	IXC	616731
14	Pandacoin	PND	615669
15	Infinitecoin	IFC	488227
16	Megacoin	MEC	440813
17	Worldcoin	WDC	438287
18	Novacoin	NVC	393347
19	Unobtanium	UNO	350264
20	Zetacoin	ZET	320247
21	Anoncoin	ANC	283265
22	Maxcoin	MAX	238896
23	Vertcoin	VTC	238304
24	Curecoin	CURE	237021
25	Applecoin	APC	229961
26	Goldcoin	GLD	181954
27	Devcoin	DVC	156316
28	ZcCoin	ZCC	151044
29	Mooncoin	MOON	126016
30	Diamond	DMD	122416

[a]As of December 28, 2014 in US-dollar. The average market capitalization of those 80% of coins that were excluded from this sample is about USD 12,000 implying that Diamond (DMD) is about ten times larger in terms of market capitalization than the sample average of excluded cryptocurrencies.

3. Conclusion

This paper investigates the existence of momentum effects in the cryptocurrency market. While earlier research suggested the pervasiveness and co-movement of momentum across different asset markets, the current research does not find any evidence of significant momentum payoffs in the cryptocurrency market. While cross-sectional momentum tends to generate negative payoffs that are mostly insignificant, two investigated TSMOM strategies tend to generate positive payoffs during the sample period that are, however, only marginally significant. Hence, our results indicate that new digital financial markets seem to be more efficient than traditional asset markets. Future research is encouraged to clarify why momentum appears to be unprofitable in cryptocurrency markets. It could be also an interesting issue to explore the profitability of risk-managed momentum in cryptocurrency markets.

Table A.3
Formation period returns of momentum portfolios.

Panel A. Sample of all cryptocurrencies strategy					
	Loser (L)				Winner (W)
12-1-1	−19.35	72.31	149.07	268.46	1167.23
6-1-1	−62.62	4.40	52.36	123.58	629.46
1-0-1	−44.55	−18.39	−0.76	22.52	176.38
Panel B. Sample of top-30 cryptocurrencies					
	Loser (L)				Winner (W)
12-1-1	−11.64	67.08	138.49	253.74	922.08
6-1-1	−55.15	3.42	47.28	115.17	486.75
1-0-1	−37.55	−14.92	0.02	21.51	134.35

Appendix

See Fig. A.1 and Tables A.1–A.3

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