Momentum trading in cryptocurrencies: Short-term returns and diversification benefits

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Abstract

We test for the presence of momentum effects in cryptocurrency market and estimate dynamic conditional correlations (DCCs) of returns between momentum portfolios of cryptocurrencies and traditional assets. First, investment portfolios are constructed adherent to the classic J/K momentum strategy, using daily data from twelve cryptocurrencies for over a period of three years. We identify the existence of momentum effect, which is highly significant for short-term portfolios but disappears over the longer term. Second, we show that cross correlations of weekly returns between momentum portfolio of cryptocurrencies and traditional assets are unlike correlations of returns between traditional assets. Third, we find that momentum portfolios of cryptocurrencies not only offer diversification benefits but also can be a hedge and safe haven for traditional assets.

Keywords: Momentum, Cryptocurrency, Dynamic Conditional Correlation

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1 Introduction

Cryptocurrency market has become a recurring investment issue and for this reason there has been a spectacular growth in research that seeks to understand the nature of this market.[1] Hitherto, empirical literature has substantially improved our knowledge regarding the behaviour and characteristics of cryptocurrencies. In particular, cryptocurrencies tend to follow long memory processes (Phillip et al., 2018), but vary in the degree of informational (in)efficiency (Urquhart, 2016; Bariviera, 2017; Nadarajah and Chu, 2017). Cryptocurrencies have no intrinsic value and thus are more susceptible to speculative bubbles than other currencies (Cheah and Fry, 2015). Highly risky (Pelster et al., 2019) and volatile (Dwyer, 2015; Katsiampa, 2017; Chaim and Laurini, 2018) cryptocurrencies can be appealing to speculative traders (de la Horra et al., 2019). Notably, they can benefit traders who expect that past winners will be future winners and past losers will continue to lose in the future (Kristoufek, 2013; Grobys and Sapkota, 2019). This signifies momentum trading, which shorts worst performing assets and takes long positions in top performing ones (Jegadeesh and Titman, 1993).

In parallel with the body of research on momentum trading in equity, foreign exchange and commodity markets (e.g. Miffre and Rallis, 2007; Menkhoff et al., 2012), cryptocurrencies provide a fertile ground for momentum strategies. First, cryptocurrencies are not subject to short-selling constraints on many trading platforms (e.g., `Etoro.com`). Second, momentum strategies are appealing due to negligible costs required to store digital assets. Third, according to `Bitinfocharts.com` transaction costs are low and vary depending upon the market exchange platform. Hence, returns from momentum trading are unlikely to be affected by the costs of implementing the strategy. To the best of our knowledge, only Grobys and Sapkota (2019) investigate momentum trading in cryptocurrencies. In Grobys and Sapkota (2019), the trading strategies comprise 12, 6 and 1-month formation periods, and a 1-month holding period. Interestingly, they do not find evidence of significant momentum returns. A plausible explanation is that cryptocurrency returns are extremely volatile (Baek and Elbeck, 2015), which may trigger intra-monthly reversal effects. In the light of this explanation, the momentum strategies we construct exploit short-term formation and holding periods.

Another strand of literature, which has become a milestone in the cryptocurrency research only recently, examines whether and, if so, how cryptocurrencies are dynamically correlated with traditional financial assets. In this regard, Platanakis and Urquhart (2019) find that cryptocurrencies can be regarded as excellent candidates for a well-diversified portfolio of assets and may offer diversification benefits for short-term investments (Corbet et al., 2018). In addition, while bitcoin is isolated from traditional assets Baur et al. (2018), it exhibits lagged correlation with them (Corbet et al., 2019).

Against this background, we test whether short-term momentum strategies have persis-

[1]In February 2019, cryptocurrencies are numbered to be 2062 with their total market capitalisation exceeding the \$121 billion (`Coinmarketcap.com`).

tently positive returns and we explore their diversification, hedging and/or safe haven benefits for investors.

We make four contributions. First, by designing and applying shorter-term momentum strategies (up to 1 month), this study departs from Grobys and Sapkota (2019), who centre on momentum strategies longer than 1 month. Second, in contrast to Grobys and Sapkota (2019), where the momentum portfolios are not risk adjusted, we consider the risk premium over the risk-free interest rate, and we scale our momentum portfolios by a risk-adjustment factor. Third, the momentum strategies in this study factor in a reasonable transaction cost, and thus are more aligned with real-world circumstances surrounding cryptocurrency investors' decisions. Fourth, our research contributes to the literature that evaluates the diversification benefits (e.g., Platanakis and Urquhart, 2018), and hedging and safe haven properties of cryptocurrencies (e.g. Bouri et al., 2017a,b). However, while Bouri et al. (2017a,b) focus specifically on Bitcoin, we ask if the above mentioned properties apply to a momentum portfolio of cryptocurrencies.

2 Data and methodology

Our sample consists of daily closing prices during the period of 1/12/2015 to 29/1/2019 for 12 cryptocurrencies retrieved from `Coinmarketcap.com`. The selection is based on (i) cryptocurrencies with largest market capitalisation (see Table 1, Mcap $\geq$ \$100 million), and (ii) having more than three years of data. Thus the momentum portfolios have an adequate number of observations to provide us with meaningful inference. Table 1 and Figure 1 display the daily returns of these cryptocurrencies.

[INSERT TABLE 1 AND FIGURE 1 HERE]

We use the so-called J/K strategy (Jegadeesh and Titman, 1993) to construct the momentum portfolios, where J is the formation period (in number of days), and K is the holding period. This strategy selects cryptocurrencies on the basis of cumulative returns over the past J days. At the beginning of day t the cryptocurrencies are ranked in descending order on the basis of their returns in the past J days. Based on these rankings, the 12 cryptocurrencies are divided into two portfolios. The "winners" portfolio (Winners) is an equally-weighted portfolio of the top 6 cryptocurrencies, whereas the "losers" portfolio (Losers) is an equally-weighted portfolio of the bottom 6 cryptocurrencies. For robustness, we also consider the top 3 and bottom 3 cryptocurrencies. The momentum strategy buys the winner portfolio and sells the loser portfolio, $MOM = W - L$, and MOM is the weekly percentage return on a momentum portfolio. It closes out the position on day $t + K$. Then, cumulative returns on individual currencies are calculated over the past J days.

Additionally, similarly to Barroso and Santa-Clara (2015), we construct a risk-adjusted momentum portfolio. To this end, a momentum portfolio is adjusted for both the risk free rate (RF) and transaction cost (TC). The latter is set to 26 basis points per trade, following Brauneis and Mestel (2018), Kraken.com, and Bitinfocharts.com:

$$Adj.MOM_t = \frac{\sigma^{target}}{\sigma_t^{MOM}}(MOM_t - RF_t - TC), \tag{1}$$

where MOM is the return on an (unscaled) momentum portfolio as previously defined. This risk management strategy uses a rolling-window average volatility (σ_t^{MOM}) relative to the previous six periods in order to target a constant volatility (σ^{target}).[2] The ratio ($\frac{\sigma^{target}}{\sigma_t^{MOM}}$) implies that in periods of low (high) volatility in the market, momentum traders invest larger (smaller) amounts in the (unscaled) momentum portfolio. As a result, returns on a risk-adjusted momentum portfolio become less volatile. It is worth noting that a momentum portfolio is by construction a 100% self-financed long-short strategy, which can be scaled without assuming leverage costs.

We now examine the dynamic correlations between a momentum portfolio of cryptocurrencies and other traditional assets at the weekly frequency (J/K=7/7).[3] To this end, we employ a VAR(1)-DCC-MGARCH(1,1) model, which encompasses dynamic conditional correlations, developed by Engle (2002). Although empirical studies have explored the risk and return characteristics of cryptocurrencies as financial assets by means of portfolio optimization models, generalized variance decomposition and various performance metrics (Corbet et al., 2018; Platanakis et al., 2018; Phillip et al., 2018), the VAR(1)-DCC-MGARCH(1,1) could draw a more articulated picture for the subsequent three reasons. First, it is equipped to detect variations over time in correlations. Second, it examines the pairwise dynamic volatility spillovers between unanticipated asset returns. Third, it controls for heteroskedasticity and high volatility.

We assume that the conditional mean model follows a parsimonious VAR(1) as follows:

$$\mathbf{Y}_t = \phi_\mathbf{0} + \mathbf{\Phi}\mathbf{Y}_{t-1} + \epsilon_\mathbf{t}, \qquad \epsilon_\mathbf{t} = \mathbf{H}_t^{1/2}\mathbf{v}_t, \tag{2}$$

$\mathbf{Y}_t$ is a m-dimensional vector, which comprises percentage weekly returns of traditional assets. Specifically, in line with (Bouri et al., 2017b; Corbet et al., 2018), we consider the S&P500 composite index (S&P500), crude oil (Oil), 10-year yield to maturity of the Treasury bond (Yield), EUR/USD exchange rate (\$/€) and volatility index of S&P500 stock index options (VIX). Data on these variables are retrieved from Datastream. We also add return on the momentum portfolio (MOM). $\mathbf{Y}_{t-1}$ consists of lagged returns, ϵ_t is a vector of random disturbance terms, $\mathbf{v_t}$ is a vector of normal, identically and independently distributed innovations, and $\mathbf{H_t}$ is the conditional variance and covariance matrix:

$$\mathbf{H}_t = \mathbf{D}_t^{1/2}\mathbf{R}_t\mathbf{D}_t^{1/2}, \tag{3}$$

[2]Our volatility target is equal to the long-term volatility for each time-series.

[3]While traditional assets are typically traded five days a week, cryptocurrencies can be purchased and sold 24/7. This leads to a different number of observations over the same time span. Momentum strategies need some time to be implemented; for instance, a buy-and-hold strategy for 7 days indicates that cryptocurrency returns from 7 days are transformed into a weekly cumulative return.

where $\mathbf{D_t}$ is a diagonal matrix of conditional variances from the univariate GARCH(1,1), and $\mathbf{R_t}$ is the time-varying quasicorrelation matrix (see more in Engle, 2002).

To formally assess if a momentum portfolio of cryptocurrencies can be regarded as a diversifier, hedger or safe haven, we consider the following OLS regression equation (Ratner and Chiu, 2013; Bouri et al., 2017a,b):

$$DCC_t = a_0 + a_1 DUM(q10)_t + a_2 DUM(q05)_t + a_3 DUM(q01)_t + \varepsilon_t, \tag{4}$$

where DCC is the pairwise dynamic conditional correlation (an off-diagonal element of matrix $\mathbf{R_t}$) between 7/7 momentum (6W-6L) and any other traditional asset. DUM is a dummy variable, which takes on value of 1 at the lower percentiles (i.e., q= 10%, 5% and 1%) of the traditional asset's return distribution. On general principles, an asset is regarded as a diversifier (weak hedge, stronger hedge) if, on average, it is positively correlated (uncorrelated, negatively correlated) with another asset or portfolio, respectively; whereas it is perceived as a safe haven if it exhibits negative or no correlation with another asset over a period of distress (Ratner and Chiu, 2013). Hence, if the constant term (a_0) is positive and significant (insignificant, negative and significant), the momentum portfolio of cryptocurrencies can be perceived as a diversifier (weak hedge, strong hedge) (Bouri et al., 2017a,b). If the coefficients a_1, a_2 and a_3 are either insignificant or negative, the portfolio is either a weak or a strong safe haven against movements in another asset or portfolio, respectively (Bouri et al., 2017a,b).

3 Empirical results

We begin this section by reporting the momentum strategies. Table 2 shows 9 momentum strategies with J and K taking values of 7, 15 and 30 days. Although the Winners' portfolios generally dominate Losers, results are only significant for shorter-term momentum (7/7, 7/15, 7/30, and 15/7), which partially vindicates the findings reported in Grobys and Sapkota (2019). The 7/7 strategy is the most profitable; it yields a 19% weekly rate of return, 12% of which are attributed to a long position of Winners and 7% to a short position of Losers. We also examine the profitability of momentum trading in the top 3 and bottom 3 cryptocurrencies. Similarly, the 7/7 strategy yields a positive and significant return of 32%. Controlling for volatility and transaction costs, short-term momentum returns remain positive and significant (see Adj.MOM in Table 2). As expected (Barroso and Santa-Clara, 2015), Adj.MOM is sightly higher than MOM, attesting that the proposed risk management strategy benefits momentum traders in the cryptocurrency market. In this regard, Figure 2 illustrates graphically how returns on the 7/7 strategies evolve over a period of 164 weeks (09/12/2015-29/1/2019).

[INSERT TABLE 2 AND FIGURE 2]

We now examine if momentum returns are correlated with traditional assets (see Table 3 and Figure 3). We find that correlations among the traditional assets are significantly different from zero (Table 3, Panel B). For instance, DCCs between S&P500-Yield, S&P500-VIX, S&P500-Oil, Oil-Yield, Oil-VIX, and Yield-VIX are significant with coefficients 29%, -79%, 23%, 21%, -16% and -20%, respectively. By contrast, momentum seems to be disentangled from traditional assets (Panel A), where correlations are insignificant and range between -6% and 9.2%. Consequently, a momentum portfolio of cryptocurrencies can be regarded as a vehicle of risk diversification.

[INSERT TABLE 3 AND FIGURE 3]

Furthermore, Table 4 shows that a momentum portfolio of cryptocurrencies can be both a strong hedge (negative a_0) and a weak safe haven (with insignificant $a_1,\ a_2\ and\ a_3$) against adverse movements in Oil, Yield, $/€, and VIX. A momentum portfolio of cryptocurrencies can also be a diversifier (positive a_0) and a strong safe haven (negative a_2) against movements in S&P500.

[INSERT TABLE 4]

4 Conclusion

This paper investigates the performance of momentum strategies in cryptocurrency market and examines the diversification and hedging benefits of momentum trading. We show that positive returns can be derived from momentum strategies in the short run. This finding, in combination with previous research (Grobys and Sapkota, 2019), implies that cryptocurrency market is inefficient in the short-term and efficient over the longer term. The correlations of returns between a momentum portfolio of cryptocurrencies and traditional assets are lower than the correlations between traditional assets. Therefore, investors should consider a momentum portfolio of cryptocurrencies as a vehicle of risk diversification and/or hedging. Future research should address portfolio optimisation with momentum strategies, where time-varying correlations can be conducive to the rebalancing of a diversified portfolio of assets.

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Table 1: Descriptive statistics

Variable	Obs	Mean	SD	Min	Max	Unit root[a]		Mcap[b]
						Price	Return	
Bitcoin	1155	0.1950	4.0159	-20.7530	22.5119	-1.52	-33.78	61,044,262,622
XRP	1155	0.3688	7.7800	-61.6273	102.7356	-2.40	-34.27	13,191,291,588
Ethereum	1155	0.4150	6.4548	-31.5469	30.2770	-1.50	-32.84	11,396,282,341
Litecoin	1155	0.1909	5.8459	-39.5151	51.0348	-1.83	-33.59	1,923,945,742
Stellar	1155	0.3356	8.5946	-36.6358	72.3102	-2.15	-31.27	1,641,391,038
Monero	1155	0.4118	7.2121	-29.3176	58.4637	-1.84	-35.00	741,813,802
Dash	1155	0.3022	6.1876	-24.3225	43.7746	-1.80	-35.77	595,813,352
NEM	1155	0.5201	8.8716	-36.1450	99.5577	-2.46	-35.57	424,252,008
Dogecoin	1155	0.2355	7.0266	-49.2867	51.8345	2.27	-31.59	231,532,343
Bytecoin	1155	0.2764	12.6300	-91.0302	159.7832	-6.79	-41.88	112,431,779
Digibyte	1155	0.3245	9.9728	-36.1404	116.5601	-2.47	-34.44	102,459,744
Bitshares	1155	0.2126	8.0565	-39.1702	51.9989	-2.22	-32.23	100,788,311
S&P500	164	0.1371	1.6372	-7.9703	6.4144	-1.07	-11.53	-
Oil	164	0.1418	4.9999	-16.6928	16.1250	-1.59	-11.87	-
Yield	164	0.1477	4.0824	-14.9779	19.3372	-1.10	-12.53	-
\$/€	164	-0.0416	1.0930	-3.6838	2.9218	-2.06	-14.142	-
VIX	164	0.2129	14.4016	-34.9925	70.6579	-3.82	-13.674	-
7/7 MOM(6W-6L)	164	19.39	14.99	3.73	97.28	-	-6.063	-
7/7 Adj.MOM(6W-6L)	158	21.37	11.21	2.98	53.79	-	-7.310	-

Note: The first 12 variables reported are daily returns of each cryptocurrency. [a]We use the Augmented Dickey–Fuller test to test for a unit root in both the price and return on cryptocurrencies without intercept or trend. The test statistic is reported in the column "Unit root". The critical values for daily and weekly series are -3.430 and -3.489, respectively. All return series appear to be stationary. [b]Market capitalisation in dollars as it was on 30/01/2019. Returns are calculated as $return_t = 100 * ln(Price_t / Price_{t-1})$.

Table 2: Momentum portfolios

J	Portfolio:	6 Winners - 6 Losers		
J	K=	7	15	30
7				
	Winners	12.102	6.641	14.780
	Losers	-7.294	3.729	9.777
	MOM	19.396***	2.912*	5.003
	Adj.MOM	21.37***	3.735***	5.273*
15				
	Winners	3.227	2.282	18.044
	Losers	1.246	6.175	20.202
	MOM	1.980**	-3.894	-2.157
	Adj.MOM	2.209***	-4.266	2.242
30				
	Winners	2.669	7.101	18.456
	Losers	1.664	4.093	14.112
	MOM	1.005	3.009*	4.345
	Adj.MOM	1.387	2.027	0.317

J	Portfolio:	3 Winners - 3 Losers		
7				
	Winners	20.463	7.282	19.240
	Losers	-11.541	4.096	10.626
	MOM	32.004***	3.186*	8.613*
	Adj.MOM	37.213***	4.909**	14.468***
15				
	Winners	2.930	2.375	8.252
	Losers	1.017	6.716	3.018
	MOM	1.913*	-4.341	5.234
	Adj.MOM	2.827***	-7.123	2.034
30				
	Winners	2.766	18.980	16.746
	Losers	0.705	24.657	13.719
	MOM	2.061*	-5.678	3.028
	Adj.MOM	2.484**	3.162*	-0.097

Note: Percentage momentum returns for every strategy are reported in this table. J is the formation period, and K the holding period. ***,** and * denote significance at a 1%, 5% and 10% level, based on an one sided t-test [e.g $H_0 : MOM = (Winners - Losers) \leq 0$ and $H_a : MOM > 0$]

Table 3: Pairwise DCC

Panel A: Momentum & traditional assets		
	coefficients	p-value
MOM(6W-6L)-S&P500	0.0589	0.459
MOM(6W-6L)-Yield	0.0058	0.943
MOM(6W-6L)-VIX	0.0130	0.873
MOM(6W-6L)-$/€	-0.0129	0.873
MOM(6W-6L)-Oil	-0.0288	0.72
Adj.MOM(6W-6L)-S&P500	0.0863	0.321
Adj.MOM(6W-6L)-Yield	-0.0360	0.668
Adj.MOM(6W-6L)-VIX	-0.0301	0.726
Adj.MOM(6W-6L)-$/€	0.0105	0.908
Adj.MOM(6W-6L)-Oil	-0.0149	0.862
MOM(3W-3L)-S&P500	0.0066	0.937
MOM(3W-3L)-Yield	-0.0252	0.766
MOM(3W-3L)-VIX	0.0368	0.663
MOM(3W-3L)-$/€	-0.0602	0.473
MOM(3W-3L)-Oil	-0.0564	0.507
Adj.MOM(3W-3L)-S&P500	0.0923	0.283
Adj.MOM(3W-3L)-Yield	-0.0018	0.983
Adj.MOM(3W-3L)-VIX	-0.0171	0.843
Adj.MOM(3W-3L)-$/€	0.0043	0.96
Adj.MOM(3W-3L)-Oil	-0.0034	0.969
Panel B: Traditional assets		
	coefficients	p-value
S&P500-Yield	0.2875	0
S&P500-VIX	-0.7870	0
S&P500-$/€	0.0318	0.7
S&P500-Oil	0.2348	0.003
Oil-Yield	0.2053	0.009
Oil-VIX	-0.1609	0.051
Yield-VIX	-0.1980	0.014
$/€-Oil	0.0123	0.88
$/€-Yield	0.1227	0.129
$/€-VIX	-0.0892	0.275

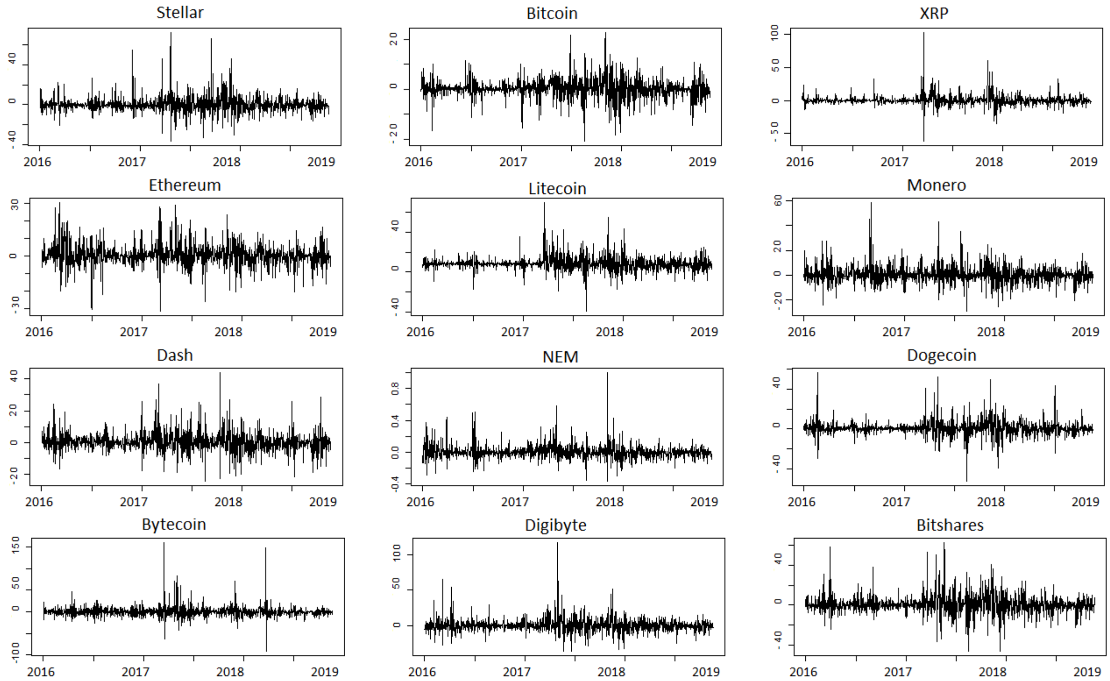
Note: Average dynamic conditional correlations over the period 1/12/2015 - 29/1/2019 based on the 7/7 momentum strategies are summarised in this table. The momentum strategies consider both plain and adjusted momentum from either 6 Winners and 6 Losers (6W-6L) or 3 Winners and 3 Losers (3W-3L).

Table 4: Hedge and safe haven of momentum strategies

	a_1 (10% quantile)	a_2 (5% quantile)	a_3 (1% quantile)	a_0
S&P500	0.0108	-0.0602**	0.0501	0.0175***
	(0.0197)	(0.0272)	(0.0408)	(0.0042)
Oil	-0.0385	0.0479	-0.0401	-0.0339***
	(0.0332)	(0.0474)	(0.0979)	(0.0076)
Yield	0.0068	-0.0056	0.0528	-0.0120***
	(0.0206)	(0.0285)	(0.0428)	(0.0044)
\$/€	0.0278	-0.0376	0.0231	-0.0597***
	(0.0269)	(0.0400)	(0.0800)	(0.0061)
VIX	-0.001	-0.0130	-0.0672	-0.0085**
	(0.0189)	(0.0253)	(0.0519)	(0.0040)

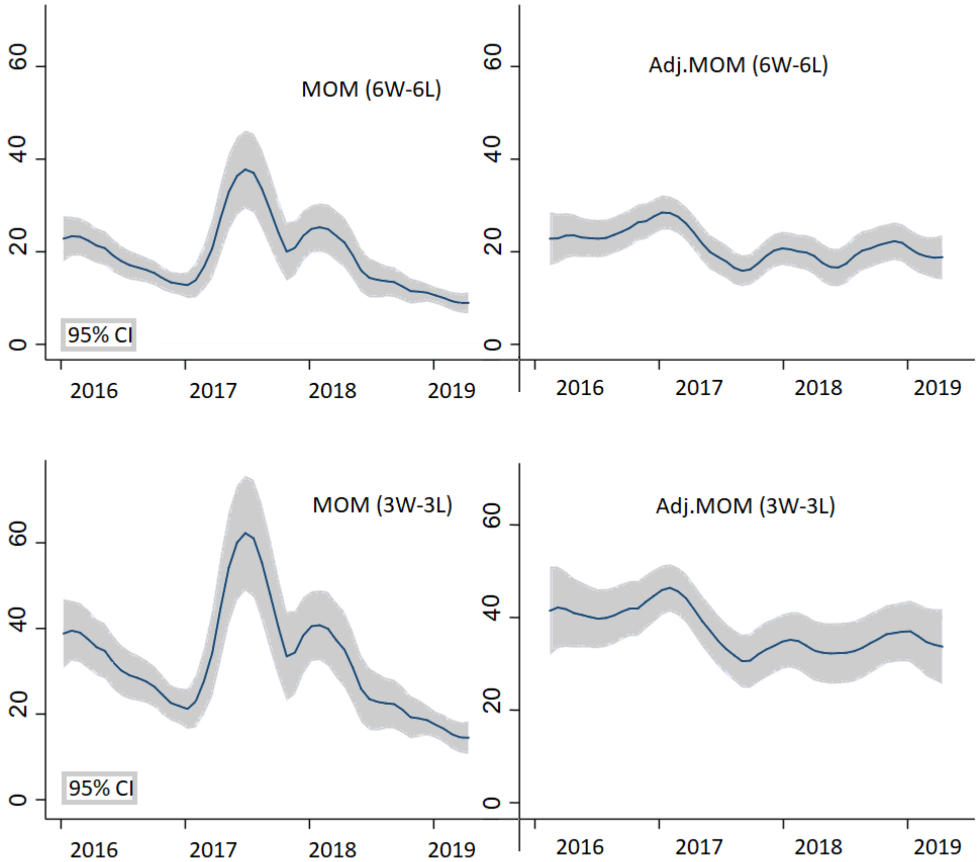
Note: Standard errors are reported in parentheses. ***,** and * denote significance at a 1%, 5% and 10% level. The dependent variable is the DCC between momentum and other traditional assets from Equation 4.

Figure 1: Cryptocurrency returns



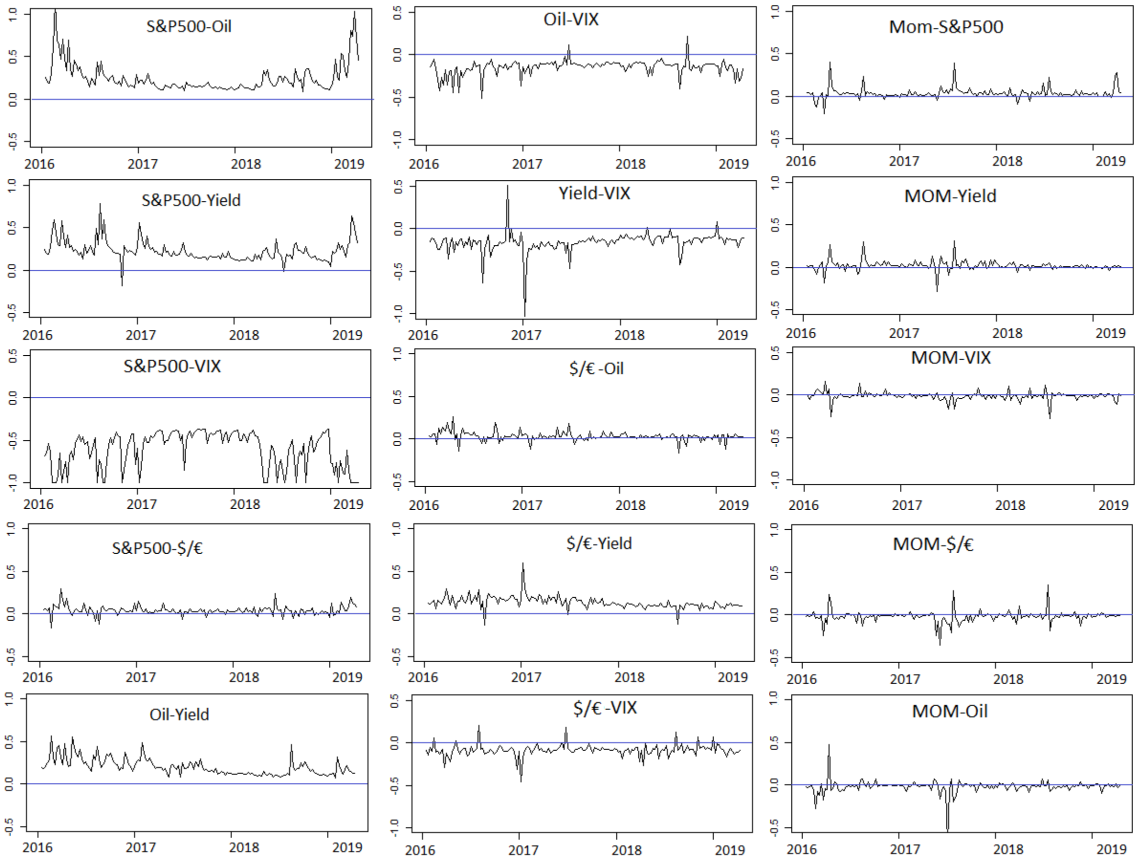
Note: Daily returns on 12 cryptocurrencies are displayed. Returns are calculated as $return_t = 100 * ln(Price_t/Price_{t-1})$. Horizontal axis represents the time from 1/12/2015 to 29/1/2019 and vertical axis the percentage returns.

Figure 2: Percentage returns on 7/7 momentum strategies



Note: Time-series have been smoothed with the Epanechnikov kernel function. Grey area corresponds to the 95% confidence interval. Horizontal axis represents the time and vertical axis the returns.

Figure 3: Pairwise DCC



Note: The model used is the VAR(1)-DCC-MGARCH(1,1), conditional covariance is defined in Equation (3) and mean equation in (2). The vertical axis reports the DCC and horizontal axis the time.