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Momentum or reversal: Which is the appropriate third factor for cryptocurrencies?

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ABSTRACT

Shen et al. (2020) propose a three-factor pricing model for cryptocurrencies by including market, size, and reversal factors. However, evidence from cryptocurrencies during a more recent sample period suggests the existence of a momentum effect rather than a reversal effect. Consequently, we introduce and test a three-factor pricing model including market, size, and momentum factors (MSM three-factor model). This MSM three-factor model outperforms the quasi-cryptocurrency CAPM (Q-C-CAPM) of Shen et al. (2020), with greater explanatory power.

1. Introduction

A number of recent empirical studies indicate that the Bitcoin market is weak-form inefficient and that cryptocurrency prices are predictable, contrary to the efficient market hypothesis (EMH) (Nadarajah and Chu, 2017; Tiwari et al., 2018). Tests of semi-strong form market efficiency also indicate market inefficiency. For example, using 456 cryptocurrencies, Wei (2018) shows that return predictability decreases as liquidity increases, and that while Bitcoin returns are less predictable than many cryptocurrencies, most cryptocurrency prices are predictable. Other tests, including those using Google trends data (Urquhart,2018), the number of tweets (Shen et al.,2019) and economic policy uncertainty (Demir et al.,2018) also reject the semi-strong form of market efficiency.

To explain anomalous pricing behaviors, one traditional approach is to incorporate pricing factors into the standard CAPM. For instance, Fama and French (1993) develop a three-factor CAPM in an augmentation of the standard two-factor CAPM to include small-minus-big size portfolios (SMB) and high-minus-low book to market value (HML) to capture size and book to market effects, respectively. Carhart (1997) puts forward a four-factor model which augments the Fama–French three-factor CAPM to capture pricing momentum (winner-minus-loser factor (WML)) in line with the momentum returns observed by Jegadeesh and Titman (1993). Recently, Fama and French (2015) extend their model to include robust-minus-weak (RMW) profitability and conservative-minus-aggressive (CMA) investment patterns stock return.

Inconsistent with traditional markets, recent cryptocurrency studies also examine whether observed inefficiencies in pricing can be explained by related market factors. Rohrbach et al. (2017) test the performance of momentum strategies for a number of currencies including G10 currencies, emerging market currencies, and cryptocurrencies. They report that momentum strategies generate the highest Sharpe ratios for more volatile currencies. Emerging market currencies and cryptocurrencies outperform G10 currencies in terms of the Sharpe ratio. Bianchi and Dickerson (2019) show that momentum returns suitably explain mis-pricing in cryptocurrency returns. This finding is contrary to Grobys and Sapkota (2019) who employ data from 2014 to 2018. They report negative and

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Table 1
Returns of J–K portfolios.
The J–K portfolios are formed based on J-month lagged returns and held for K months. The first row and column indicate the values of J and K for the different strategies, respectively. The cryptocurrencies are ranked in ascending order on the basis of J-month lagged returns and an equal-weight portfolio of cryptocurrencies in the lowest part return decile is the sell portfolio while the highest return decile is the buy portfolio. The average weekly returns of these portfolio are presented in this table. The t-statistics are reported in parentheses. ***, ** and * indicates the significance levels at 1%, 5% and 10%, respectively.

	J	K=	1	2	3	4
1	Buy		1.0592	1.0745	1.0892**	1.0927**
			(1.1385)	(1.6275)	(1.9929)	(2.2909)
1	Sell		0.068***	0.0518***	0.0501***	0.0497***
			(5.4568)	(7.7609)	(8.9076)	(9.9510)
1	Buy–Sell		0.9912	1.0227	1.0391*	1.043**
			(1.0652)	(1.5494)	(1.9013)	(2.1880)
2	Buy		3.7699*	3.441*	2.6908*	2.323**
			(1.7004)	(1.8816)	(1.8868)	(2.1050)
2	Sell		–0.0269***	0.0038	0.0094**	0.0164***
			(–20.3242)	(0.7490)	(2.4821)	(4.2675)
2	Buy–Sell		3.7968*	3.4372*	2.6814*	2.3066**
			(1.7125)	(1.8796)	(1.8803)	(2.0906)
3	Buy		3.8158*	3.5038*	2.7423*	2.3643**
			(1.7010)	(1.8837)	(1.8840)	(2.1004)
3	Sell		–0.0233***	0.0068	0.013***	0.0172***
			(–17.9254)	(1.2060)	(2.8707)	(4.2265)
3	Buy–Sell		3.8391*	3.497*	2.7293*	2.347**
			(1.7114)	(1.8800)	(1.8751)	(2.0850)
4	Buy		3.9177*	3.5846*	2.8017*	2.4128**
			(1.6913)	(1.8764)	(1.8830)	(2.0985)
4	Sell		–0.0208***	0.0089	0.0121***	0.0145***
			(–15.5694)	(1.4405)	(2.6925)	(3.8283)
4	Buy–Sell		3.9384*	3.5757*	2.7896*	2.3983**
			(1.7003)	(1.8717)	(1.8749)	(2.0859)

significant payoffs in 143 cryptocurrencies. However, the short sample size may limit the reliability of their results. Grobys and Sapkota (2019) are constrained by data availability.[1] Kakushadze (2018) applies a four-factor model and finds that the momentum factor dominates other factors including size, volume, and volatility for predicting crypto-asset return.

An analysis released by *Masterthecrypto*[2] shows a portfolio of cryptocurrencies with small capitalization earns a higher return than a portfolio consisting only of Bitcoin. While Shen et al. (2020) indicate a reversal effect in the cryptocurrency market, we find that the momentum effect, rather than the reversal effect, acts as a key factor driving cryptocurrency returns. We also find small cryptocurrencies tend to have higher returns than big ones, with momentum returns positively associated with smaller size. Hence, we construct our three-factor pricing model (MSM three-factor model) including market (*MER*), size (*SMB*), and momentum (*UMD*) factors. Furthermore, our MSM three-factor pricing model exhibits higher explanatory power than quasi-cryptocurrency CAPM (Q-C-CAPM) and this performance is insensitive to the alternative measurements of these factors.

2. Data, variables, and model

2.1. Data

Cryptocurrency trading data is obtained from https://coinmarketcap.com/. The sample contains cryptocurrencies whose trading days are larger than one year. The sample period ranges from August 13th 2016 to August 9th 2019 with 156 weekly observations in total. We elect to start from 2016 because most cryptocurrencies emerged after 2016 and have since increased instantly in price, capitalization, and trading volumes. Prior to 2016, there are not enough liquidity cryptocurrencies for us to construct the pricing factor.[3] We employ the short-term T-Bill rate as the risk-free asset, obtaining it from the U.S. Department of the Treasury.

2.2. Momentum returns

If cryptocurrency prices either overreact or underreact to new information, trading strategies that choose cryptocurrencies based on their prior returns are likely to generate predictable returns. Bianchi and Dickerson (2019) indicate positive and significant returns

[1] Our sample size is larger as we employ 1,084 cryptocurrencies in total.
[2] For more details, please see https://masterthecrypto.com/bitcoin-vs-alt-coins-returns-comparison-gains-bitcoin-altcoins/
[3] There were only 66 cryptocurrencies traded in 2013. However, 2016 to 2017, this number jumped from 644 to 1,335. (Data source: https://www.statista.com/statistics/863917/number-crypto-coins-tokens/)

Table 2
Summary statistics for 25 portfolios formed on size and momentum.
The first row and column indicate the values of sizes and prior returns for the different quintiles, respectively. The average weekly returns of these portfolio are presented in this table. The *t*-statistics are reported in parentheses. ***, ** and * indicates the significance levels at 1%, 5% and 10%, respectively.

Size quintiles	Prior returns quintiles						
	Down	2	3	4	Up	Up–Down	*t*(Up–Down)
Small	0.0741	0.0595	0.0558	0.0596	0.1166	0.0425***	(5.438)
2	0.0493	0.0316	0.0305	0.0339	0.0993	0.0499***	(5.904)
3	0.0504	0.0333	0.0324	0.0338	0.0977	0.0473***	(6.017)
4	0.0447	0.0270	0.0265	0.0293	0.0898	0.0451***	(5.861)
Big	0.0275	0.0120	0.0115	0.0139	0.0705	0.0429***	(6.220)
Small–Big	0.0466***	0.0475***	0.0443***	0.0457***	0.0462**		
t(Small–Big)	(7.670)	(7.597)	(7.884)	(7.578)	(2.353)		

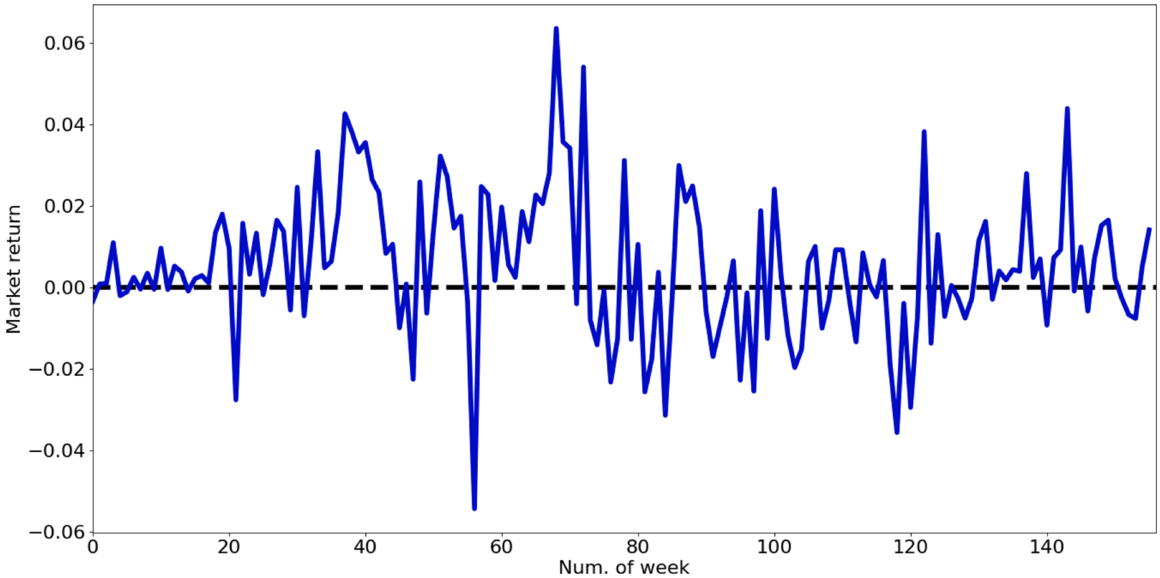

Fig. 1. Weekly market return over sample period.

for the short-term momentum strategies of cryptocurrencies. We further examine the predicted momentum returns under a week-frequency using J–K strategy (Jegadeesh and Titman, 1993). Specifically, J–K strategy selects cryptocurrencies on the basis of returns over past J periods and holds them for K periods. Our J–K strategy is constructed as follows: securities are ranked in ascending order based on their returns over the past J weeks. We form equally-weighted portfolios where the top decile portfolio is defined as 'losers' while the bottom decile is defined as 'winners.' In each week, the strategy buys the 'winners' and sells the 'losers.' The formation and holding periods are set to 1, 2, 3, and 4 weeks. This gives 16 portfolios in total.

Table 1 reports returns of these zero-cost portfolios. Results show pervasive positive returns for buy-sell portfolios; as well as significant momentum effect, especially when the formation period is set to 4. We also find that the 1–4 strategy of buy-sell portfolios has the lowest returns (the mean is 1.043) with the highest significance (*t*-statistic is 2.1880). Therefore, this specification is selected to construct the momentum factor (*UMD*).

Our momentum effect is contrary to the reversal effect found by Shen et al., 2020). We form our J–K portfolios using a cryptocurrency sample from a more recent period and exclude those without sufficient trading days. Our findings are consistent with Liu and Tsyvinski (2020) who indicate the existence of a momentum effect by employing cryptocurrencies with capitalization over 1 million USD.

2.3. Market, size, and momentum factors

We apply capitalization-weighted cryptocurrency market returns as shown in Eq.(1).

$$r_{m,t} = \sum_{i=1}^{n} r_{i,t} \times \frac{Cap_{i,t}}{TotalCap_t} \tag{1}$$

Table 3
Descriptive statistics of $r_{m,t}$ and three factors.
The left-side correlations represent Pearson tests, and the right-side correlations represent Spearman tests. ***, ** and * indicates the significance levels at 1%, 5% and 10%, respectively.

	Summary statistics	Correlation					
	Mean	Std.	Skewness	Kurtosis	MER	SMB	UMD
$r_{m,t}$	0.0053	0.0174	0.1467	4.0310			
MER	–0.7035	2.1417	0.6556	1.8593	1	–0.210**	–0.063
SMB	1.5821	2.2534	2.6551	6.7065	–0.081	1	0.439**
UMD	0.7396	2.6282	1.8019	14.6063	–0.083	0.341**	1

where $r_{m,t}$ is the market returns of the portfolio in week t,$r_{i,t}$ and $Cap_{i,t}$ are the returns and capitalization of the i_{th} cryptocurrency in week t, and $TotalCap_t = \sum_{i=1}^{n} Cap_{i,t}$. The market factor proxied by excess return is constructed as follow:

$$MER = r_{m,t} - r_{f,t} \tag{2}$$

where $r_{m,t}$ is the market returns of the portfolio in week t,$r_{f,t}$ is the risk-free rate proxied by the T-Bill rate. Table 2 displays summary statistics for 25 portfolios formed on size and momentum.

Fig. 1 shows the weekly market return. We find that $r_{m,t}$ over the sample period exhibits a preponderance of positive values. Furthermore, a positive $r_{m,t}$ is generally followed by a higher value, evidencing a momentum effect.

The size and momentum factors are constructed using the market capitalization and prior one-week performance. As for the size factor, we define the top 10% of market capitalization as big portfolios while the bottom 10% as small portfolios, consistent with Fama and French (2012). For the momentum factor, we employ breakpoints at the 30th and 70th percentiles. Consequently, according to the prior one-week return, we obtain three portfolios: up (top 30%), mid (medium 40%), and down (bottom 30%). We form six capitalization-weighted portfolios at the intersections of two portfolios on size and three portfolios on momentum. Our size factor *SMB* (small minus big) is the difference of average returns between three small-cryptocurrency portfolios (S/U,S/M, and S/D) and three big-cryptocurrency portfolios (B/U,B/M, and B/D):

$$SMB = \frac{1}{3}(Small\ Up + Small\ Medium + Small\ Down) - \frac{1}{3}(Big\ Up\ + Big\ Medium + Big\ Down) \tag{3}$$

We construct the momentum factor, up minus down(*UMD*) using a 1–4 strategy, which uses the average returns between the two high prior return portfolios (S/U and B/U) and the two low prior return portfolios ($S/D$and B/D). Descriptive statistics of $r_{m,t}$ and three factors are shown in Table 3.

$$UMD = \frac{1}{2}(Small\ Up + Big\ Up) - \frac{1}{2}(Small\ Down\ + Big\ Down) \tag{4}$$

2.4. Model performance

We specify the benchmark quasi-cryptocurrency-CAPM (Q-C-CAPM) as follows:

$$r_{i,t} - r_{f,t} = \alpha + \beta_{t,1} MER_t + \varepsilon_t \tag{5}$$

where $r_{i,t}$ is the weekly cryptocurrency return of i_{th} portfolio.$MER_t = (r_{m,t} - r_{f,t})$ is the weekly excess cryptocurrency market return, $r_{f,t}$ is the risk-free rate, α is the intercept term, and ε_t is the residual.

Our MSM three-factor model is written as follows:

$$r_{i,t} - r_{f,t} = \alpha + \beta_{t,1} MER_t + \beta_{t,2} SMB_t + \beta_{t,3} UMD_t + \varepsilon_t \tag{6}$$

where $r_{i,t}$ is the weekly cryptocurrency return of ith portfolio, andMER_t is the cryptocurrency market excess return in week t defined above. SMB_t and UMD_t are size and momentum factors respectively defined below, α is the intercept term, and ε_t is residual.

3. Empirical results

3.1. Descriptive statistics

Table 3 reports a summary of descriptive statistics of our three factors: *MER, SMB, UMD* and $r_{m,t}$. The mean value of $r_{m,t}$ is positive with a value of 0.0053. And the $r_{m,t}$ shows a rather smaller standard deviation compared with the other three factors. The mean of *MER* factor is negative while the means of *SMB* and *UMD* are both positive. MER, SMB, and UMD all show a distribution of a positive skewness. However, only MER shows a platykurtic distribution. Noting that the SMB and UMB both show leptokurtic, this indicates that these two factors contain more cross-sectional variations. Moreover, the correlation of these three factors is relatively low compared with each other, which suggests that there is no impact of multicollinearity in our estimated model.

Table 4
Intercepts from regressions of portfolios on size and momentum with 5 × 5 sorts.
The regressions use the Q-C-CAPM and our three–factor models to explain the returns on 25 portfolios of cryptocurrencies. The 5 × 5 results include five size and return quintiles. $|a|$ is the average absolute intercept for a set of regressions. R^2 is the average adjusted R^2. $s(a)$ is the average standard error of the intercepts. ***, ** and * indicates the significance levels at 1%, 5% and 10%, respectively.

Panel A: Intercepts from Q-C-CAPM and MSM three-factor model										
a				$t(a)$						
	Down	2	3	4	Up	Down	2	3	4	Up
Q-C-CAPM										
Small	−0.1135	−0.1202	−0.1207	−0.1202	−0.1187	−1.9548	−2.1488	−2.1665	−2.1544	−2.1081
2	−0.1156	−0.1232	−0.1236	−0.1235	−0.1216	−1.9987	−2.2229	−2.2342	−2.2336	−2.1782
3	−0.1157	−0.1232	−0.1233	−0.1233	−0.1214	−2.0001	−2.2135	−2.2174	−2.2188	−2.1684
4	−0.1166	−0.1237	−0.1240	−0.1240	−0.1220	−2.0303	−2.2320	−2.2415	−2.2444	−2.1877
Big	−0.1188	−0.1254	−0.1256	−0.1256	−0.1239	−2.0979	−2.2823	−2.2910	−2.2928	−2.2481
MSM three-factor model										
Small	−0.1099	−0.1166	−0.1172	−0.1167	−0.1152	−1.7593	−1.9393	−1.9564	−1.9450	−1.9020
2	−0.1108	−0.1185	−0.1190	−0.1188	−0.1173	−1.7933	−2.0023	−2.0134	−2.0126	−1.9608
3	−0.1108	−0.1184	−0.1187	−0.1185	−0.1170	−1.7947	−1.9938	−1.9978	−1.9989	−1.9516
4	−0.1118	−0.1189	−0.1194	−0.1192	−0.1177	−1.8229	−2.0107	−2.0202	−2.0227	−1.9698
Big	−0.1140	−0.1206	−0.1210	−0.1209	−0.1196	−1.8861	−2.0581	−2.0666	−2.0680	−2.0259
Panel B: Summary statistics for regressions										
	$\|a\|$	R^2	$s(a)$					$\|a\|$	R^2	$s(a)$
Q-C-CAPM	0.1215	0.2621	0.00669				MSM			
Three-factor model	0.1171	0.2727	0.00644							

Table 5
Intercepts from MSM three-factor model using alternative factor definition.
The table reports intercepts: a and t-statistics: $t(a)$ for the intercepts. $|a|$ is the average absolute intercept for a set of regressions. R^2 is the average adjusted R^2. $s(a)$ is the average standard error of the intercepts.

Panel A: Intercepts from three-factor regressions										
a				$t(a)$						
	Down	2	3	4	Up	Down	2	3	4	Up
MCM three-factor model										
Small	−0.1078	−0.1147	−0.1152	−0.1147	−0.1131	−1.5649	−1.7290	−1.7441	−1.7333	−1.6933
2	−0.1078	−0.1153	−0.1159	−0.1154	−0.1134	−1.5867	−1.7709	−1.7797	−1.7784	−1.7293
3	−0.1081	−0.1154	−0.1158	−0.1153	−0.1134	−1.5888	−1.7647	−1.7690	−1.7686	−1.7238
4	−0.1088	−0.1156	−0.1161	−0.1157	−0.1137	−1.6121	−1.7773	−1.7852	−1.7864	−1.7363
Big	−0.1110	−0.1174	−0.1178	−0.1174	−0.1157	−1.6688	−1.8206	−1.8277	−1.8281	−1.7883
Panel B: Summary statistics for regressions										
	$\|a\|$	R^2	$s(a)$							
MCM three-factor model	0.1140	0.2781	0.00601							

3.2. Asset pricing tests for size-momentum portfolios

Table 4 reports results of Q-C-CAPM and MSM three-factor pricing models to illustrate the weekly excess returns of portfolios with 5 × 5 sorts on size and momentum. The intercepts are negative for all portfolios. Furthermore, within the same momentum quintile group, intercepts show larger values for portfolios with larger market capitalization. This finding is persistent for both Q-C-CAPM and MSM three-factor models. We further find that intercept values of Q-C-CAPM also exceed those of the MSM three-factor model. We also observe that intercept values are smaller for MSM three-factor model compared with the Q-C-CAPM model.

Average absolute values of intercepts using Q-C-CAPM are bigger than those derived from MSM three-factor model (0.1215 compared to 0.1171). Moreover, the MSM three-factor model exhibits a larger average adjusted R^2 than Q-C-CAPM (0.2727 compared to 0.2621). Hence, the MSM three-factor model has a larger explanatory power than Q-C-CAPM. After adding up the SMB and UMD factors, the standard error of intercepts decreases from 0.00669 to 0.00644. To sum up, results suggest that our MSM three-factor model outperforms the Q-C-CAPM.

3.3. Robustness tests

In robustness tests, we continue to employ the size-momentum sort to establish portfolios. Since the top 10% of cryptocurrencies' market capitalization accounts for 80% of the whole market, we define big ones with the top 10% market capitalization and small ones with the bottom 10%. Also, we establish breakpoints of prior weekly returns at the 30th and 70th percentiles to define 'up,' 'mid,' and 'down' portfolios, respectively. Thus, we get six portfolios under 2 × 3 sorts: *S/U*,*S/M, S/D*,*B/U*,*B/M*, and *B/D*. We construct *SMB* and

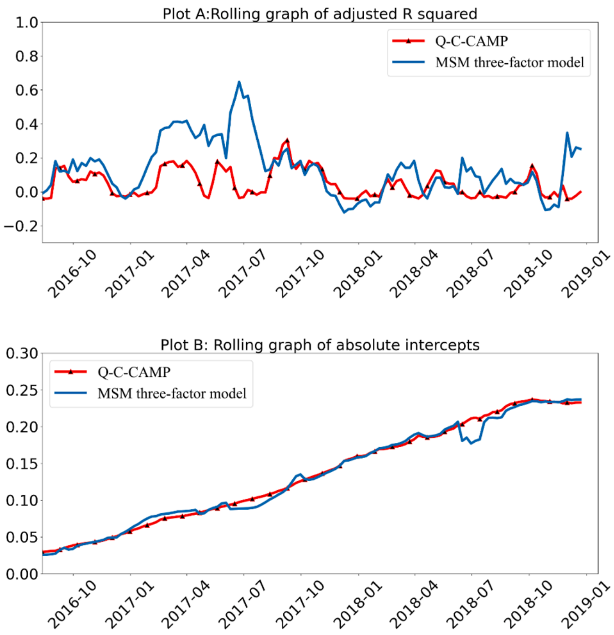

Fig. 2. Rolling graph of adjusted R^2 and absolute intercepts.

Table 6

Intercepts from regressions to explain weekly excess returns using Top 300 cryptocurrencies.

The regressions use the Q-C-CAPM and our MSM three-factor model to explain the returns on 25 portfolios of cryptocurrencies. The 5 × 5 results include five size and return quintiles. $|a|$ is the average absolute intercept for a set of regressions. R^2 is the average adjusted R^2. $s(a)$ is the average standard error of the intercepts. ***, ** and * indicates the significance levels at 1%, 5% and 10%, respectively.

Panel A: Intercepts from Q–C–CAPM and MSM three–factor model										
A				$t(a)$						
	Down	2	3	4	Up	Down	2	3	4	Up
Q-C-CAPM										
Small	0.2253	−0.0631	−0.0626	−0.0625	−0.0605	0.1141	−1.0543	−1.0422	−1.0464	−0.9991
2	0.1617	−0.1223	−0.1220	−0.1220	−0.1216	0.1024	−2.1648	−2.1460	−2.1577	−2.1209
3	0.1741	−0.1223	−0.1220	−0.1221	−0.1219	0.1028	−2.1552	−2.1386	−2.1501	−2.1245
4	0.1734	−0.1223	−0.1219	−0.1220	−0.1217	0.1024	−2.1546	−2.1333	−2.1476	−2.1242
Big	0.1423	−0.1228	−0.1225	−0.1226	−0.1222	0.0960	−2.1777	−2.1589	−2.1725	−2.1387
MSM three-factor model										
Small	−0.0481	−0.0508	−0.0500	−0.0500	−0.0481	−0.0481	−0.0206	−0.7199	−0.7067	−0.7111
2	−0.0538	−0.1093	−0.1091	−0.1089	−0.1083	−0.0538	−0.0288	−1.6556	−1.6403	−1.6491
3	−0.0587	−0.1093	−0.1091	−0.1089	−0.1086	−0.0587	−0.0294	−1.6474	−1.6338	−1.6425
4	−0.0596	−0.1091	−0.1089	−0.1087	−0.1083	−0.0596	−0.0298	−1.6465	−1.6290	−1.6401
Big	−0.0598	−0.1099	−0.1097	−0.1096	−0.1090	−0.0598	−0.0341	−1.6666	−1.6512	−1.6617
Panel B: Summary statistics for regressions										
	$\|a\|$	R^2	$s(a)$					$\|a\|$	R^2	$s(a)$
Q–C–CAPM	0.1232	0.2015	0.0239				MSM three–factor model	0.0890	0.2458	0.00550

UMD the same way, consistent with Section 2.3. Our MSM three-factor model is estimated and Table 5 reports the results. The average absolute values of intercepts decrease from 0.1171 to 0.1140. However, the average adjusted R^2 increase slightly from 0.2727 to 0.2781. Moreover, the standard error of intercepts becomes smaller from 0.00644 to 0.00601.

As cryptocurrencies are volatile, results over a full sample may not give a full picture. Consequently, we estimate a rolling window regression with the window length of half year (26 weeks) as well as a step of 1 week. Fig. 2 shows the results. As for average adjusted R^2, MSM three-factor model outperforms Q-C-CAPM most of the time, especially in the year 2017. Furthermore, intercepts of MSM three-factor model are relatively lower than the Q-C-CAPM.

Next, we select the *Top 300* cryptocurrencies that have the highest liquidity and market capitalization.[4] Applying the same breakpoint in Section 2, Table 6 reports weekly excess returns on 5 × 5 sorts using Q-C-CAPM and MSM three-factor model. Regression

[4] https://steemit.com/steemit/@tellmehowblog/list-of-top-300-cryptocurrencies-name

results show that the average absolute values and standard errors of intercepts under MSM three-factor model are both lower than those of Q-C-CAPM. Average adjusted R^2 increases from 0.2015 to 0.2457 after SMB and UMD factors are employed. This evidence shows that our MSM three-factor model dominates the Q-C-CAPM. Hence, we conclude the model performance is robust to alternative measurements of factors.

4. Conclusions

Employing a cryptocurrency dataset during a recent period, we observe the existence of momentum effects but not reversal effects. Moreover, cryptocurrencies with small market capitalization tend to have higher returns than big ones. Especially, momentum returns increase as market capitalization gets smaller. Evidence shows that our MSM three-factor model exhibits a larger explanation power than the Q-C-CAPM. And the MSM three-factor model captures more risk premium because of its lower values of intercepts. These findings are robust to alternative definitions of our factors and different samples, including *Top 300* cryptocurrencies with the highest liquidity and market capitalization. Hence, our MSM three-factor model outperforms the Q-C-CAPM. Given the enormous interest of individual and institutional investors in the role of cryptocurrencies in portfolios, our results should be of great interest.

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