“Pairs trading in cryptocurrency market: A long-short story”

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PAIRS TRADING IN CRYPTOCURRENCY MARKET: A LONG-SHORT STORY

Abstract

Pairs trading that is built on 'Relative-Value Arbitrage Rule' is a popular short-term speculation strategy enabling traders to make profits from temporary mispricing of close substitutes. This paper aims at investigating the profit potentials of pairs trading in a new finance area – on cryptocurrencies market. The empirical design builds upon four well-known approaches to implement pairs trading, namely: correlation analysis, distance approach, stochastic return differential approach, and cointegration analysis, that use monthly closing prices of leading cryptocoins over the period January 1, 2018, – December 31, 2019. Additionally, the paper executes a simulation exercise that compares long-short strategy with long-only portfolio strategy in terms of payoffs and risks. The study finds an inverse relationship between the correlation coefficient and distance between different pairs of cryptocurrencies, which is a prerequisite to determine the potentially market-neutral profits through pairs trading. In addition, pairs trading simulations produce quite substantive evidence on the continuing profitability of pairs trading. In other words, long-short portfolio strategies, producing positive cumulative returns in most subsample periods, consistently outperform conservative long-only portfolio strategies in the cryptocurrency market. The profitability of pairs trading thus adds empirical challenge to the market efficiency of the cryptocurrency market. However, other aspects like spectral correlations and implied volatility might also be significant in determining the profit potentials of pairs trading.

Keywords cryptocurrency, market efficiency, pairs trading, cointegration, long-short strategy, simulations

JEL Classification C58, D53, G12

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INTRODUCTION

Contemporary valuation models often characterize portfolio optimizations as a function of price correlations in asset markets (Fabozzi et al., 2013). Hence, in financial literature, a considerable amount of efforts has been giving focus to understand the trading correlations and outline strategies to manage risks (Meissner, 2016). Modern portfolio theory tracing back to Markowitz (1952) suggests that investors can potentially maximize returns while even minimizing risks through selecting complementary assets with low price correlations. Later the findings of many studies that include Bernoulli (1954), Joyce and Vogel (1970), Markowitz (1999), Rubenstein (2002), and Saji (2014) lend support to the validity of Markowitz (1952). Financial assets like stocks show very close correlations during significant volatility, and their relations appear to be low under normal market conditions (Cao et al., 2013).

Despite abundance in the literature on price correlations, virtually the studies exploring the profit potentials of trading with substitute assets having high price correlations are not much extensive. The purpose of this paper is to discuss the profit potentials of pairs trading, a trading strategy builds on 'Relative-Value Arbitrage Rule' that uses assets with high positive correlations. In pairs trading, traders pick two investment assets and trade only those assets based on their relative perfor-

mance (Vidyamurthy, 2004). Pairs trader will look for two assets with a high positive correlation, wait for a divergence in their prices, and then trade on the expectation that the assets will revert to their historic correlation. Pairs trading thereby extracts profits from temporary mispricing of close substitutes (Gatev et al., 2006). The trader will go long on the relatively underpriced asset and make a short on the relatively overpriced asset; a profit may be made by relaxing his position upon the convergence of the spread, or the measure of relative mispricing (Do et al., 2006). More precisely, pairs trading consists of the simultaneous opening of long and short positions in two correlated assets with a balance point between them (Whistler, 2004). This type of strategy looks for profits from market inefficiencies irrespective of bullish and bearish market conditions (Blazquez et al., 2018). However, one notable feature in this regard is that prior researchers execute studies on pairs trading mainly in the context of stock market investments. This study has the unique feature of pushing the existing frontiers of knowledge on pairs trading to an entirely new asset class of cryptocurrencies.

1. LITERATURE AND HYPOTHESES DEVELOPMENT

Cryptocurrencies can be used both as a means of payment and as a financial asset (Giudici et al., 2020). Earlier the crypto coins (more specifically Bitcoin) transactions were used for illicit activities (Bohme et al., 2015). However, with the emergence of more opaque cryptocurrencies the illegal share of Bitcoin activity declined over time (Foley et al., 2019). However, Corbet et al. (2018) made some interesting reviews on the role of cryptocurrencies as a credible investment asset class and as a valuable and legitimate payment system. As the value of cryptocurrencies is measured in terms of fiat currency, which fluctuates widely in markets, one should view cryptocurrencies more like investment assets than money itself (Saksonova & Kuzmina-Merlino, 2019). Indeed, the volatile behavior of the prices of cryptocurrencies makes them more a purely speculative asset than a new type of money (Glaser et al., 2014; Baur et al., 2018).

The formation of a profitable investment portfolio including cryptocurrencies is relatively new to financial market participants. Andrianto and Diputra (2017) analyzed three cryptocurrencies together with other assets such as stocks, commodities, and foreign currencies. The study finds that cryptocurrencies can increase portfolio efficiency in part by lowering portfolio variance. On the other hand, Bouri et al. (2017) observed the performance of a portfolio included with Bitcoin and cryptocurrencies was found to be a poor hedge. Moreover, its hedging and safe haven properties vary over time. Petukhina et al. (2020) hold quite an opposite view and claimed that cryptocurrencies add value to a portfolio, and the optimization approach is even able to increase the return of a portfolio and lower the volatility risk. Similarly, Lee et al. (2018) produced empirical evidence to consider cryptocurrencies as a good investment choice to help diversify portfolio risks. The correlations between cryptocurrencies and traditional assets are consistently low while the average daily return of most cryptocurrencies is higher than that of traditional investments.

As one of the pioneering studies on pairs trading in cryptocurrency markets, Lintilhac and Tourin (2017) applied an approach based on stochastic control with some theoretical results, backtesting the strategy only on Bitcoin across three different exchanges. Leung and Nguyen (2019) used the cointegration method backtesting a number of trading rules over relatively small sample data. Fil and Kristoufek (2020) applied the distance and cointegration methods on high-frequency data of a basket of 26 liquid cryptocurrencies. The study finds that higher frequency trading delivers significantly better performance than others. However, these results are based on a relatively small sample period from January 2018 to September 2019, hence seem to be infallible.

In pairs trading, price correlations and information inefficiency are central to analysis (Liew & Wu, 2013). Correlations between the financial asset prices become high during times of high market volatilities (Kupiec & Sharpe, 1991). Dirican and Canoz (2017), Smith and Kumar (2018), and Kumar and Ajaz (2019) found co-movement in cryptocurrency markets. Many studies have already found that cryptocurrencies markets are in-

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efficient (Urquhart, 2016; Al-Yahyaee et al., 2018; Ahmed et al., 2020). Moreover, these markets exhibit positive disposition effects in bearish conditions and reverse disposition effects during bullish times (Haryanto et al., 2020).

The versatile techniques of measuring the potentials of pairs trading include the statistical approach of distance and correlation, the mathematical process of stochastic differential residuals, and the econometric method of cointegration. Chiu and Wong (2015) used correlation technique, Gatev et al. (2006) and Smith and Xu (2017) used distance technique, Jurek and Yang (2007) used stochastic technique, Do and Faff (2010) applied stochastic differential technique, and Vidyamurthy (2004) used cointegration technique to investigate this issue in different country contexts, but mainly on stocks and ETFs. Jurek and Yang (2011) and Blazquez et al. (2018) compared the results of different techniques for determining their relative strengths and weaknesses.

Previous research has already been proved price correlations and market inefficiencies of cryptocurrency markets. Only very few studies researched the application of pairs trading to cryptocurrencies. Moreover, their investigations are limited in scope even for the most standard pairs trading methods. Hence, assuming market inefficiencies and positive price correlations, the study aims to explore the evidence-based claims on the profitability of pairs trading strategies in cryptocurrencies markets. More precisely, the paper attempts to explain how the traditional buy-hold strategy of portfolio is defeated by the mean reversion strategy of pairs trading. The potentials of profits from arbitrage trading indicate market inefficiency. The study wishes to interpret findings to supplement Van den Broek and Sharif (2018) as evidence for profitable arbitrage to traders who can short their investments.

Based on the empirical literature reviewed, the following hypotheses are formulated:

H1: There are cointegrated pairs in the cryptocurrency markets.

H2: There are differences in the profit potentials of pairs trading across cryptocurrency markets.

H3: Long-short strategy of pairs trading defeats the general buy-hold strategy of investing in cryptocurrency markets.

2. DATA AND METHODOLOGY

For executing its empirical analysis, daily price data were collected on four cryptocurrencies for the period January 1, 2018 – December 31, 2019. All the price data series are in US Dollar terms and publicly available online. The sample consists of four non-privacy cryptocurrencies (Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Neocoin (NEO)), which gives due representation to both small-cap and large-cap coins. The choice of cryptocurrencies for the sample is purely arbitrary, but not random. The trading pairs forming out of these coins with varying market capitalizations (market cap) expect to examine the size effect on the profit potentials of paired trade steadily.

To investigate whether profit potentials of trading with paired coins in cryptocurrencies markets are time-varying or not, the study divides the whole sample period into four sub-sample frames or panels, each of which has six months duration fixed again on an arbitrary basis. The first sample period (Panel A) from January 1, 2018, to June 30, 2018, observes a terrific price boom with high volatility in the cryptocurrencies market. The second period (Panel B) spans from July 1, 2018, to December 31, 2018, and reveals the distressing investments with a steep decline in coin prices. The third sample period (Panel C) ranges from January 1, 2019, to June 30, 2019, and allows for the effects of regained momentum in price trends after fading off the bearish rally of the previous period. Finally, the sample period of Panel D, which is from July 1, 2019, to December 31, 2019, witnesses substantial consolidation in prices with modest volatility in crypto markets. The study estimates all the models designed in this paper using each sub-sample data and such analysis can make a better comparison of the arbitrage profitability through pairs trading in cryptocurrencies markets at different market cycles.

The implementation of the empirical design of this paper involves two stages. The study intends to produce out of sample evidence where it forms

pairs over each sub-sample period and then trades them in the next 6-month period based on a simulated portfolio with beta weights assigned by cointegration estimations during the formation period. However, regression estimation of the first sample period itself decides the portfolio weights of trading pairs during that period, as there was no previous estimation. The rules observe the general outline of Gatev et al. (2006) according to which one should find correlations between cryptocoins at first, and then take a long-short position strategy expecting them to converge at some point.

To repeat, distance, correlation, stochastic differential residuals, and cointegration analyses are the popular techniques measuring the potentials of pairs trading. This paper wishes to employ these techniques for empirical analysis on the potentials of pairs trading in cryptocurrencies markets. However, empirical findings mainly rest with cointegration analysis, while the rest techniques expect to produce results supplement to cointegration findings.

As specified in Ehrman (2006) and Chiu and Wong (2015), the study chooses pairs of coins according to the correlation coefficient existing between them and then determines the residual series using a ratio of prices with equation 1, to decide the long-run persistence of their relations.

$$r = \frac{\rho_{xt}}{\rho_{yt}}, \tag{1}$$

where ρ_{xt} and ρ_{yt} are respectively the prices of cryptocoin '*x*' and '*y*' at moment '*t*'.

Nath (2003) and Gatev et al. (2006) use a distance method for their empirical testing on pairs trading in stock markets. The distance method computes the distance between two moving together assets. Accordingly, the distance, as implied by its name means the total sum of squares of the difference between the standardized (normalized) prices of two-coin series (equation 2). The study generates the residual series by the difference in normalized asset prices.

$$D = \left(\sum_{i=1}^{n} \rho_{xi} - \rho_{yi} \right)^2, \tag{2}$$

where ρ_{xi} and ρ_{yi} are normalized asset prices based on their mean and standard deviations.

$$\rho_{ai} = \frac{\rho_{xt} - E(\rho_{xt})}{\sigma_i}, \tag{3}$$

where ρ_{xt} is the price of the asset '*x*' at moment '*t*', $E(\rho_{xt})$ is the mean or expected value of ρ_{xt} and $\acute{o}_i$ is the volatility or standard deviation of asset *x*.

It is expected that the pair of stocks with the highest correlation is also the one with the least distance between them.

Do et al. (2006) use stochastic differential residuals of stock return series to study the potentials of pairs trading in stock markets. The Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT) models are used to decide the balance between the trading assets. Residual series are obtained with equation (4):

$$D_t = (\gamma_{xt}) - (\gamma_{yt}) - \delta(\gamma_{mt}), \tag{4}$$

where D_t is the stochastic differential return, γ_{xt} is the return of asset *x* at moment *t*, γ_{yt} is the return of asset *y* at moment *t*, δ is the difference between market betas or risk coefficients and γ_{mt} is the return of benchmark index. δ is a vector of exposure differentials and can be expressed as:

$$\delta = \left[(\beta_{1x} - \beta_{1y}) \cdot (\beta_{2x} - \beta_{2y}) \ldots (\beta_{nx} - \beta_{ny}) \right]. \tag{5}$$

While applying this model in our analysis, the main issue the study face is that no data on market beta is readily available as there is no benchmark to compare cryptocurrencies' returns. Hence, a return series is computed with equation (6), which is the weighted average of the top ten return series of cryptocoins. The study considers the market capitalization of respective cryptocurrencies as the weight (w_i) for the computation of benchmark returns.

$$\gamma_{mt} = \sum_{i=1}^{n} w_i \gamma_{it}. \tag{6}$$

Then, an OLS (Ordinary Least Squares) regression is run of each of the return series against this weighted average return series to compute market betas of respective coins with equation (7):

$$\gamma_{it} = \alpha_0 + \beta_i (\gamma_{mt}) + \varepsilon_t. \tag{7}$$

In equation (6), α_0 is the intercept, β_i is the risk coefficient of asset *i* and ε_t is the error term.

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Cointegration provides a valid model for pairs trading (Vidyamurthy, 2004). Cointegration assumes that the prices of two cryptocoins may behave differently in the short-run, but will converge in the long run. Such a price trend implies that the return series in the cryptocurrency market are mean-reverting, which is the underlying assumption of pairs trading strategy (Vidyamurthy 2004). Engle and Granger (1987) formulate the idea of cointegration and present statistical procedures to test for cointegration under an OLS framework. The standard procedure of which involves three steps; carry out Augmented Dickey-Fuller (ADF) tests on the null hypothesis that each of the variables listed has a unit root with equation (8); estimate the cointegrating regression with equation (9), and run an ADF test on the residuals from the cointegrating regression with equation (11).

$$\Delta\rho_t = \lambda\rho_{t-i} + \sum_{i=1}^{m} \beta_i \Delta\rho_{t-i} + \phi_0 + \varepsilon_t, \qquad (8)$$

where Δ is the first difference operator, ε_t is an error term, and *m* is the number of lagged first differenced term and is determined such that ε_t is approaching white noise. If the variables integrate at the same order, then proceed to estimate the possible cointegrating regression.

$$\rho_{xt} = \alpha_0 + \gamma_i \rho_{yt} + \varepsilon_t, \qquad (9)$$

where γ_i is the cointegrating coefficient of pair *i*, α_0 is the intercept, and ε_t is the error term.

Once the variables are cointegrated, then OLS regression yields "super consistent" estimator for the cointegrating parameter. Now, one can obtain the residual of equation (9) with equation (10).

$$e_{xt} = \rho_{xt} - \alpha_0 - \gamma_1 \rho_{yt} - \varepsilon_t. \qquad (10)$$

In this case, the first figure denotes the endogenous variable of cointegration model, that is the price of coin *x*, followed by the long-term balance value and, finally, its exogenous variable of coin γ.

Next, the study should ensure that real cointegrating relationship exists between cryptocoin price series and estimate the residual sequence, denoted by $\hat{e}_t$, from cointegrating regression equation. Once the deviations from long run equilibrium are found stationary, then variables are said to be cointegrated. The ADF test can be used on $\hat{e}_t$ series, using the regression of the form with v_t as the error term:

$$\Delta\hat{e}_t = a_1\hat{e}_{t-1} + \sum_{i=1}^{m} \delta_i \Delta\hat{e}_{t-1} + v_t. \qquad (11)$$

As $\hat{e}_t$ is a residual, the search process includes neither a constant nor a time trend. If the study finds that $\hat{e}_t \sim I(0)$ then reject the null hypothesis that the cryptocoin price series are not cointegrated.

3. RESULTS AND DISCUSSION

Table 1 compares the summary statistics on the price behavior of four cryptocurrencies included in the sample. Since this paper intends to explore the empirical evidence on pairs trading in crypto markets through understanding their price correlations, the absolute prices are interpreting, but not the values of return variables. The price volatility heads higher in Bitcoin and Ethereum, while lower for Litecoin and Neocoin. Bitcoin show higher volatility over the periods of Panel A and Panel C than over the periods of Panel B and Panel D. In fact, the reductions in deviations from mean values are quite persisting for Ethereum and Neocoin. In particular, the price volatility in crypto markets appears to change over time.

The price distributions in specific crypto markets, Ethereum and Litecoin, are found approximately normal, while the frequency distributions for Bitcoin and Neocoin are more tightly concentrated around their average values. Similarly, the Jarque-Bera test rejects the null hypothesis of the normal distribution of cryptocurrency series in almost all panels of the study. Additionally, deviation from normality is much higher in Panel C as compared to that in the remaining panels. Such heterogeneity on crypto coin prices has necessary implications for pair trading strategies.

The spirit of pairs trading is to use pairs of assets whose price movements are correlated with each other (Wang, 2009). The best pair of assets will be the pair whose distance between the prices is the lowest with a high degree of correlations (Ramos-Requena et al., 2020). The study observes these rules to make primary inferences on the potentials of pairs trading in the crypto market. As ex-

Table 1. Summary statistics of cryptocurrencies

Source: Author's elaboration.

Panel	Cryptocurrencies	Mean	Median	Maximum	Minimum	SD	Skewness	Kurtosis	Jarque-Bera
Panel A	BTC	9106.24	8671.53	17069.79	5853.98	2270.90	1.25	4.55	64.84*
	ETH	717.13	686.34	1388.02	368.89	231.95	0.68	2.83	13.89*
	LTC	141.55	140.00	228.51	74.05	40.67	0.24	2.30	55.42*
	NEO	83.19	74.35	189.38	28.18	35.10	0.55	2.40	11.66*
Panel B	BTC	5982.92	6461.39	8397.24	1344.78	1334.44	-0.95	3.09	28.08*
	ETH	249.43	217.15	498.76	83.76	119.15	0.67	2.37	16.97*
	LTC	49.93	53.36	89.12	13.51	16.36	0.18	2.48	3.04
	NEO	18.42	17.35	40.56	5.59	9.05	0.66	2.77	14.05*
Panel C	BTC	5615.64	5024.95	12666.45	2333.34	2333.27	1.04	3.15	30.78*
	ETH	176.81	159.31	339.39	60.88	61.17	0.80	2.45	20.41*
	LTC	80.06	78.77	142.26	30.64	32.78	0.16	1.90	9.37*
	NEO	10.23	9.42	19.61	2.73	2.78	1.05	4.42	45.58*
Panel D	BTC	9128.59	9223.10	12543.41	1461.83	1559.90	-0.45	4.67	27.74*
	ETH	186.10	181.52	311.97	39.02	40.29	0.73	5.00	47.71*
	LTC	60.41	57.45	100.25	16.95	17.16	0.58	2.63	11.48*
	NEO	10.03	9.44	17.94	2.40	2.46	1.16	5.17	78.12*

Note: * means significant at 1% level.

pected, the correlation coefficient and the distance between different pairs of cryptocurrencies is inversely related (Table 2). More precisely, the pair of cryptocurrencies with the highest correlation is also the one with the least distance between their prices. Ethereum and Neocoin in Panel A and B, Bitcoin and Neocoin in Panel C, and Bitcoin have the highest correlation coefficient and least distance of all potential pairs in respective panels. Similarly, the pairs of Bitcoin and Litecoin in Panel A and B, and Litecoin and Neocoin in panel D have the lowest correlations with the most distance between their prices. However, in Panel C, the analysis finds some anomalies while observing the rule of negative relations between correlation and distance methods that are seemingly due to the abnormal variations in price movements in the crypto market during that period relative to the rest of the sample periods.

If one overlooks the price correlations between cryptocurrencies in Panel C, the values of their Pearson correlation coefficients are relatively stable with a short-range deviation of 5 to 10 points across panels. This means that the trend in the correlation-distance relations reveals that a pair of coins correlated with current days or months has a certain level of confidence that the pair will remain correlated for the next few days or months. Such a trend in price correlations implies the exploit of the same pair of coins and in the same order for making profits out of arbitrage trading in crypto markets.

As mentioned earlier, this paper considers the price level data of four cryptocurrencies included in the sample. Generally, the price level data has a unit root with non-stationarity properties (Granger & Newbold, 1986). Cointegration becomes an over-

Table 2. Correlation and distance

Source: Author's elaboration.

Panels	Measure	BTC and ETH	BTC and LTC	BTC and NEO	ETH and LTC	ETH and NEO	LTC and NEO
Panel A	Correlation	0.842	0.564	0.743	0.609	0.905	0.726
	Distance	102.073	252.973	155.134	157.088	37.782	100.458
Panel B	Correlation	0.753	0.678	0.780	0.815	0.973	0.847
	Distance	103.865	157.624	100.541	92.892	13.791	78.858
Panel C	Correlation	0.90	0.778	0.91	0.794	0.91	0.656
	Distance	135.702	75.488	30.178	253.840	180.058	117.408
Panel D	Correlation	0.847	0.780	0.651	0.844	0.819	0.635
	Distance	42.801	70.218	115.887	48.459	69.171	126.124

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Table 3. Augmented Dickey-Fuller (ADF) tests on cryptocurrencies prices

Source: Author's elaboration.

Panel	(with intercept and trend)	BTC	ETH	LTC	NEO
Panel A	Level	–1.8817	–1.2527	–1.2556	–1.4745
		[0.3403]	[0.6510]	[0.6497]	[0.5448]
	First Difference	–13.8617*	–12.8309*	–13.9917*	–14.3703*
		[0.0000]	[0.0000]	[0.0000]	[0.0000]
Panel B	Level	–0.1049	–1.6566	–1.4567	–1.6034
		[0.0000]	[0.4516]	[0.5534]	[0.4788]
	First Difference	–17.9864*	–16.3170*	–16.2343*	–16.7610*
		[0.0000]	[0.0000]	[0.0000]	[0.0000]
Panel C	Level	–1.8977	–1.9115	–1.2967	–2.7333
		[0.3328]	[0.3264]	[0.6307]	[0.7050]
	First Difference	–3.6872*	5.3606*	–7.7564*	–5.2938*
		[0.0051]	[0.0000]	[0.0000]	[0.0000]
Panel D	Level	–0.5443	–1.8121	–1.734	–2.0398
		[0.8783]	[0.3738]	[0.4125]	[0.2697]
	First Difference	–12.8026*	–15.0055*	–15.9442*	–10.9519*
		[0.0000]	[0.0000]	[0.0000]	[0.0000]

Note: * means significant at 1% level; figures in parentheses indicate p values.

riding requirement for any economic model using non-stationary time series data (Brooks, 2008). If the variables do not cointegrate, then there are problems of spurious regression. Hence, it is essential to identify the chance of spuriously correlated prices that are not de facto cointegrated (Gatev et al., 2006).

As mentioned earlier the study follows Engle and Granger (1987) cointegration approach, where the first step is to examine every price variable in the sample to confirm the order of integration. As one might anticipate, the ADF test results reported in Table 3 reveal that all the price series in the observed crypto markets contain a unit root, hence are not stationary. However, while taking the first differences of the price series induces stationarity. A statistically valid model would be, therefore, one in the first differences of the price data.

Given that, all the closing values of the crypto markets in 16 cases of four panels are shown to be I(1), that is integrated of order 1, the next stage in the analysis is to test for cointegration by forming a potentially cointegrating regression and testing its residuals for non-stationarity. In the cointegration modeling, the dependent variable is the cryptocurrency with lower average prices, and the independent variable is the cryptocurrency that has higher average prices in respective pairs. The cointegration results reported in Table 4 confirm the statistical significance of the beta coefficients in cointegrating vectors. Moreover, the explanatory power of the prediction model is more than 75% in the majority of cases that substantiate the strong positive price movement and high potentials for pairs trading in crypto markets. Additionally, the size of the coefficients is almost consistent in models, which is independent of the time observed. Hence, the potentials of pairs trading in crypto markets have high persistence and are not at all time-varying. Constants in the models are statistically insignificant in most cases; hence have no implication in the regression estimated. Durbin-Watson (DW) statistic is close to 2 in estimation models, implying that there is little evidence of autocorrelation.

To repeat, as specified earlier in the estimation process, to examine whether the two cryptocurrency price series are strictly cointegrated or not, the study should estimate the residual sequence from equation (9) and then test the residuals to ensure that they are I(0), integrated at the level. Once, $\hat{e}_t$ the series of the estimated residuals of the cointegrating equation are found to be stationary, and then the prices in markets are considered cointegrated.

Since the ADF test statistics reported in Table 5 are statistically significant even at the 1% level, the null hypothesis of a unit root in the test regression residuals is strongly rejected. Clearly, the residuals

Table 4. Engle-Granger cointegration analysis of cryptocurrencies

Source: Author's elaboration.

Panels	Model	BTC and ETH	BTC and LTC	BTC and NEO	ETH and LTC	ETH and NEO	LTC and NEO
Panel A	Constant	–0.417	–0.214	–0.028	–0.141	–0.011	–0.032
	Coefficient	0.019*	0.004*	0.001**	0.215*	0.049*	0.110**
	R^2	0.884	0.520	0.763	0.504	0.769	0.356
	DW	1.683	2.045	1.848	2.003	1.893	1.722
Panel B	Constant	–0.931	–0.233	–0.050	–0.192	0.029	–.054
	Coefficient	0.035*	0.006*	0.003*	0.110**	0.084*	0.185**
	R^2	0.741	0.465	0.568	0.252	0.806	0.189
	DW	2.149	2.149	1.812	2.015	1.829	2.141
Panel C	Constant	–0.237	0.044	–0.016	0.085	–0.003	–0.029
	Coefficient	0.026*	0.005***	0.002*	0.175**	0.057*	0.068***
	R^2	0.840	0.165	0.746	0.197	0.826	0.183
	DW	1.951	1.776	2.257	1.846	2.208	1.623
Panel D	Constant	–0.417	–0.214	–0.028	–0.141	–0.011	–0.031
	Coefficient	0.019*	0.004*	0.001*	0.215*	0.049*	0.110**
	R^2	0.884	0.520	0.763	0.504	0.769	0.356
	DW	1.683	2.045	1.848	2.003	1.893	1.722

Note: * means significant at 1% level, ** means significant at 5% level, *** means significant at 10% level.

from the cointegration regression can be considered stationary. Thus, it is concluded that the cryptocurrency series in every pair are cointegrated. Additionally, the study analyses graphically the residual series formed by each pair of cryptocurrencies in respective panels during the test period. An analysis of Figures 1-4 shows that the residual series have a decreasing trend in almost all panels. Adding soundness to the results, the stationarity tests on the residual series generated by distance and stochastic differential methods produce results similar to that on the cointegration residuals.

Table 5. Augmented Dickey-Fuller (ADF) tests on residual series

Source: Author's elaboration.

Sector	Model	BTC and ETH	BTC and LTC	BTC and NEO	ETH and LTC	ETH and NEO	LTC and NEO
Panel A	Cointegration	–5.854*	–4.865*	–11.181*	–14.788*	–12.317*	–13.412*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Distance	4.250*	3.564*	2.650***	3.592*	3.171**	2.978*
		(0.000)	(0.007)	(0.082)	(0.006)	(0.023)	(0.009)
	Stochastic Differential	11.449*	13.613*	4.508*	11.795*	11.598*	11.795*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B	Cointegration	–12.156*	–14.963*	–13.446*	–14.260*	–13.602*	–15.907*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Distance	5.993*	3.447**	5.178*	4.820*	7.773*	4.469*
		(0.000)	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)
	Stochastic Differential	12.561*	6.546*	6.610*	7.136*	13.185*	14.850*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C	Cointegration	–12.969*	–11.433*	–15.156*	–11.962*	–14.612	–8.667*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Distance	–1.198	–6.838*	–3.891*	1.912	–2.678***	2.346
		(0.678)	(0.000)	(0.002)	(0.326)	(0.092)	(0.158)
	Stochastic Differential	12.331*	13.661*	13.821*	11.813*	13.206*	11.380*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel D	Cointegration	–11.687*	–13.875*	–12.836*	–13.649*	–13.518*	–11.715*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Distance	–3.164**	–4.734*	–4.548*	–4.209*	–3.502***	3.229**
		(0.022)	(0.000)	(0.000)	(0.000)	(0.074)	(0.018)
	Stochastic Differential	11.381*	14.142*	13.040*	13.967*	14.380*	14.288*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: * means significant at 1% level, ** means significant at 5% level, *** means significant at 10% level.

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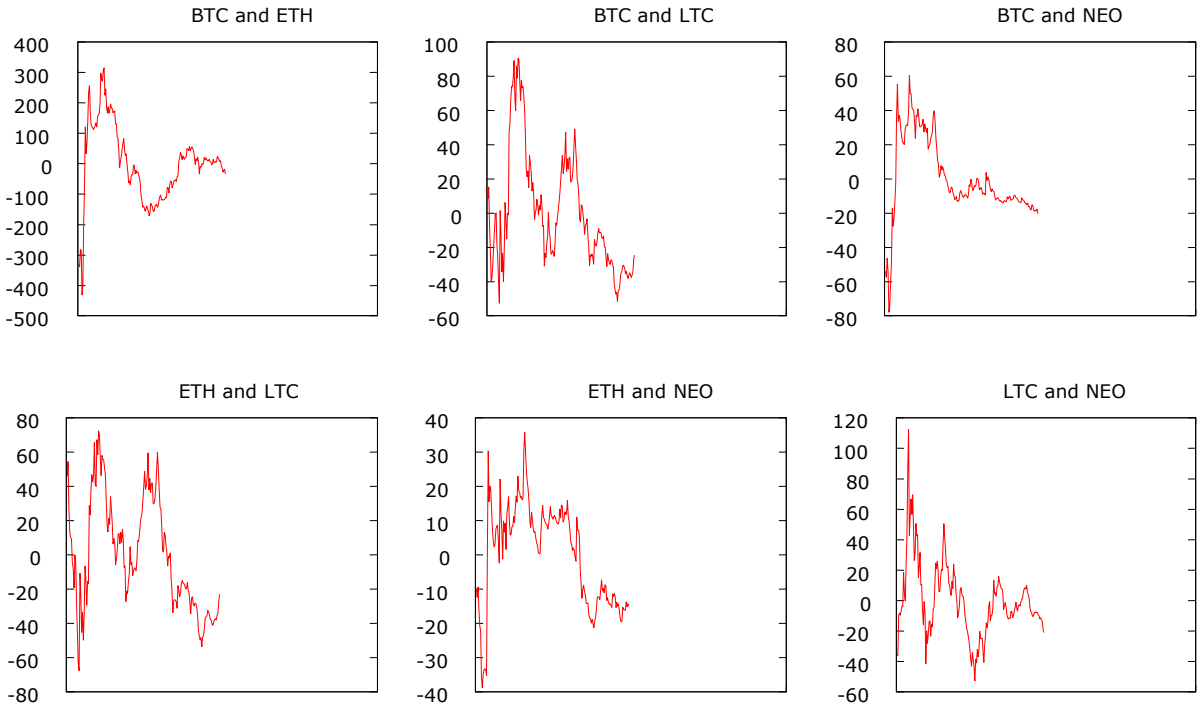

Figure 1. Cointegration residuals in Panel A

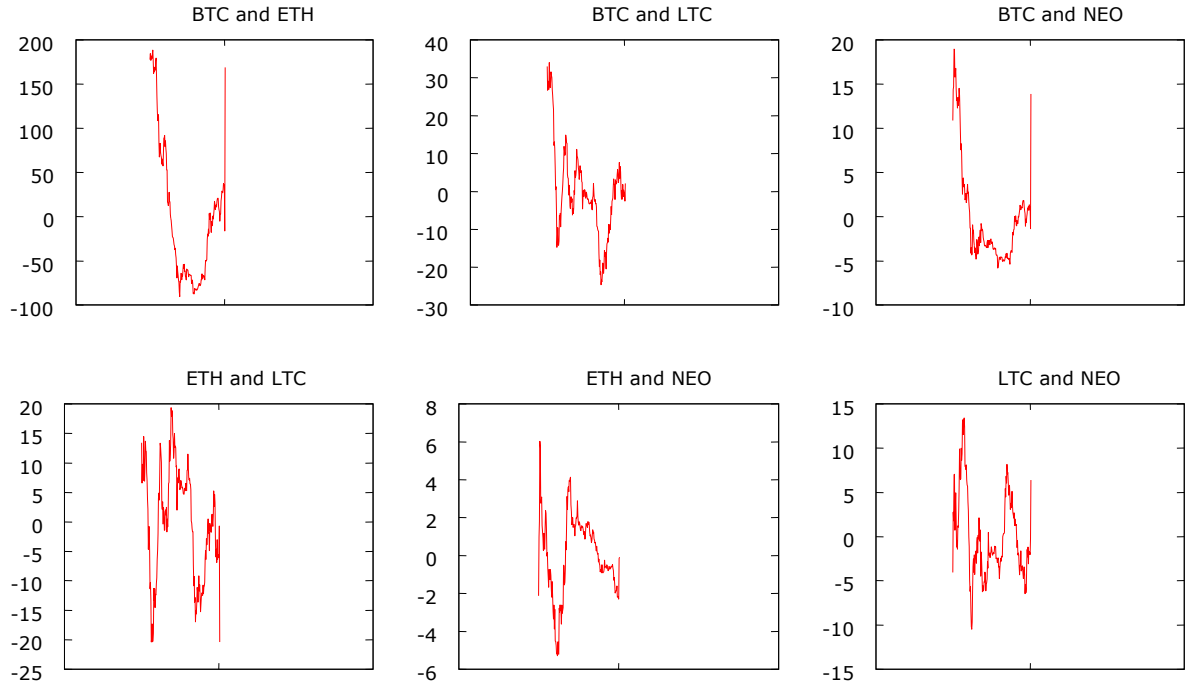

Figure 2. Cointegration residuals in Panel B

Motivated by the findings on pairs trading potentials, with a simulated exercise this study goes one step further to illustrate the evidence of excess profits that would have been generated by pairs trading in cryptocurrencies markets during the period of observations. The paper lists out the payoffs of all possible pairs that could be built on four cryptocurrencies during four sub-sample periods. Then form two sets of portfolios for every trading pair, long-only portfolios and long-short portfoli-

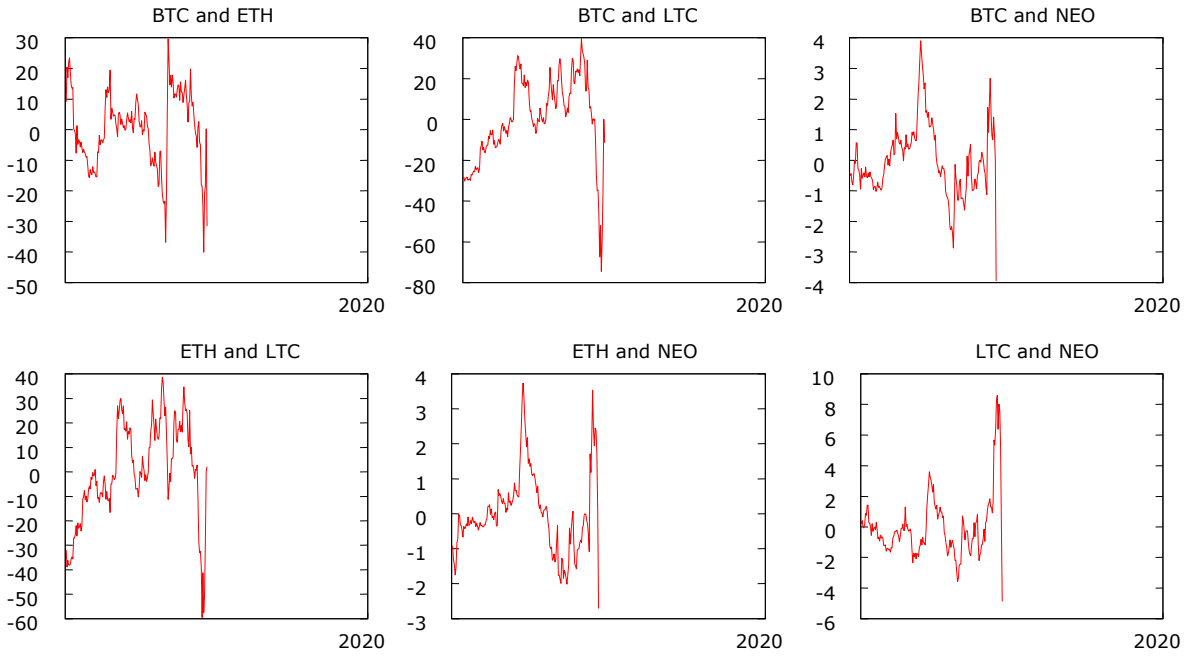

Figure 3. Cointegration residuals in Panel C

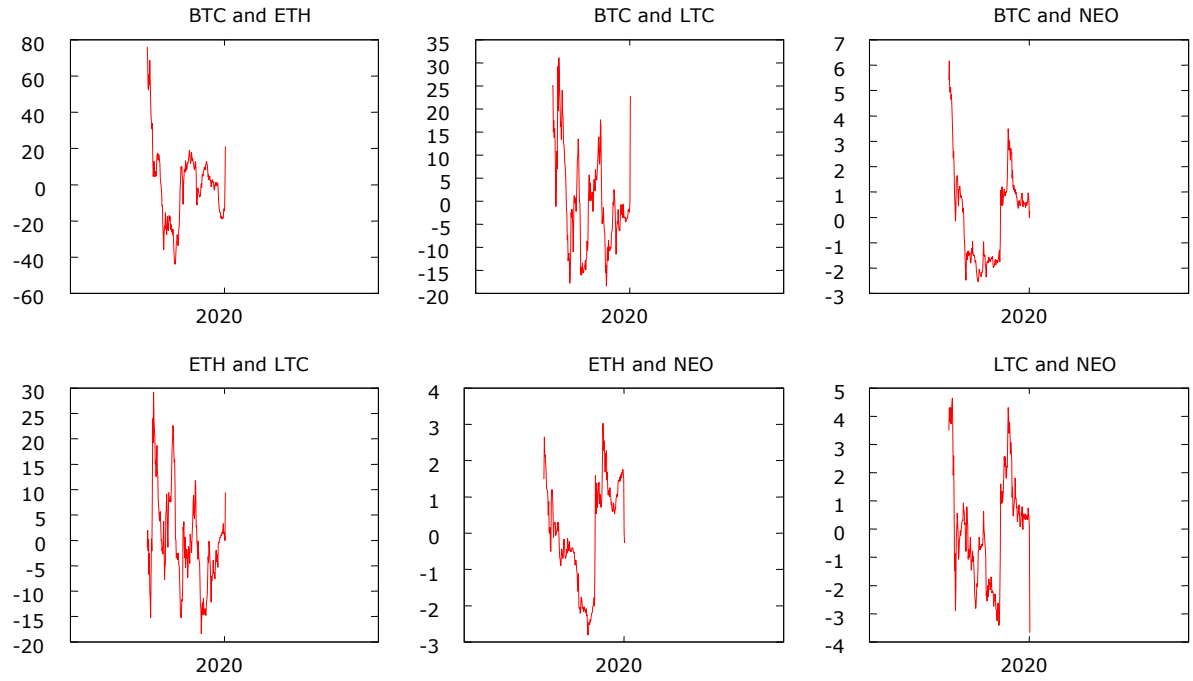

Figure 4. Cointegration residuals in Panel D

os, to evaluate the profit potential of pairs trading strategy in cryptocurrencies markets relative to the buy-hold strategy of general portfolio theory.

While explaining the testing process, the study needs to decide the relative weight of cryptocurrencies in respective trading pairs. The relative weight of a specific pair is the delta that is the optimal trade or hedge ratio. A hedge is achieved by taking opposite positions in two related asset markets simultaneously so that any loss sustained from adverse price movement in one market should, to some extent, be offset by favorable cash inflows from the other (Hull, 2005). The objective of computing the hedge ratio is to minimize the variance of portfolio returns (Krokhmal et al., 2001). The

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Table 6. Profit payoffs from pairs trading in simulated exercises

Source: Author's elaboration.

Sector	Strategy	Performance measures	BTC and ETH	BTC and LTC	BTC and NEO	ETH and LTC	ETH and NEO	LTC and NEO
Panel A	Pair Trading	Cumulative Profit (USD)	347.03	55.67	37.18	768.89	857.52	35.70
		SD in USD (Risk)	34.880	7.327	6.35	9.89	7.63	6.95
		Profit Per Unit of Risk(USD)	10.450	7.51	5.86	77.73	112.33	5.13
	Portfolio	Cumulative Profit (USD)	–895.64	–211.25	–516.28	–173.42	–88.34	–134.52
		SD in USD (Risk)	90.53	15.49	41.48	13.405	12.03	13.55
		Profit Per Unit of Risk(USD)	–6.53	–8.32	–12.45	–12.94	–7.34	–9.92
Panel B	Pair Trading	Cumulative Profit (USD)	1527.91	30.74	10.17	203.63	34.94	0.91
		SD in USD (Risk)	9.99	1.41	0.929	2.02	1.23	0.77
		Profit Per Unit of Risk(USD)	152.88	21.88	10.95	101.10	28.43	1.18
	Portfolio	Cumulative Profit (USD)	–489.79	–68.29	–36.05	42.10	–26.04	–47.03
		SD in USD (Risk)	20.48	3.84	2.02	10.22	1.30	2.269
		Profit Per Unit of Risk(USD)	–23.92	–17.79	–17.82	4.12	–20.09	–20.72
Panel C	Pair Trading	Cumulative Profit (USD)	969.45	29.68	2.241	386.42	37.67	0.345
		SD in USD (Risk)	7.74	3.43	0.462	4.22	0.57	0.49
		Profit Per Unit of Risk(USD)	125.25	8.64	4.845	91.49	66.38	7.09
	Portfolio	Cumulative Profit (USD)	359.25	162.34	16.05	169.47	16.48	14.13
		SD in USD (Risk)	13.32	6.21	0.89	6.67	0.82	0.80
		Profit Per Unit of Risk(USD)	26.98	26.09	19.23	25.40	20.10	17.67
Panel D	Pair Trading	Cumulative Profit (USD)	932.99	51.63	4.62	391.64	3.94	74.35
		SD in USD (Risk)	5.869	2.22	0.38	2.51	0.44	0.38
		Profit Per Unit of Risk(USD)	158.95	23.16	12.22	156.14	9.02	196.30
	Portfolio	Cumulative Profit (USD)	–245.60	–113.74	–11.73	–144.99	–12.43	–15.75
		SD in USD (Risk)	11.23	5.685	0.88	4.35	0.65	0.76
		Profit Per Unit of Risk(USD)	–21.87	–20.01	–14.36	–33.36	–18.84	–20.59

rationale behind the use of delta as a proxy for the relative weight of cryptocoins is to compute profits that would have been earned from pairs trading at a minimum variance level. If this is the case, then the appropriate hedge ratio (number of units of a cryptocurrency to sell per unit of another cryptocurrency buy/held) will be the slope estimate or beta coefficient of the cointegration model where the lower-priced cryptocurrencies are regressed against the higher-priced cryptocurrencies. More specifically, the beta coefficients of the cointegration estimation model determine the relative weight of cryptocurrencies in respective pairs.

The essence of pairs trading is the formation of the long-short position that consists of the simultaneous opening of long and short positions in two related assets (cryptocurrencies) with a balance point between them. Once the trader has paired up cryptocurrencies, then he needs to make a short position on coins that has a higher value and then hold a long position in the coin, which has a lower value in respective pairs. In another sense, the traders should sell the overpriced coins and buy the underpriced ones simultaneously from the market. In particular, the strategy is to sell cryptocoins that have done well relative to their match and purchase that have done poorly. The trading model is 'day trading' where traders make sell and buy contracts at opening prices and the same expire at their closing prices. Moreover, corresponding to the long-short portfolio of every pair of coins, the study assumes a long-only portfolio where the trader buys both coins at their opening prices and sells at closing prices.

The paper computes the profits of respective portfolios daily, and the total of successive daily profits of a paired portfolio over a timeframe produces its cumulative profit. The standard deviations of daily profits measure the risks of portfolios and the cumulative profit of the portfolio divided by its risk gives the profit per unit of risk assumed by the trader during a specific sample period. All the figures of profits and risks of pairs trading are in US Dollar terms. Matching all cryptocurrencies against each other in every sub-sample period expects to eliminate all kinds of discrepancies that otherwise would have been existing in the profitability analysis of pair trading strategies.

Beginning January 1, 2018, and continuing for each successive non-overlapping 6-month period through December 31, 2019, the study forms separate portfolios of long-short and long-only strategies with different pairs of cryptocurrencies. For this purpose, the portfolios' cumulative profits, risks, and profit per unit of risk as to the performance metric over the 24-month study period are considered. Panel A of Table 6 reports the results of the non-overlapping 6-month test period to begin in January 2018. The results confirm that long-short portfolio outperforms the long-only portfolio in all the six pairs of cryptocurrencies considered. The payoffs from pairs trading are positive in all cases, while the usual portfolio strategies have produced losses. The performance, in absolute terms of profit, is superior in pairs formed by Ethereum and Neocoin, and Ethereum and Litecoin. These two portfolios are found superior performers in terms of return-risk measure of profit per unit of risk. The traders might have found good profit from their paired portfolio comprised of Bitcoin and Ethereum with long-short strategy.

The results of Panel B show that the pair involving large-cap cryptocurrencies like Bitcoin and Ethereum produced extreme profits, while the portfolio involving Ethereum and Litecoin made a decent profit compared to the rest pairs in the panel. These two pairs were found as excellent performers in risk-return terms too and reveal that the risk differences could account for return discrepancies among pairs in the panel. In Panel B also, the common portfolio strategy of long-only position in the crypto market would cause distress to traders in the crypto market. However, in Panel C covering the period of larger price volatility in crypto markets, long-only portfolio strategy was able to outperform the long-short strategy, particularly in pairs involving the small-cap crypto like Litecoin and Neocoin. However, both profit and profit to risk measures of trading pairs like Bitcoin and Ethereum, and Ethereum and Litecoin were considerably greater than those of long-only portfolios. While these portfolios continued with their superior performance in Panel D, unlike other panels, the performance of small-cap crypto pairs like Neocoin and Litecoin, in terms of a profit-risk ratio is notably higher than the remaining pairs.

CONCLUSION

This study, using the most recent 718 daily price data of four cryptocurrencies markets, empirical evidence on the pairs trading potentials in crypto markets. The results obtained show that trade with a pair of cryptocoins having larger correlations produces lower return differentials. The cointegration results substantiate relatively strong positive price movement and high potentials for pairs trading in crypto markets. There exists a long-run convergence relationship of prices in cryptocurrency markets that implies the profit potentials of pairs trading. The results also reveal that cointegration coefficient, as a proxy to the optimal allocation ratio for pairs trading in crypto markets is significant in producing profits with fewer amounts of risks.

The paper finds that trading with suitably formed pairs of cryptocoins exhibits profits, which are superior to conservative profit estimates of portfolio management. The simulation exercise compares the payoffs and risks of the statistical arbitrage technique of pairs trading with the long-only portfolio strategy in cryptocoins markets. The findings show that the long-short strategy of pairs trading consistently defeats the general buy-hold strategy of investing in cryptocurrency markets. Moreover, most of the time during the study period, the average buy-hold strategy daily fails to produce profits in cryptocurrency trading. The persistence of larger profits from pairs trading relative to the traditional buy-hold strategy concedes the presence of temporary trends in the mispricing of cryptocoins, which are independent of the market conditions and revert to their original correlations. This finding definitely will be a great help to investors who are potentially interested in a trading strategy that offers greater returns with limited exposure to market risks.

Although the profits made by large-cap crypto pairs in the simple form are significantly higher than those made by small-cap pairs, the comparison of their profits with capital investments may generate

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the reverse ranking. This issue will be more persisting while incorporating the impact of margins on the funds needed for trading. However, the paper observes self-financing trade rules as the objective is only to discuss the profit potentials of pairs trading and an interesting avenue of future research would be to address the issue of margin mechanism in pairs trading potentials of crypto markets. Moreover, the findings are limited in explaining the effect of market cap and the time-varying information properties of the price movements in crypto markets. Hence, these results could certainly be validated by using a large sample of cryptocoins and a longer timeframe.

AUTHOR CONTRIBUTIONS

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Formal analysis: Saji Thazhungal Govindan Nair.
Funding acquisition: Saji Thazhungal Govindan Nair.
Investigation: Saji Thazhungal Govindan Nair.
Methodology: Saji Thazhungal Govindan Nair.
Project administration: Saji Thazhungal Govindan Nair.
Resources: Saji Thazhungal Govindan Nair.
Software: Saji Thazhungal Govindan Nair.
Supervision: Saji Thazhungal Govindan Nair.
Validation: Saji Thazhungal Govindan Nair.
Visualization: Saji Thazhungal Govindan Nair.
Writing – original draft: Saji Thazhungal Govindan Nair.
Writing – review & editing: Saji Thazhungal Govindan Nair.

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