This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3024619, IEEE Access

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier XXX

Pairs Trading in Cryptocurrency Markets

MIROSLAV FIL[1], and LADISLAV KRISTOUFEK[2]

[1]Institute of Economic Studies, Faculty of Social Sciences, Charles University, Prague, Czech Republic, EU (e-mail: miroslav.fil@seznam.cz)

[2]Institute of Economic Studies, Faculty of Social Sciences, Charles University, Prague, Czech Republic, EU (e-mail: LK@fsv.cuni.cz)

Corresponding author: Ladislav Kristoufek (e-mail: LK@fsv.cuni.cz).

Support from the Charles University PRIMUS program is highly appreciated (project PRIMUS/19/HUM/17).

ABSTRACT Pairs trading is a strategy based on exploiting mean reversion in prices of securities. Even though these strategies have been shown to perform well for equities, their performance is unknown for the field of cryptocurrencies, usually perceived as inefficient and predictable. We apply the distance and cointegration methods to a basket of 26 liquid cryptocurrencies traded on the Binance exchange, specifically at 5-minute, 1-hour and daily frequencies. In our backtests, the strategies underperform classical benchmarks. However, the results are quite sensitive to parameter settings and external factors such as transaction costs or execution windows. Higher-frequency trading delivers significantly better performance, and while the most common daily distance method returns -0.07% monthly, this increases to 11.61% monthly for 5-minute frequency. Additionally, we find evidence of simple mean-reverting behavior in intraday prices that is missing in daily data, and which provides further support for the inefficiency of cryptocurrency markets.

INDEX TERMS cryptocurrencies, intraday trading, pairs trading

I. INTRODUCTION

CRyptocurrencies are a form of electronic cash that emerged after publication of the influential whitepaper by Nakamoto [1], which eventually resulted in the birth of Bitcoin in 2009. The drivers of Bitcoin price were found to include both standard currency factors such as usage in trade or money supply as well as its popularity and public interest [2], [3], [4]. Nonetheless, Bitcoin price formation has been subject to speculative behavior and price bubbles [5].

Cryptocurrencies can be traded in the same way as traditional securities, although there are some specific differences. For example, crypto-markets are unusually global and continuously open while also being easily accessible even to retail investors. Furthermore, there are some unique risks, such as exchange closures [6]. However, standard trading strategies should still be applicable, as they are not dependent on those characteristics. Al-Yahyaee et al. [7] found that Bitcoin markets are more inefficient than stock or forex markets, indicating that trading might have an even greater potential to be profitable here than elsewhere.

We apply pairs trading, which is a mean-reversion contrarian trading strategy that tries to find a long-run stable state between prices of two securities – a so-called pair. If the prices of the pair diverge far enough in the short run, we short the higher-priced one and vice versa, leading to profit if the price spread returns to its long-run equilibrium. This strategy was first shown to be highly profitable in US equities by Gatev et al. [8]. Research since then has focused on various methodologies and geographies, although interest in pairs trading seems to be declining as its returns have substantially decreased in recent years [9].

However, the profitability of pairs trading in cryptocurrencies is still largely unexplored even though pairs trading has been noted to still perform well in illiquid bear markets [10], [11] and with intraday data [12], [13], both of which characteristics are typical for the crypto-markets. While high-frequency data for traditional markets is typically proprietary, most relevant cryptocurrency exchanges make even 1-minute binned price series available for free. Since cryptocurrencies are commonly perceived as inefficient, illiquid and suffering from frequent bear markets, the market conditions should be ideal for pairs trading to thrive.

Here we contribute in multiple areas. First, we rigorously evaluate the most commonly applied pairs trading approaches in the cryptocurrency space, including a sensitivity analysis to parameter specification which is often ignored. The cryptocurrency literature has been rapidly expanding and even though there is a large body of work on translating standard market phenomena to the cryptocurrency space, replications of pairs trading are missing. Second, we contribute to the literature on intraday pairs trading, another scarcely explored area in which the strategy has recently seen

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/.

success despite failing when applied on daily data only. Our results offer a new perspective on the decreasing profitability observed in other pairs trading literature, especially as high-frequency trading is becoming increasingly prevalent even in ordinary markets [14], [15].

II. LITERATURE REVIEW

Pairs trading has its roots in traditional stock markets and can be understood as a form of mean reversion in particular. Mean-reverting behavior of stocks has notably been observed by Fama & French [16], who found that negative autocorrelation in stock returns can predict 25% to 40% of 5-year return variance. This mean reversion was turned into a trading strategy by Jegadeesh [17], who modelled the autoregressive behavior and found a difference of 2.49% per month between portfolios with the highest and lowest predicted returns, respectively.

This would contradict the validity of the Efficient Market Hypothesis (EMH) [18], [19] which has generally been found to stand up relatively well, even though it has been challenged since its early years [20], [21]. The EMH implies that all information is instantly incorporated into the prices of securities and no systematic mispricings should last. In a broad sense, all research trying to forecast the returns of securities challenges the EMH. However, Timmermann & Granger [22] argue that the non-stationary and self-selecting nature of market trading makes formal testing of market efficiency and searching for long-term stable trading strategies difficult. Nonetheless, the success of pairs trading can be understood as another occurrence contradicting the EMH. It might, however, be that pairs trading is simply another instance of the mean-reverting property [17].

This was demonstrated not to be the case by Gatev et al. [8], whose work constitutes the first academic treatment of pairs trading and it introduces the baseline distance method for pairs formation. Investigation of the US stock market from 1962 to 1997 has shown that pairs trading in this setting generates excess annualized profit of up to 12% over the market. Furthermore, bootstrapping randomly formed pairs fails to generate such profits, which means that the pairs trading returns are different from the previously studied mean reversion effect, and the pairs trading procedure increases returns beyond just buying losers and selling winners.

A short-term violation of the Law of One Price is suggested to be the source of those profits, viewing pairs as close economic substitutes. Effective arbitrage as dictated by the EMH, which would not allow for the existence of excess returns, is believed to be hindered by factors such as short-sale constraints or bankruptcy risk. In a later revision of the same paper, Gatev et al. [23] notice that pairs trading returns are decreasing over time, which was further confirmed in other more recent works [24]. The mechanics behind varying pairs trading profitability are not entirely clear, although Jacobs & Weber [25] conduct a large cross-sectional study of 34 international stock markets and find that pairs trading is most profitable in either emerging markets or markets with a large number of pairs.

Pairs trading is a general framework, and the later work modifies either pairs selection, trading rules, or both. Another very popular pairs formation approach is the cointegration method outlined by Vidyamurthy [26], which tries to trade cointegrated pairs. In order to improve trading rules, Elliott et al. [27] proposed to model the mean-reversion as an Ornstein-Uhlenbeck process while Liew & Wu [28] have investigated the profitability of pairs trading based on copulas. Attempts to better identify trading opportunities also include using technical analysis [29] and deep reinforcement learning [30]. Other researched approaches are genetic algorithms [31] and Hurst exponents [32]. While more sophisticated methods typically show better performance than baseline approaches, they have only a small body of research supporting them. Explicit comparisons between methods are rare and do not appear to have a clear winner even when conducted [9], [33].

Furthermore, it appears that pairs trading is sensitive to market conditions, and profitability is declining overall. While Gatev et al. [8] found profits to be robust to trading costs, other more recent works [9], [24], [34] suggest that reasonable transaction costs and execution lag are often enough to nearly eliminate excess returns in post-2000 backtests. That said, the strategy reacts positively to market illiquidity and other limits to arbitrage, and it subsequently performs much better in bear markets, during which liquidity is known to decrease [10], [11], [25]. However, a big part of literature on the effect of market friction focuses only on the distance method with basic trading rules as noted in the survey by Krauss [35].

Studies using intraday pairs trading are comparatively few, and are often limited in terms of their industry coverage or timeframe. However, double-digit annual excess returns over the market can be observed even for US stocks during the 2010s with high-frequency trading [12], [13], a period in which daily pairs trading was otherwise noted to perform poorly [9], [24]. Ultimately, research of high-frequency pairs trading is somewhat rare due to data availability. Intraday data in standard markets is frequently either proprietary with high purchasing costs or simply not available.

Even though pairs trading is generally understood to be a statistical arbitrage strategy, the basic idea of pairs selection and subsequent trading is very general. Long/short or equity market neutral strategies are in spirit very similar to pairs trading, and they were historically heavily used by hedge funds with solid success [36], [37]. Such strategies might find pairs based on fundamental factors such as those from the Fama-French three-factor model [38] rather than directly relying on statistical arbitrage.

Research into application of pairs trading to cryptocurrencies specifically is limited in scope even for the most standard pairs trading methods. Lintilhac & Tourin [39] consider an approach based on stochastic control with mostly theoretical results, backtesting the strategy only on Bitcoin across three different exchanges. And Leung & Nguyen [40] use the cointegration method and backtest a number of trading rules,

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3024619, IEEE Access

but they only use daily data for four cryptocurrencies total. There is a comparatively larger body of non-peer reviewed literature in the form of university theses. In comparison to our study, the above-noted works typically suffer from only including a subset of our examined methods with shorter backtest periods, limiting the admissible pairs to single digit numbers, relying on daily data with no intraday focus, or a combination of the preceding.

Other than that, many traditional trading strategies have been adapted from stock markets with success. Even simple technical trading rules such as moving average or trading range breakout are frequently found to outperform buy-and-hold benchmarks, producing excess returns of the order of 8.76% p.a. along with lower volatility than buy-and-hold [41], [42], [43]. Machine learning techniques such as gradient boosting trees or long-short term memory networks, often augmented with the use of social media data in particular, were likewise found to produce significant excess returns [44], [45], [46], [47].

Sustained evidence of profit opportunities would hint towards market inefficiency. Explicit tests of cryptocurrency markets typically conclude that they are inefficient, particularly in comparison to traditional stock markets [7]. However, efficiency seems to be improving over time [48], [49], [50]. While most efficiency studies use daily data, the conclusions have been found to vary depending on intraday sampling frequency [51], and a higher sampling frequency seems to imply lower informational efficiency [52]. Efficiency remains a challenge especially for less liquid cryptocurrencies, and liquidity influences both volatility and return predictability [52], [53], [54], [55]. Explicit mean-reversion in cryptocurrencies in the sense of Jegadeesh [17] has mixed evidence [56], [57], [58].

Cryptocurrency markets are an interesting target for pairs trading for several reasons. Apart from significant market inefficiency suggesting existence of profit opportunities, cryptocurrency markets are also known to be susceptible to bubbles, leading to frequent bear markets [5], [59]. Additionally, liquidity is frequently a concern there [60], [61]. Those factors were found to contribute positively to pairs trading performance in traditional stock markets, and cryptocurrencies are also unique in the wide-spread availability of high-frequency data, which is another area in which pairs trading appears to be successful.

III. METHODOLOGY

A. DATA

The data used come from Binance[1], a leading cryptocurrency exchange at the time of writing. It provides up to 1-minute resolution data on all its traded cryptocurrencies, which can be freely downloaded using its public API. For our backtests, we use three different frequencies – daily, hourly and 5-minute data. As the Binance exchange did not operate in fiat currencies or stablecoins at the time of writing, Bitcoin is a numeraire.

We start with raw price data for 181 cryptocurrencies and proceed with those that were traded from Jan 2018 to Sept 2019, meaning that any cryptocurrency that was listed or delisted at some point during that period is left out to achieve a balanced panel. Furthermore, we apply a top-30% volume filter to mitigate liquidity-related issues. After the preprocessing, we are left with a final set of 26 cryptocurrencies[2].

[1] https://www.binance.com/en

B. METHODS

A pairs trading strategy proceeds in a pairs formation stage followed by a trading period. During the formation stage, pairs that appear to have a long-run relationship are identified, and a measure of spread between the prices of cryptocurrencies constituting the pair is defined. In the trading period, positions are opened if the spread diverges far enough from its long-run mean and are closed once it reverts. There are two prominent approaches to pairs formation – the distance method and the cointegration method.

The distance method starts by computing pairwise sums of squared deviations between the two normalized logarithmic price series of assets i and j, simply labeled as P here:

$$SSD_{ij} = \sum_t (P_{it} - P_{jt})^2 \tag{1}$$

Following Gatev et al. [8], we then pick the top 20 pairs that minimize this metric, indicating that their price movement is the most similar. The spread between two assets i and j at time t is then defined as

$$spread_{ijt} = P_{it} - P_{jt} \tag{2}$$

and trades can be performed based on its values. Specifically, we short the spread when its normalized value exceeds 2 and close the position once it crosses zero or at the end of trading. We proceed analogously when it decreases below -2. Those trading rules are very common and are adopted directly from Gatev et al. [8].

The cointegration method was outlined by Vidyamurthy [26] and only differs in the pairs formation stage. Here, we use the Engle-Granger cointegration test [62] to filter out pairs. The spread is defined as the residual from the cointegration regression in the Engle-Granger setting, and trading proceeds in the same way as for the distance method.

We utilize a one-period execution lag for all trade orders following Gatev et al. [8] to approximate the bid-ask spread since contrarian trading strategies might be unknowingly buying for bid prices and vice versa.

[2] Tickers (cryptocurrencies): ADA (Cardano), ARN (Aeron), BAT (Basic Attention Token), BNB (Binance Coin), DGD (DigiByte), ELF (aelf), ENJ (Enjin Coin), EOS (EOS), ETC (Ethereum Classic), ETH (Ethereum), ICX (ICON), IOTA (MIOTA), LINK (Chainlink), LTC (Litecoin), MDA (Moeda Loyalty Points), MTL (Metal), NEO (NEO), QTUM (Qtum), TRX (TRON), WAVES (Waves), WTC (Waltonchain), XLM (Stellar), XMR (Monero), XRP (Ripple), XVG (Verge), ZRX (0x).

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3024619, IEEE Access

TABLE 1. Description of basic scenarios

Frequency	Formation	Trading	Jump	Tx cost	Exec. lag	Threshold
Daily	4 mth	2 mth	1 mth	30 bps	1 d	2 SDs
Hourly	20 d	10 d	10 d	30 bps	1 h	2 SDs
5-Minute	6 d	3 d	3 d	30 bps	5 min	2 SDs

C. TRANSACTION COSTS

Transaction costs estimates are based on the work of Do & Faff [10]. The three key aspects of transaction costs are commissions, market impact and short-selling costs. Commissions on Binance are 10/10 bps for maker/taker as a baseline and decrease to as low as 2/4 bps for the highest volume trading level.

For the market impact, we reuse the estimate centered around the year 2000 for US equities of 20 bps [10]. Importantly, we do not take short-selling costs into account because short-selling in the crypto-space is currently at best limited to a select few currencies and tends to be literally impossible to execute in our use case.

In particular, as of June 2019, Binance added margin support for some of the most common coins (which do not include all of ours even given our heavy preprocessing), but even Bitcoin has a borrowing fee of 7.3% p.a, far higher than the sub-1% estimates by D'Avolio [63] for US stocks.

IV. RESULTS

The two methods are backtested using various sampling frequencies and a parameter sensitivity analysis is performed as well. Furthermore, we include comparison to two baseline strategies. First, we use a simple buy-and-hold long-only strategy for Bitcoin over our period of examination. We proxy the USD price of Bitcoin by BTCUSDT since Binance does not support fiat currencies, and thus does not have BTCUSD directly. Second, we backtest the random-pairs-formation method via bootstrap as proposed by Gatev et al. [8], simulating 30 random runs for each examined frequency and averaging the results. This method proceeds by forming pairs randomly (instead of using the pairs selection criteria that we discussed previously), but its setup is otherwise identical to the distance method. This approach is meant to decouple the added value of more complex pairs formation from simple mean-reversion in the trading stage.

A. BASE SCENARIOS

The methods are backtested using daily, hourly and 5-minute frequencies. We also conduct a sliding-window cross-validation to increase the robustness of our results, meaning that apart from setting the length of formation and trading periods, we define a jump time by which we increment the starting date for every iteration of the backtest. The base scenario configuration is summarized in Table 1.

Table 2 shows the results averaged across all iterations. The distance method fails to perform on daily data, delivering zero returns with a barely positive Sharpe ratio. The proportion of round-trip trades is quite low at 24%, meaning that the pairs almost never naturally converge. Furthermore, the maximum drawdown is high, greater than 26%, and the percentage of winning trades is weak at just 46%. The pairs trade on average only 0.475 times per month.

The performance of the distance method increases significantly with higher frequency, delivering a 3.1% profit for the hourly frequency and an 11.6% profit for the 5-minute data, with Sharpe ratios of 4.1 and 22, respectively. The other metrics have also greatly improved.

The cointegration method performs much better in the daily setting, with a 1.36% monthly profit, and it outperforms the distance method in the auxiliary metrics as well, having a maximum drawdown of only 24.89%, a proportion of winning trades equal to 50.33% and a Sharpe ratio of 1.1.

However, this method does not scale as well with the frequency, and the performance actually worsens for the hourly data to 1.11%, although it increases to 4.16% at the 5-minute resolution. Despite the lower raw returns, the method actually performs much better in terms of all other applied metrics. It trades more often with a higher proportion of roundtrip and winning trades, but this does not translate into an actual performance improvement. The amount of cointegrated pairs also increases significantly with higher frequencies, changing from 22 to 36 on the 5-minute scale.

B. ALTERNATIVE SCENARIOS

It is apparent that the presented results might be sensitive to parameter settings. Even though we have previously maintained the standard parameter settings as described in the Methods section, we now present a robustness check for the most important parameters.

Table 3 highlights that both the transaction costs and the execution lag are very important and exhibit quite similar effect magnitudes. While daily trading is still only slightly profitable, at roughly 0.5% monthly, the returns of hourly trading skyrocket, with cointegration at approximately 4% and distance at 6% monthly. Transaction costs are particularly important for the highest frequency backtests, as they also trade the most often. Even the execution lag exerts an order-of-magnitude effect on profits as we move from daily to higher frequency.

These results show that even modest transaction costs are very harmful to profits, particularly if we trade often, which is not surprising. Taking the execution lag effect as an approximation of the bid-ask spread and subsequently liq-

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3024619, IEEE Access

TABLE 2. Results of base scenarios

	Daily Dist.	Coint.	Random	Hourly Dist.	Coint.	Random	5-Minute Dist.	Coint.	Random	Market BTC
Monthly profit	-0.07%	1.36%	-0.59%	3.10%	1.11%	1.97%	11.61%	4.16%	6.54%	0.43%
Annualized Sharpe	0.034	1.1	-0.62	4.1	0.66	2.4	22	12	12	0.19
Monthly number of trades	0.475	0.575	0.354	3.53	4.64	2.45	14.8	18.2	9.42	None
Roundtrip trades	23.65%	25.79%	14.37%	28.33%	38.68%	20.76%	37.15%	43.19%	25.68%	None
Length of position (days)	33.3	32.1	35.1	5.6	4.8	5.8	1.6	1.4	1.7	None
Pct of winning trades	46.06%	50.33%	33.03%	47.67%	52.73%	37.68%	53.24%	58.16%	40.99%	None
Max drawdown	26.32%	24.89%	29.48%	13.69%	15.81%	15.89%	9.02%	10.18%	10.32%	67.44%
Nominated pairs	20.0	22.2	20.0	20.0	26.1	20.0	20.0	36.3	20.0	None
Traded pairs	82.00%	87.69%	65.65%	85.42%	92.59%	68.86%	89.85%	94.74%	73.41%	None

TABLE 3. Results of alternative scenarios

	Daily Dist.	Coint.	Hourly Dist.	Coint.	5-Minute Dist.	Coint.
No lag						
- Monthly profit	0.38%	1.53%	5.97%	4.17%	16.80%	7.43%
- Annualized Sharpe	0.39	1.1	7.9	5.1	31	19
No transaction costs						
- Monthly profit	0.26%	1.70%	5.60%	4.06%	22.87%	17.00%
- Annualized Sharpe	0.35	1.4	8.0	5.0	44	39

uidity, it seems that liquidity is a limiting factor as well, and executing trades is likely to be difficult. Having the execution lag equal to one period in every case can be understood as relaxing this constraint for higher frequencies, as then, the 5-minute scenarios can execute the trade far quicker than the daily ones, which appears to be a contributing factor to performance.

Table 4 shows the effect of altering the threshold and introducing a stop-loss based on a grid search. It appears that a stop-loss is extremely harmful and that including it underperforms the base scenarios significantly. This result can possibly be explained through spuriously cointegrated pairs having spreads that are equally likely to move in either direction, whereas in the case of true cointegration, introducing a stop-loss has a negative expected value, thus decreasing the overall performance.

It also appears that the 2-standard-deviation trigger is more of a local minimum, and utilizing either 1 or 3 standard deviations would have been advantageous, especially for the distance method. However, it is not unexpected that parameters taken from other literature are suboptimal, especially since explicit parameter fine-tuning is not commonly performed, and the viability of such gold-standard rules present in the pairs trading literature is questionable [64], [65].

The previous results already indicate that the returns are very volatile. From Table 5, we see that the mean is not significantly different from zero except for the 5-minute case. The range is enormous, pairs can lose or gain greater than 100% (as we are trading on margin) within a period, and the kurtosis ranges from mid-double-digits in the lower frequencies to mid-hundreds for the 5-minute data, further evidencing a high number of outliers. Even when the mean is positive, the proportion of positive returns is less than 50%, indicating a long right tail.

C. BASELINE BENCHMARKS

For comparison, Figure 1 displays the buy-and-hold and daily versions of distance, cointegration and random methods[3]. Over this period, we observe a significant sub-period difference in behavior of the cointegration and distance methods. While they are initially fairly well-matched in the 2018 bear market, cointegration then exhibits a period of very strong performance following the bull market in spring 2019. This event ultimately makes the method outperform the buy-and-hold benchmark at the end of the examination period, producing an annualized excess return of 17.56% on top of the market's 5.25% p.a. On the other hand, the distance method fails to break even and has slightly negative profits at -1.33% p.a. The market benchmark performs particularly poorly when risk-adjusted in terms of its Sharpe ratio at 0.19 and a maximum drawdown of 67.44%, which came to be during the 2018 bear market.

Table 2 further shows evaluation of the random pairs trading method for all our trading frequencies. The random method achieves the worst monthly profit across daily scenarios at -0.59%, and its auxiliary metrics such as percentage of winning trades or roundtrip trades are the weakest by far. However, it performs much better at intraday frequencies, achieving monthly returns of 1.97% and 6.54% at hourly and 5-minute frequencies, respectively. This result makes it significantly more successful than the cointegration method

[3]In order to stay faithful to the setup described in Table 1 and form a profit time series over the whole examination period, we had to drop every second daily backtest so that the trading periods are non-overlapping. This causes a slight discrepancy in profit measures described in this section from Table 2.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3024619, IEEE Access

TABLE 4. Various Daily stop-loss and opening triggers

			Distance			Cointegration		
			Threshold			Threshold		
			1 SD	*2 SD*	*3 SD*	*1 SD*	*2 SD*	*3 SD*
Stop-loss	2	Monthly profit	-0.67%	None	None	-0.03%	None	None
		Annualized Sharpe	-0.47	None	None	-1.9	None	None
	3	Monthly profit	0.02%	-1.84%	None	-0.29%	0.78%	None
		Annualized Sharpe	0.039	-1.8	None	-0.49	0.48	None
	4	Monthly profit	0.21%	-1.50%	-0.22%	1.22%	1.26%	0.67%
		Annualized Sharpe	0.2	-1.5	-0.26	0.99	1.0	0.6
	5	Monthly profit	0.76%	-1.11%	-0.16%	1.45%	1.41%	0.31%
		Annualized Sharpe	0.76	-1.1	-0.0081	1.2	1.2	0.33
	6	Monthly profit	1.19%	-0.61%	0.86%	1.60%	1.89%	0.92%
		Annualized Sharpe	1.3	-0.5	0.98	1.3	1.7	0.91

TABLE 5. Descriptive statistics of return distributions

	Daily		Hourly		5-Minute	
	Dist.	Coint.	Dist.	Coint.	Dist.	Coint.
Mean	-0.00001	0.00036	0.00006	0.00003	0.00002	0.00001
SD	0.0556	0.0535	0.0153	0.0175	0.00604	0.00644
Max	1.04	1.3	0.462	0.905	0.451	0.669
Min	-0.794	-0.673	-0.679	-1.32	-0.394	-1.0
J-B (p-value)	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Skewness	-0.486	0.452	-0.554	-0.88	-0.19	-1.7
Kurtosis	33.8	49.1	99.8	257	133	619
Positive	49.06%	47.85%	49.38%	48.99%	48.21%	48.42%
t-stat	-0.018	0.73	1.5	0.73	3.5	2.8

in both absolute and risk-adjusted returns at those timescales, although its auxiliary metrics remain poor.

The distance method's profitability exhibits similar but even stronger scaling with frequency. This indicates that the distance method is not as defunct as its daily backtest might suggest, but it rather implies that the technique presents higher demands on trade execution than a daily frequency with one period lag allows. The market appears efficient enough for the profit opportunity to be largely arbitraged away by the time the daily strategies execute their trades. This observation is supported by the remarkable performance of the random-pairs-formation strategy with intraday prices, which suggests a strong pattern of intraday mean-reversion that is not replicated at all for the daily frequency.

V. CONCLUSION

We have shown that under some conditions, pairs trading can perform well in the cryptocurrency space, particularly with higher-frequency trading. However, the overall performance trails that of the benchmark literature with comparable settings.

The profitability of our trading strategies varies strongly with respect to parameter specification. Overall, the cointegration method appears to stably achieve a moderately good performance while the distance method is less robust and scales strongly with higher frequency. Additionally, exogenous factors such as transaction costs or execution windows are extremely important, and their exact determination is thus vital.

Regarding the popular belief that cryptocurrencies are easily predictable and majorly inefficient, the evidence that we present suggests otherwise, at least for daily sampling frequency. We attribute this finding to the ever-changing nature and dynamics of the crypto-markets, driven strongly by exogenous factors. Even though the markets can be perceived as inefficient on a statistical basis through the standard tests, building profitable trading strategies proves rather difficult, as the market might still remain inefficient in the retrospect-to-be, yet the dynamics in the testing period are likely largely different from those in the training period, making the strategies unprofitable or only weakly profitable for the given risk levels.

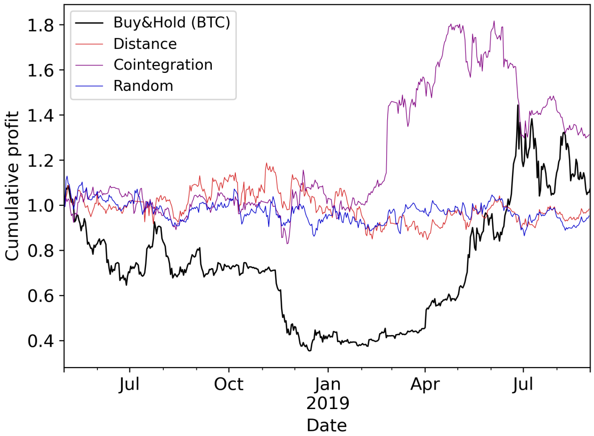
High-frequency trading performs much better, but it is questionable to what extent the gains could be converted to actual real-world performance under liquidity and other constraints. We also note that better success with intraday trading is consistent with other research on lower market efficiency of high-frequency cryptocurrency prices [42], [51], [52], [66], and our results with randomly selected pairs do support major inefficiency, especially in intraday prices.

Furthermore, the varying performance across trading frequencies might help to shed more light on the recent decline of pairs trading profitability in traditional markets [9], [23], [24]. It is possible that the poor performance of pairs trading in standard equities can be alleviated with higher frequency trading, but large-scale studies on this topic are missing.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3024619, IEEE Access

FIGURE 1. Profitability of daily scenarios compared to market



The unprecedented availability of high-frequency data in cryptocurrency markets plays an important role here.

REFERENCES

[1] Satoshi Nakamoto. Bitcoin: A Peer-to-Peer Electronic Cash System, November 2008.

[2] Ladislav Kristoufek. *BitCoin* meets *Google Trends* and *Wikipedia*: Quantifying the relationship between phenomena of the Internet era. Scientific Reports, 3:3415, December 2013.

[3] Ladislav Kristoufek. What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. PLOS ONE, 10(4):e0123923, April 2015.

[4] Pavel Ciaian, Miroslava Rajcaniova, and d'Artis Kancs. The economics of BitCoin price formation. Applied Economics, 48(19):1799–1815, April 2016.

[5] Shaen Corbet, Brian Lucey, and Larisa Yarovaya. Datestamping the Bitcoin and Ethereum bubbles. Finance Research Letters, 26:81–88, September 2018.

[6] Tyler Moore and Nicolas Christin. Beware the Middleman: Empirical Analysis of Bitcoin-Exchange Risk. In Ahmad-Reza Sadeghi, editor, Financial Cryptography and Data Security, Lecture Notes in Computer Science, pages 25–33. Springer Berlin Heidelberg, 2013.

[7] Khamis Hamed Al-Yahyaee, Walid Mensi, and Seong-Min Yoon. Efficiency, multifractality, and the long-memory property of the Bitcoin market: A comparative analysis with stock, currency, and gold markets. Finance Research Letters, 27:228–234, December 2018.

[8] Evan G Gatev, William N Goetzmann, and K. Geert Rouwenhorst. Pairs Trading: Performance of a Relative Value Arbitrage Rule. Working Paper 7032, National Bureau of Economic Research, March 1999.

[9] Hossein Rad, Rand Kwong Yew Low, and Robert W. Faff. The Profitability of Pairs Trading Strategies: Distance, Cointegration, and Copula Methods. SSRN Scholarly Paper ID 2614233, Social Science Research Network, Rochester, NY, June 2015.

[10] Binh Do and Robert Faff. Are Pairs Trading Profits Robust to Trading Costs? Journal of Financial Research, 35(2):261–287, 2012. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1475-6803.2012.01317.x.

[11] David A. Bowen and Mark C. Hutchinson. Pairs trading in the UK equity market: risk and return. The European Journal of Finance, 22(14):1363–1387, November 2016. Publisher: Routledge _eprint: https://doi.org/10.1080/1351847X.2014.953698.

[12] Johannes Stübinger and Sylvia Endres. Pairs trading with a mean-reverting jump–diffusion model on high-frequency data. Quantitative Finance, 18(10):1735–1751, October 2018. Publisher: Routledge _eprint: https://doi.org/10.1080/14697688.2017.1417624.

[13] Bo Liu, Lo-Bin Chang, and Hélyette Geman. Intraday pairs trading strategies on high frequency data: the case of oil companies. Quantitative Finance, 17(1):87–100, January 2017. Publisher: Routledge _eprint: https://doi.org/10.1080/14697688.2016.1184304.

[14] Andrei Kirilenko, Albert S. Kyle, Mehrdad Samadi, and Tugkan Tuzun. The Flash Crash: High-Frequency Trading in an Electronic Market. The Journal of Finance, 72(3):967–998, 2017. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12498.

[15] Albert J. Menkveld. High frequency trading and the new market makers. Journal of Financial Markets, 16(4):712–740, November 2013.

[16] Eugene Fama and Kenneth French. Permanent and Temporary Components of Stock Prices. Journal of Political Economy, 96(2):246–73, 1988.

[17] Narasimhan Jegadeesh. Evidence of Predictable Behavior of Security Returns. The Journal of Finance, 45(3):881–898, 1990.

[18] P. Samuelson. Proof That Properly Anticipated Prices Fluctuate Randomly. Industrial Management Review, 6(2):41–49, 1965.

[19] Eugene F. Fama. The Behavior of Stock-Market Prices. The Journal of Business, 38(1):34–105, 1965. Publisher: University of Chicago Press.

[20] Eugene F. Fama. Efficient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance, 25(2):383–417, 1970. Publisher: [American Finance Association, Wiley].

[21] S. Basu. Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis. The Journal of Finance, 32(3):663–682, 1977. Publisher: [American Finance Association, Wiley].

[22] Allan Timmermann and Clive W. J. Granger. Efficient market hypothesis and forecasting. International Journal of Forecasting, 20(1):15–27, January 2004.

[23] Evan Gatev, William N. Goetzmann, and K. Geert Rouwenhorst. Pairs Trading: Performance of a Relative-Value Arbitrage Rule. SSRN Scholarly Paper ID 1095996, Social Science Research Network, Rochester, NY, 2006.

[24] Binh Do and Robert Faff. Does Simple Pairs Trading Still Work? Financial Analysts Journal, 66(4):83–95, 2010.

[25] Heiko Jacobs and Martin Weber. On the determinants of pairs trading profitability. Journal of Financial Markets, 23:75–97, March 2015.

[26] Ganapathy Vidyamurthy. Pairs Trading: Quantitative Methods and Analysis. Wiley, Hoboken, N.J, 1 edition edition, August 2004.

[27] Robert J. Elliott, John Van Der Hoek *, and William P. Malcolm. Pairs trading. Quantitative Finance, 5(3):271–276, June 2005.

[28] Rong Qi Liew and Yuan Wu. Pairs trading: A copula approach. Journal of Derivatives & Hedge Funds, 19(1):12–30, February 2013.

[29] Timofei Bogomolov. Pairs trading based on statistical variability of the spread process. Quantitative Finance, 13(9):1411–1430, September 2013. Publisher: Routledge _eprint: https://doi.org/10.1080/14697688.2012.748934.

[30] Saeid Fallahpour, Hasan Hakimian, Khalil Taheri, and Ehsan Ramezanifar. Pairs trading strategy optimization using the reinforcement learning method: a cointegration approach. Soft Computing, 20(12):5051–5066, December 2016.

[31] Chien-Feng Huang, Chi-Jen Hsu, Chi-Chung Chen, Bao Rong Chang, and Chen-An Li. An Intelligent Model for Pairs Trading Using Genetic Algorithms. Intell. Neuroscience, 2015:16:16–16:16, January 2015.

[32] J. P. Ramos-Requena, J. E. Trinidad-Segovia, and M. A. Sánchez-Granero. Introducing Hurst exponent in pair trading. Physica A: Statistical Mechanics and its Applications, 488(C):39–45, 2017.

[33] Nicolas Huck and Komivi Afawubo. Pairs trading and selection methods: is cointegration superior? Applied Economics, 47(6):599–613, 2015. Publisher: Taylor & Francis Journals.

[34] David Bowen, Mark C. Hutchinson, and Niall O'Sullivan. High-Frequency Equity Pairs Trading: Transaction Costs, Speed of Execution, and Patterns in Returns. The Journal of Trading, 5(3):31–38, June 2010. Publisher: Institutional Investor Journals Umbrella Section: Article.

[35] Christopher Krauss. Statistical Arbitrage Pairs Trading Strategies: Review and Outlook. Journal of Economic Surveys, 31(2):513–545, 2017. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/joes.12153.

[36] William Fung and David A. Hsieh. The risk in hedge fund strategies: Theory and evidence from long/short equity hedge funds. Journal of Empirical Finance, 18(4):547–569, September 2011.

[37] Turan G. Bali, Stephen J. Brown, and K. Ozgur Demirtas. Do Hedge Funds Outperform Stocks and Bonds? Management Science, 59(8):1887–1903, March 2013. Publisher: INFORMS.

[38] Eugene F. Fama and Kenneth R. French. Common Risk Factors in the Returns On Stocks And Bonds. Journal of Financial Economics, 33:3–56, 1993.

[39] P. S. Lintilhac and A. Tourin. Model-based pairs trading in the bitcoin markets. Quantitative Finance, 17(5):703–716, May 2017.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3024619, IEEE Access

[40] Tim Leung and Hung Nguyen. Constructing cointegrated cryptocurrency portfolios for statistical arbitrage. Studies in Economics and Finance, 36(4):581–599, January 2019. Publisher: Emerald Publishing Limited.
[41] Klaus Grobys, Shaker Ahmed, and Niranjan Sapkota. Technical trading rules in the cryptocurrency market. Finance Research Letters, 32:101396, January 2020.
[42] Shaen Corbet, Veysel Eraslan, Brian Lucey, and Ahmet Sensoy. The effectiveness of technical trading rules in cryptocurrency markets. Finance Research Letters, 31:32–37, December 2019.
[43] Robert Hudson and Andrew Urquhart. Technical trading and cryptocurrencies. Annals of Operations Research, August 2019.
[44] Laura Alessandretti, Abeer ElBahrawy, Luca Maria Aiello, and Andrea Baronchelli. Anticipating Cryptocurrency Prices Using Machine Learning, November 2018. ISSN: 1076-2787 Library Catalog: www.hindawi.com Pages: e8983590 Publisher: Hindawi Volume: 2018.
[45] Franco Valencia, Alfonso Gómez-Espinosa, and Benjamín Valdés-Aguirre. Price Movement Prediction of Cryptocurrencies Using Sentiment Analysis and Machine Learning. Entropy, 21(6):589, June 2019. Number: 6 Publisher: Multidisciplinary Digital Publishing Institute.
[46] Tianyu Ray Li, Anup S. Chamrajnagar, Xander R. Fong, Nicholas R. Rizik, and Feng Fu. Sentiment-Based Prediction of Alternative Cryptocurrency Price Fluctuations Using Gradient Boosting Tree Model. Frontiers in Physics, 7, 2019. Publisher: Frontiers.
[47] Ross C. Phillips and Denise Gorse. Predicting cryptocurrency price bubbles using social media data and epidemic modelling. In 2017 IEEE Symposium Series on Computational Intelligence (SSCI), pages 1–7, November 2017.
[48] Vu Le Tran and Thomas Leirvik. Efficiency in the markets of cryptocurrencies. Finance Research Letters, 35:101382, July 2020.
[49] Andrew Urquhart. The inefficiency of Bitcoin. Economics Letters, 148:80–82, November 2016.
[50] Ladislav Kristoufek. On Bitcoin markets (in)efficiency and its evolution. Physica A: Statistical Mechanics and its Applications, 503:257–262, August 2018.
[51] Aylin Aslan and Ahmet Sensoy. Intraday efficiency-frequency nexus in the cryptocurrency markets. Finance Research Letters, 35:101298, July 2020.
[52] Ahmet Sensoy. The inefficiency of Bitcoin revisited: A high-frequency analysis with alternative currencies. Finance Research Letters, 28:68–73, March 2019.
[53] Wang Chun Wei. Liquidity and market efficiency in cryptocurrencies. Economics Letters, 168:21–24, July 2018.
[54] Alexander Brauneis and Roland Mestel. Price discovery of cryptocurrencies: Bitcoin and beyond. Economics Letters, 165(C):58–61, 2018. Publisher: Elsevier.
[55] Khamis Hamed Al-Yahyaee, Walid Mensi, Hee-Un Ko, Seong-Min Yoon, and Sang Hoon Kang. Why cryptocurrency markets are inefficient: The impact of liquidity and volatility. The North American Journal of Economics and Finance, 52:101168, April 2020.
[56] Shaen Corbet and Paraskevi Katsiampa. Asymmetric mean reversion of Bitcoin price returns. International Review of Financial Analysis, October 2018.
[57] Douglas Eduardo Turatti, Fernando Henrique de Paula e Silva Mendes, and João Frois Caldeira. Testing for mean reversion in Bitcoin returns with Gibbs-sampling-augmented randomization. Finance Research Letters, July 2019.
[58] Qing Cheng, Xinyuan Liu, and Xiaowu Zhu. Cryptocurrency momentum effect: DFA and MF-DFA analysis. Physica A: Statistical Mechanics and its Applications, 526:120847, July 2019.
[59] John Fry and Eng-Tuck Cheah. Negative bubbles and shocks in cryptocurrency markets. International Review of Financial Analysis, 47:343–352, October 2016.
[60] Yuanyuan Zhang, Stephen Chan, Jeffrey Chu, and Hana Sulieman. On the Market Efficiency and Liquidity of High-Frequency Cryptocurrencies in a Bull and Bear Market. Journal of Risk and Financial Management, 13(1):1–14, 2020. Publisher: MDPI, Open Access Journal.
[61] Hio Loi. The Liquidity of Bitcoin. International Journal of Economics and Finance, 10:13, 2017.
[62] Robert Engle and Clive Granger. Co-integration and Error Correction: Representation, Estimation, and Testing. Econometrica, 55(2):251–76, 1987.
[63] Gene D'Avolio. The Market for Borrowing Stock. SSRN Scholarly Paper ID 305479, Social Science Research Network, Rochester, NY, February 2002.
[64] Nicolas Huck. The high sensitivity of pairs trading returns. Applied Economics Letters, 20(14):1301–1304, September 2013.
[65] K. F. Law, W. K. Li, and Philip L. H. Yu. A single-stage approach for cointegration-based pairs trading. Finance Research Letters, 26:177–184, September 2018.
[66] Thomas Günter Fischer, Christopher Krauss, and Alexander Deinert. Statistical Arbitrage in Cryptocurrency Markets. Journal of Risk and Financial Management, 12(1):31, March 2019. Number: 1 Publisher: Multidisciplinary Digital Publishing Institute.

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2020.3024619, IEEE Access

MIROSLAV FIL obtained his B.Sc. in economics at Institute of Economic Studies, Faculty of Social Sciences, Charles University, Prague, Czech Republic. At the moment, he is a masters student of computer science at the University of Oxford. His primary research interests include reproducibility, automatic hyper-parameter tuning and meta-analysis of quantitative research.

LADISLAV KRISTOUFEK obtained his Ph.D. in economics at Charles University, Prague, Czech Republic, in 2013 (dissertation thesis on bivariate long-range dependence in financial time series). He is a Full Professor of Economics at Institute of Economic Studies, Faculty of Social Sciences, Charles University, Prague. Since 2018, he also has served as the Vice-Dean for Student Affairs of the Faculty. In 2014 and 2015, he spent six months in the Behavioural Research Group at the Warwick Business School. His research interests are broad and mostly interdisciplinary, starting with his interest in interdisciplinary overreach of physics and complex systems into economics and finance, followed by utilizing online data in economics and finance, and extending to energy economics and various other (sub)fields. He has authored approximately 70 articles in the IF journals (including in Nature Energy, Journal of Economic Dynamics and Control, and Energy Economics). His papers on Bitcoin from 2013 and 2015 are among the first economics and finance-related cryptocurrency papers and are still highly cited (each with more than 500 citations as of August 2020).

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/.