

Pairs Trading in Cryptocurrency Markets

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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]–[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

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area in which the strategy has recently seen 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, 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]–[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]–[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]–[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]–[55]. Explicit mean-reversion in cryptocurrencies in the sense of Jegadeesh [17] has mixed evidence [56]–[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

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

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

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:

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

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

$$spread_{ijt} = P_{it} - P_{jt} \quad (2)$$

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 Vidya-murthy [26] and only differs in the pairs formation stage.

²Tickers (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).

¹<https://www.binance.com/en>

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

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.

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

TABLE 3. Results of alternative scenarios.

	Daily		Hourly		5-Minute	
	Dist.	Coint.	Dist.	Coint.	Dist.	Coint.
<i>No lag</i>						
- 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
<i>No transaction costs</i>						
- 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

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

TABLE 4. Various Daily stop-loss and opening triggers.

			Distance			Cointegration		
			1 SD	Threshold 2 SD	3 SD	1 SD	Threshold 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

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 liquidity, 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].

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

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

³In 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.

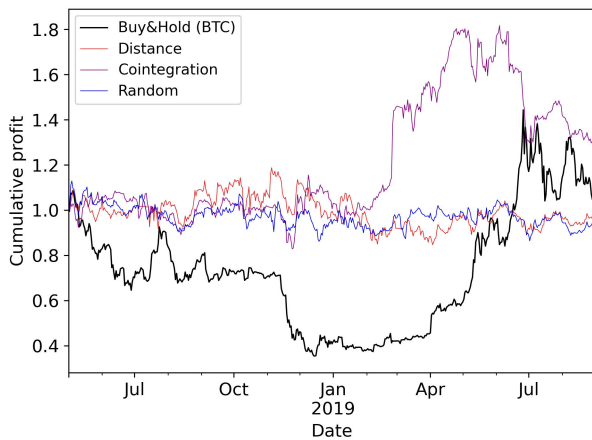


FIGURE 1. Profitability of daily scenarios compared to market.

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

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