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Directional Movement Distribution in the Bitcoin Markets

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The crypto exchanges operate primarily on the internet, where the speed of information spreading is significant. Therefore, it is expected that there should be no significant differences among the individual exchanges concerning the same asset being traded. Prices should quickly reach comparable values on all stock exchanges, and they should return to equilibrium in a relative time frame. Hence, the investors, while making decisions on the selection of a cryptocurrency market, should be guided primarily by the exchange security considerations, its flexibility, availability of a product offer, and costs of order processing. The work aims to check whether virtual currency exchanges differ from each other in the context of directional movement, both in an upward and downward trend. To achieve the objective of the paper, we used Directional Movement Index, supported by the Directional Indicators, to compare the distribution of the strength of the directional movement across three different cryptocurrency exchanges (Bitstamp, Coinbase, Kraken) within the up and the downward price movement phase. The comparison is made based on the results of the non-parametrical tests such as Wilcoxon test, Hodges Lehmann test, Ansari-Bradley test, and Conover test. The results show that theoretically, the choice of a cryptocurrency exchange in an upward trend will cause no significant difference for an investor and its strategy. However, the choice of a stock exchange in a downward trend may have a substantial impact on the rates of return.

Keywords: *Volatility; Bitcoin; Directional Movement; DMI; ADX; Distribution.*

Introduction

The economics of the cryptocurrency market is problematic, and, thus still, unexplored. The followers of cryptocurrencies stress many advantages like anonymity, lack of control, independence, versatility, as well as immense implementation potential. Some partisans perceive in cryptocurrencies, especially in bitcoin a successor of a global currency like the US Dollar. The opponents use almost the same arguments against cryptocurrencies. The market for cryptocurrencies is organized in a specific way. There is not one cryptocurrency market or exchange, where all cryptocurrencies are traded, but there are over 200 different active exchanges. Some of them allow to exchange cryptocurrencies to the most popular fiat currencies, and some of them are dedicated to exchange cryptocurrencies to other cryptocurrencies. The cryptocurrency market is not subject to such a restrictive controls and legal restrictions as traditional financial markets, which in combination with traded assets class means that investors are more likely not only to lose their assets due to hacker attacks on crypto exchanges but are also sensitive to negative information about cryptocurrencies and legal attempts to limit their trade ((FSB, 2018)).

Crypto-markets operate primarily on the internet, in a mass medium to which it is easy and almost no-cost access, where the speed of information spreading is significant. Therefore, there should be no significant differences between the individual exchanges in relation to the same asset being traded. Prices should quickly reach comparable level on all stock exchanges and return to equilibrium in a comparable time frame. Therefore, the potential investors and participants of the cryptocurrency markets when making decisions on the selection of exchange should be guided primarily by the exchange security considerations, its flexibility, availability of a product offer and costs of order processing. The verity of exchanges and traded cryptocurrencies, unrestricted information access, high speed of information processing and relative low transaction costs can be a good starting point for meeting the prerequisites of market efficiency and in the future, it may be a fulfillment of the hypothesis of an effective market (EMH). (Fama, 1970) assumed that the current market prices incorporate at any time all available information, which implies, that the future prices cannot be foreseen, based on the past prices, hence the abnormal returns cannot be achieved. Three forms of EMH are being distinguish (Jensen, 1978; Naseer & Tariq, 2015; Plastun *et al.*, 2019):

1. The weak form: the current prices incorporate all historical data, hence it is impossible to predict the future market development and receive the abnormal returns based on the technical trend analysis.

2. The semi-strong form: the current prices incorporate all historical and public information, such as dividend announcements, public news, political events, therefore the fundamental analysis is inefficient

3. The strong form: the current prices incorporate complete knowledge about the traded asses including historical, public and private information

There is an extensive amount of papers trying to analyze the EMH from the various perspectives and referring to different markets. The received results are not homogeneous. While analyzing different forms of efficiency, the most authors support the week efficiency form, e.g. (Alexander, 1961a, 1961b; Fama & Blume, 1966; Granger, 1975; Hawawini, 1984; Fama E. , Efficient Capital Markets II, 1991; Lo, 1997), before the semi-strong form, e.g. (Hadi, 2006; Dhar & Chhaochharia, 2008; Mackey & Bacon, 2017). However many authors reported the contradictory or mixed results, e.g. (Hamid *et al.,* 2010) exanimated the Asia Pacific markets and concluded, that the monthly prices don't follow a random walk and arbitrage across this markets is possible. Dahel & Laabas (1999) claimed that EMH is valid for the Kuweit, but invalid for Bahrain, Saudi Arabia and Oman within the years 1994–1998. Worthington & Higgs (2004) compered 20 European countries (16 developed and 4 emerging economies). They concluded, that only five developed countries (Germany, Ireland, Portugal, Sweden, the United Kingdom) follow random walk in the strict sense and other five (France, Finland, Netherlands, Norway, Spain) follow the random walk hypothesis. Among emerging economies only Hungary fulfills the presumption of the week form of efficiency. Joseph et al. (2017) didn't support the semi-strong form of EMH based on research conducted over 40 companies listed on the Bahrain Stock Exchange.

In the extensive literature on issues related to virtual currencies, four main trends of interest can be distinguished: considerations of a general nature, e.g., (Rogojanu & Badea, 2015; Liu *et al.,* 2015; Gandal *et al.,* 2018; Jagwani, 2015; Dwyer, 2015; Urquhart, 2017; Corbet *et al.,* 2018; Garrat & Wallace, 2018). Technical studies focused mainly on issues related to acquisition (mining), trade and broadly understood security, e.g., (Badev & Chen, 2014; Ziegeldorf *et al.,* 2018; Biryukov & Tikhomirov, 2019; Luther & Olson, 2015; Alshamsi & Andras, 2019; Szetela *et al.,* 2016). Considerations regarding legal and tax regulations as well as potential and possible solutions that could regulate the functioning of cryptocurrencies in the financial space, e.g. (Plassaras, 2013; Mandjee, 2015; Bryans, 2014; Campbell-Verduyn, 2018). The largest group are studies on the use of quantitative methods, which are predominantly focused on the analysis of volatility, e.g., (Haubo Dyhrberg, 2016a, 2016b), (Kiss *et al.,* 2017; Muharam *et al.,* 2019) applied asymmetric GARCH and concluded that bitcoin bear resemblance to a currency like the US dollar, as well as a commodity like Gold, thus can be useful for heading, and supportive for portfolio management. Salim et al. (2018) came to different conclusions after investigated long-range memory in Bitcoin market volatility using the FIGARCH model. They noticed that the volatility of the seven bitcoin markets is random, thus in their opinion, they can't be used for heading purposes. Bouoiyour & Selmi (2016) applying Component with multiple threshold-GARCH and Asymmetric-power GARCH models showed that bitcoins' price is sensitive to negative shocks and still exhibits features of immature markets, despite that the volatility is declining compared to the period before 2015. Koutmos (2018) show using the VAR model that there are linkages between Bitcoin returns and transaction activity. The Technical analysis is rarely used in bitcoin analysis, e.g. Huang et al. (2019) used 132 technical indicators coming from the five different groups (overlap studies indicators, momentum indicators, cycle indicators, volatility indicators, and pattern recognition indicators) to investigate the predictability of future bitcoins price range. Some authors examine trading strategies on cryptocurrencies e.g., (Detzel *et al.,* 2018; Zbikowski, 2016; Feng *et al.,* 2018; Czaplinski & Nazmutdinova, 2019; Hudson & Urquhart, 2019).

Researchers while analyzing cryptocurrencies seems to omit the fact, that there are dozens of active cryptocurrency exchanges, which differ in terms of traded assets, volume, scope, fees etc. The multiplicity of exchanges causes different quotation of the same asset among different exchanges, which affects the results of analyzes based on these assets. Only few authors have compared results among different exchanges, e.g. Pieters & Vivanco (2017) claimed that the bitcoins' price varies among exchanges. Brandvolt et al. (2015) compared investigated 7 crypto-exchanges in the context of price discovery. They have also received not homogeneous results among exchanges.

Not many papers are dedicated to the research on efficiency of cryptocurrency markets, e.g., Brauneis & Mestel (2018) concluded, that bitcoin is the most efficient cryptocurrency and its efficiency is positively related to its liquidity. Demir et al. (2018) claimed that economic policy uncertainty index has the predictive power on bitcoin, which contradict the EMH. Based on the data between 2013 and 2016 Urquhart (2016) concluded that bitcoin market is inefficient, but it tends to efficiency. Nadarajah & Chu (2017) and Bariviera (2017) bitcoin doesn't support the EMH. Beside the high volatility which is distinctive for bitcoin and which, according to Shiller (1981), is a denial of the hypothesis of the efficient markets, cryptocurrencies are also characterized by the informed trading (Feng *et al.*, 2018), the price clustering (Urquhart, 2017), and the speculative bubbles (Cheah & Fry, 2015; Corbet *et al.*, 2017).

In the current literature bitcoins' markets are analyzed in the context of its volatility, security, forecasting ability, but little or even no attention was paid to present bitcoin's variability in the context of technical analysis. This paper contributes to the current research by implying the technical analysis, by using the Directional Movement Index, supported by the Directional Indicators, to compare the distribution of the strength of the directional movement across three different cryptocurrency exchanges (Bitstamp, Coinbase, Kraken) within the up and the downward price movement. The results show whether the choice of the exchange can be valuable in the context of the chosen trading strategy. The potential differences among exchanges can be seen as bitcoins' market inefficiency and space for an arbitrage.

Methodology

As a basis for our research, we used an Average Directional Movement Index (ADX), which was constructed by Wilder Jr. (1978) and described in a book "New Concepts in Technical Trading Systems". This indicator contains some advantages, which we see as desirable for cryptocurrencies. ADX was designed to support commodity trading technically, but it can also be used for financial assets. It was designed to manage market volatility based on a price range. Average Directional Movement Index, together with the two supportive lines, a positive and a negative directional movement line, can be used to detect and measure the strength and a direction of a trend. Its primer application is to decide whether to take a long or short position on trend markets. In our research, we will not discuss possible trading strategies, resulting from the signals produced by the ADX, but we will use it, to detect possible differences in trends magnitude across markets.

Average Directional Movement Index is a complex tool constructed on the basis of other indicators like Directional Movement (DM), Average True Rate (ATR), Directional Indicator (DI), True Directional Movement (TDM). Wilder, in his book described in details steps which are needed to be taken to calculate ADX. First of all, it is necessary to calculate plus and minus Directional Movement (DM) as well as True Range (TR), which are the basis for other indicators, such as plus and minus Directional Indicator, from which ADX results directly. A detailed description of the procedure in calculating ADX is presented below.

TR is understood as the largest value of the difference between either today's high and today's low, or an absolute value of today's high and yesterday's close, or an absolute value of today's low and yesterday's close. Formally a true rate is describes in eq. 1:

$$TR_t = max\begin{cases} high_t - low_t \\ |high_t - close_{t-1}| \\ |low_t - close_{t-1}| \end{cases} \quad (1)$$

The comparison of differences between two consecutive lows with the difference between their respective highs indicates the directional movement. The plus DM (+DM) is a situation when current high minus the prior high is greater than the previous low minus the current low (see eq. 2). The opposite relationship points at the minus DM (-DM). The -DM equals, therefore, current high minus the prior high and the -DM equals prior low minus the current low (see eq. 3). The Directional Movement is by assumption positive, therefore in the case when an indicator is a negative number then is set to zero. Formally:

$$+DM_t = \max\{0;\ high_t - high_{t-1}\} \quad (2)$$

$$-DM_t = \max\{0;\ low_{t-1} - low_t\} \quad (3)$$

When both -DM and +DM equals zero, then its points at an inside day, when no directional movement is observed. In order to capture a real tendency in the trend change, it is necessary to introduce a smoothing parameter. In our work, we follow the Wilders' original assumptions, and we will average indicators over 14 days. In notation, we use 14 in a low index to signal the number of days over which the smoothing will be performed.

The initial value of a smoothed true range (TR_{t_0}) is a simple sum of a TR over a number of days (see eq. 4). The same rule applies to the initial values of Directional Movement (DM_{t_0}) (see eq. 6).

$$TR_{14(t_0)} = \sum_{i=1}^{14} TR_i \quad (4)$$

The values of a smoothed TR for the next periods are calculated as a sum of thirteen times the previous value of TR and the value of a true range of a current period divided by fourteen (see eq. 5).

$$TR_{14(t_i)} = TR_{14(t_{i-1})} - \frac{TR_{14(t_{i-1})}}{14} + TR_{t_i} \quad (5)$$

This smoothing technique has the application to other smoothed indicators used in the paper and are calculated as in eq. 7-10:

$$DM_{14(t_0)} = \sum_{i=1}^{14} DM_i \quad (6)$$

$$+DM_{14(t_1)} = +DM_{14(t_0)} - \frac{+DM_{14(t_0)}}{14} + \ +DM_{t_1} \quad (7)$$

$$+DM_{14(t_i)} = +DM_{14(t_{i-1})} - \frac{+DM_{14(t_{i-1})}}{14} + \ +DM_{t_i} \quad (8)$$

$$-DM_{14(t_1)} = -DM_{14(t_0)} - \frac{-DM_{14(t_0)}}{14} + \ -DM_{t_1} \quad (9)$$

$$-DM_{14(t_i)} = -DM_{14(t_{i-1})} - \frac{-DM_{14(t_{i-1})}}{14} + \ -DM_{t_i} \quad (10)$$

The Directional Indicator (DI) is calculated as a quotient of smoothed plus or minus Directional Movement and smoothed True Range (see eq. 11-12), thus it reflects the percent of the true range that is up or down for the day. It is important to notice that on a specific day, only one from both states finds application +DI or -DI, as it is impossible to have directional movements in opposites directions on one day.

$$+DI_{14(t)} = \frac{+DM_{14(t)}}{TR_{14(t)}} \cdot 100\% \quad (11)$$

$$-DI_{14(t)} = \frac{-DM_{14(t)}}{TR_{14(t)}} \cdot 100\% \quad (12)$$

True Directional Movement (TDM) is calculated as a difference between plus Directional indicator and minus Directional indicator (see eq. 13). It gives information of a part of the price movement, which is moving non directional.

$$TDM_t = +DI_{14(t)} - -DI_{14(t)} \quad (13)$$

Directional Movement Index (DX) is a quotient of a True Directional Movement and a sum of a plus Directional Indicator and a minus Directional Indicator (see eq. 14).

$$DX_t = \frac{TDM_t}{+DI_{14(t)} + -DI_{14(t)}} \cdot 100\% \quad (14)$$

After smoothing the Directional Movement Index over 14 days, we received an Average Directional Movement Index (ADX). The applied technic is analogous to the above already described (see eq.15 - 16).

$$ADX_{14(t_0)} = \sum_{i=1}^{14} ADX_i \quad (15)$$

$$ADX_{(t_i)} = \frac{13 \times ADX_{(t_{i-1})} + DX_{t_i}}{14} \quad (16)$$

ADX finds its application in different trading strategies. It is accepted that if ADX is above 25, then prices follow a strong trend. Plus and Minus Directional Indicators are used as a support lines for ADX. Both lines are an indicator of a direction of the directional movement and complement the ADX indicator, which reflects the strength of the directional movement, hence it is important to interpret both indicators, ADX and DI, together. If the directional movement is up, than +DI > -DI. If the direction is down, than +DI < -DI.

Empirical Results

In our analysis, we compared the distribution of strength of the directional movement across different exchanges (Bitstamp [Bitstp], Coinbase [CB], Kraken[Kr]) within the up and the downward price movement phase. The investigated sample covers the period from 01.01.2015 to 25.06.2019. The data was smoothed over 14 days, which is in line with Wilders' original assumptions described in his book.

The significant differences are visible between the upward trend and the downward trend phase, both in the entire analyzed period (see table 1) and in the phase of the strong directional movement (see table 2). In both situations, the upward trend is dominated by the downward trend. Both the length and number of periods of the downward trend differ significantly from the upward price movement. It should be remembered that negative information, concerning both cryptocurrencies and crypto markets, appear systematically, which in combination with the large variability of crypto-assets and situations, in which money deposited on stock exchanges are being stolen, causes a significant sense of uncertainty among investors and greater sensitivity to negative information, but also fluctuations in rates, than is the case with traditional assets.

Table 1

Basic Statistics for ADX in Up (1) and Down (2) Trend Across three Crypto Exchanges (Coinbase, Bitstamp, Kraken)

Trend	Exchange	ADX Means	ADX N	ADX Std.Dev.	ADX Minimum	ADX Maximum	ADX Q25	ADX Median	ADX Q75
1	Coinbase	11,0%	529	4,3%	4,3%	28,9%	8,0%	10,1%	12,8%
	Bitstamp	11,0%	590	5,8%	4,1%	56,2%	7,6%	9,6%	12,6%
	Kraken	10,5%	625	3,9%	3,2%	22,3%	7,4%	9,5%	13,0%
2	Coinbase	14,7%	1070	9,0%	3,8%	48,8%	7,6%	12,3%	18,6%
	Bitstamp	12,5%	1009	7,0%	3,8%	34,0%	7,1%	10,3%	16,4%
	Kraken	12,5%	974	6,0%	2,9%	35,3%	7,9%	11,0%	15,9%
All Groups		12,4%	4797	6,8%	2,9%	56,2%	7,6%	10,5%	15,4%

Table 2

Basic Statistics for ADX in Up (1) and Down (2) Trend Across three Crypto Exchanges (Coinbase, Bitstamp, Kraken) Within the Strong Directional Movement (ADX>25)

Trend	Exchange	ADX Means	ADX N	ADX Std.Dev.	ADX Variance	ADX Minimum	ADX Maximum	ADX Q25	ADX Median	ADX Q75
1	Coinbase	26,9%	7	1,2%	0,0%	25,1%	28,9%	25,8%	27,0%	27,7%
	Bitstamp	38,1%	14	9,7%	0,9%	25,5%	56,2%	30,7%	36,2%	45,5%
	Kraken		0							
2	Coinbase	33,5%	133	6,4%	0,4%	25,0%	48,8%	28,9%	32,3%	36,0%
	Bitstamp	28,8%	84	2,5%	0,1%	25,0%	34,0%	26,9%	28,2%	30,6%
	Kraken	29,6%	39	3,3%	0,1%	25,2%	35,3%	27,0%	28,6%	32,7%
All Groups		31,6%	277	5,9%	0,4%	25,0%	56,2%	27,3%	30,2%	33,8%

The ADX distribution (see Figure 1) accompanied with the results of the Kolmogorov Smirnov Normality test (see Table 3), which assumes Normality under H0, point at the statistically significant deviation from the normal distribution (p>0.05), therefore in further research the non-parametric test will be applied.

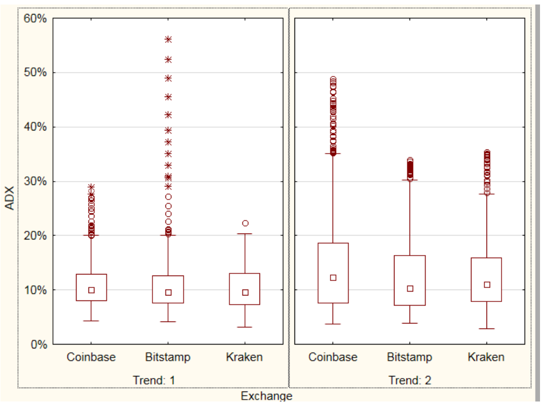

Figure 1. ADX Distribution in Upward (trend 1) and Downward (trend 2) Price Movement

Table 3

Kolmogorov-Smirnov Tests for Normality for the Full Sample, Up and Down Trend

	Full	p	Up	p	Down	p
Coinbase	0,134	<0.010	0,102	<0.010	0,127	<0.010
Bitstamp	0,136	<0.010	0,147	<0.010	0,132	<0.010
Okcoin	0,235	<0.010	0,274	<0.010	0,172	<0.010
Kraken	0,114	<0.010	0,110	<0.010	0,128	<0.010

We perform distribution analysis of ADX covering three potential scenarios. In the first case, using the Wilcoxon test, we check whether the rank distribution does not differ from each other in terms of the central measure, but may vary in terms of displacement. Assumption of the comparability of the value of the central measure but with varying degrees of data spread around the mean value will be tested using the Ansari-Bradley test. The third shift occurs when both the measures of central tendencies and the scale parameter differ, which will be checked by the Conover test. Compilation of such tests allows formulating more general conclusions resulting from possible similarities of cryptocurrency markets in terms of the strength of the directional movement. The technical details concerning above mentioned test are to be found in Sheskin (2007), Daniel (1990), Conover (1999), Hollander & Wolfe (1999).

The results of an application of a Wilcoxon test, Ansari-Bradley test, and Conover test on ADX in terms of location, shift, and dispersion respectively are summarized in Table 4. We tested the behavior of the index in its various phases. The two most natural are the upward and downward trend. Additionally, we examined whether the index behavior changes in the period with a strong trend, a situation where the ADX level exceeds 25.

Table 4

Comparison of Distribution Test Results for Cryptocurrency Markets: Bitstamp, Coinbase, Kraken

p-Value		Kruskal Wallis	Ansari Bradley	Conover
	UP	**0.1568**	**0.1184**	**0.4827**
	Down	<.0001	<.0001	<.0001
ADX>25	UP	0.0022	**0.5193**	0.0036
	Down	<.0001	0.0069	<.0001

There are visible differences in the results of the analyzed tests in the bullish market compared to the bearish market phase. They are also evident when comparing the period of strong directional movement phase within the total sample. The results show that in the upward trend, for the full sample, the p-Values were unambiguously above the significance level, hence there is no basis for rejection of the Null Hypothesis. Therefore, it can be assumed that the distributions of the directional index do not differ significantly among exchanges in the bearish market. In the strong trend phase, when ADX > 25, only in case of the Ansari Bradley test, the Null Hypothesis was not rejected. Therefor it may be assumed that, there are no significant differences in the distribution of ADX in value of the central measure but with varying degrees of data spread around the mean. The obtained results, however, do not constitute a confirmation of the assumption about the similarity of distributions, due to a small sample, which occurred for the strong directional movement phase. Considering the downward trend, for both samples, for all tests we performed, the p-values were significantly lower than the assumed level of significance, which points at the necessity of the rejection of the Null Hypothesis, assuming the distribution function are different in terms of central measure, shift in mean and dispersion in both analyzed periods. Hence the choose of the exchange by the investors during the bearish phase can cause differences in achieved returns, which in turn can affect the choice of investment strategy.

In our analysis, we performed the additional analysis, to check whether the results hold in the pair comparisons (see Table 5). The received results for the upward trend are comparable with the above presented results. The only difference is visible while comparing Coinbase and Kraken. In this case the Null Hypothesis of the Ansari Bradley should be rejected, which points ate the differences in the distribution of the trend strength in terms of the central measure. The comparison in pairs allows for applying the Hodges Lehmann test, which helps to determine the median unbiased estimate value of the shift and the associated confidence interval. The estimated shifts for the full sample in the upward trend are very low, what in the context of other tests results confirms the resemblance of the ADX distributions among all three exchanges.

Table 5

Comparison of Distribution of the Test Results in the Upward Trend, in the Bilateral Comparison

	Kruskal Wallis	Ansari Bradley	Conover	Hodges Lehmann	95% Confidence Limits*		Asymptotic Standard Error*
CB vs. Bitstp	0.1386	0.2384	0.3395	0.0032	-0.0010	0.0076	0.0022
CB vs. Kr	0.0664	**0.0336**	0.1962	0.0040	-0.0003	0.0083	0.0022
Bitstp vs. Kr	0.7005	0.2317	0.7199	0.0008	-0.0033	0.0049	0.0021

Notation: CB – Coinbase, Bitstp – Bitstamp, Kr - Kraken
** CI and Asymptotic Standard Error for Hodges Lehmann Test*

There are some differences in the downward phase while comparing crypto markets individually, i.e. Coinbase with Bitstamp and Bitstamp with Kraken, (see Table 6). In the first case, the Ansari Bradley test p-values are higher than the level of significance, which points at no significant differences in ADX distribution, in the context of central measure. The p-value close to the significance level was obtained by Kruskal Wallis test in the comparison of the Bitstamp and Kraken. In this case, it can be concluded that there may be similarities in rank distribution in terms of the central measure, but may vary in terms of displacement, which according to the Hodges Lehmann test equals 0.0046.

Table 6

Comparison of Distribution of the Test Results in the Downward Trend, in the Bilateral Comparison

	Kruskal Wallis	Ansari Bradley	Conover	Hodges Lehmann	95% Confidence Limits*		Asymptotic Standard Error*
CB vs. Bitstp	<0.0001	**0.2740**	<0.0001	-0.0126	-0.0176	-0.0077	0.0025
CB vs. Kr	0.0005	<0.0001	<0.0001	-0.0088	-0.0140	-0.0038	-0.0026
Bitstp vs. Kr	**0.0454**	<0.0001	<0.0001	**0.0046**	0.0001	0.0090	0.0023

The bilateral analysis of the strong downward trend (see Table 7) is also partially inconsistent with the results presented above for the full sample (see Table 4). Generally test confirmed dissimilarities in the ADX distribution among exchanges except for the comparison of the Coinbase and Kraken, in which case the Ansari Bradley was not able to reject the Null Hypothesis. Thus it can be assumed that the ADX for these two exchanges comes from similar distributions. While comparing Bitstamp and Kraken, the high p-value of the Kruskall Wallis test points at the similarities in the rank distribution in terms of the central measure, but it varys in terms of displacement, which according to the Hodges Lehmann test equals 0.0045.

Table 7

Comparison of Distribution Test Results for a Strong Downward in the Bilateral Comparison: Coinbase-Bitstamp, Coinbase-Kraken, Bitstamp-Kraken in the Downward Trend

	Kruskal Wallis	Ansari Bradley	Conover	Hodges Lehmann	95% Confidence Limits*		Asymptotic Standard Error*
CB vs. Bitstp	<0.0001	0.0117	<0.0001	-0.0359	-0.0496	-0.0238	0.0066
CB vs. Kr	0.0009	**0.4317**	0.0004	-0.0308	-0.0496	-0.0117	0.0097
Bitstp vs. Kr	**0.4180**	0.0179	0.0026	**0.0045**	-0.0057	-0.0165	0.0057

Conclusions

Information on the distribution of the directional movement index, which indicates the strength of the directional movement on analyzed exchanges is vital for potential investors, who are wishing to shape their investment strategies in cryptocurrencies consciously. According to the Directional Movement System, when $+DI_{14}$ crosses $-DI_{14}$, than the long position should be taken. When in contrary $-DI_{14}$ crosses $+DI_{14}$ than the short position should be an advantage. Wilders investing strategy is profitable when ADX reaches values above 25. The results show that the aware investors should carefully, in line with the planned investment strategy, choose the cryptocurrency market. While, theoretically, the choice of a cryptocurrency exchange in an upward trend will perform no significant difference for an investor and its strategy, however, the choice of a cryptocurrency exchange in a downward trend may have a considerable impact on the rates of return. There are statistically significant differences in the strength level of ADX among exchanges. The highest ADX values are reported by Coinbase ca. 49%. The other two exchanges generate values around 35%. This indicates that on the Coinbase the down trend is much stronger than on the other two markets. Also, the number of days, where the downward trend was observed varies among the exchanges. In a phase, when the strong trend was observed, only the Coinbase had the longest down run (in total over 130 days). These results show that buying the dips strategy should be the most profitable on Coinbase market. There is certainly no single, correct explanation for the causes of this phenomenon. It can be presumed that stock exchanges with shorter downturns have a more stable position among investors, and thus return to balance faster after negative information reaching the market that negatively affects bitcoin quotations or has less liquidity and even insignificant transaction may cause a faster price increase. Our results also show that the cryptocurrency market is far to meet the assumption of the effective market hypothesis and is still susceptible to arbitrage.

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