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Month of the year effect in the cryptocurrency market and portfolio management

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Purpose – to investigate the Month of the year effect in the cryptocurrency market.

Design/Method/Research Approach. A number of parametric and non-parametric technics are used, including average analysis, Student's t-test, ANOVA, Kruskal-Wallis statistic test, and regression analysis with the use of dummy variables.

Findings. In general (case of overall testing – when all data is analyzed at once) calendar the Month of the Year Effect is not present in the cryptocurrency market. But results of separate testing (data from the period "suspicious for being anomaly" with all the rest of the data, except the values which belong to the "anomaly data set") shows that July and August returns are much lower than returns on other months. These are the worst months to buy Bitcoins.

Theoretical implications. Results of this paper claim to find some holes in the efficiency of the cryptocurrency market, which can be exploited. This contradicts the Efficient Market Hypothesis.

Practical implications. Results of this paper claim to find some holes in the efficiency of the cryptocurrency market, which can be exploited. This provides opportunities for effective portfolio management in the cryptocurrency market.

Originality/Value. This paper is the first to explore Month of the Year Effect in the cryptocurrency market.

Paper type – empirical.

Keywords: Calendar Anomalies; seasonal effects; Efficient Market Hypothesis; Cryptocurrency; Bitcoin.

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Ефект місяця року на ринку криптовалют і портфельний менеджмент

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Мета роботи – дослідити ефект місяця року на ринку криптовалют.

Дизайн/Метод/Підхід дослідження. Застосовано ряд параметричних і непараметричних методів, у тому числі аналіз середніх, t-критерій Стьюдента, ANOVA, статистичний тест Крускала-Уолліса, регресійний аналіз із використанням фіктивних змінних.

Результати дослідження. В цілому (в разі загального тестування: всі дані проаналізовано одночасно) ефект місяця року не присутній на ринку криптовалют. Але результати окремого тестування (дані за період порівняно з усіма іншими даними, за винятком значень, які відносять до цього періоду), показали зміну цін на біткоіни в липні і в серпні набагато нижчу, ніж за інші місяці. Це найгірші місяці для покупки біткоінів.

Теоретичне значення дослідження. Згідно з результатами даного дослідження з'ясовано, що на ринку криптовалют присутні «провали» в ефективності, які можна застосувати з метою отримання надприбутків. Це суперечить гіпотезі ефективного ринку.

Практичне значення дослідження. Згідно з результатами даного дослідження, такі «провали» в ефективності можна застосувати під час побудови і оптимізації торгових стратегій. Це надає можливості для більш ефективного управління інвестиційним портфелем на ринку криптовалют.

Оригінальність/Цінність/Наукова новизна дослідження. Ефект місяця року на ринку криптовалют до цього не розглядався в науковій літературі.

Тип статті – емпіричний.

Ключові слова: календарні аномалії; сезонні ефекти; Гіпотеза ефективного ринку; криптовалюти; біткоін.

Автори вдячно визнають фінансову підтримку Міністерства освіти і науки України (0117U003936).

Эффект месяца года на рынке криптовалют и портфельный менеджмент

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Цель работы – исследовать эффект месяца года на рынке криптовалют.

Дизайн/Метод/Подход исследования. Применен ряд параметрических и непараметрических методов, в том числе анализ средних, t-критерий Стьюдента, ANOVA, статистический тест Крускала-Уоллиса, регрессионный анализ с использованием фиктивных переменных.

Результаты исследования. В целом (в случае общего тестирования: все данные анализируют одновременно) эффект месяца года не присутствует на рынке криптовалют. Но результаты отдельного тестирования (данные за период сравнены со всеми остальными данными, за исключением значений, которые отнесены к этому периоду), показали изменение цен на биткоины в июле и августе намного ниже, чем за другие месяцы. Это худшие месяцы для покупки биткоина.

Теоретическое значение исследования. Согласно результатам данного исследования выявлено, что на рынке криптовалют существуют «провалы» в эффективности, которые можно использовать с целью получения сверхприбыли. Это противоречит гипотезе эффективного рынка.

Практическое значение исследования. Согласно результатам данного исследования, такие «провалы» в эффективности можно использовать при построении и оптимизации торговых стратегий. Это предоставляет возможности для более эффективного управления инвестиционным портфелем на рынке криптовалют.

Оригинальность/Ценность/Научная новизна исследования. Эффект месяца года на рынке криптовалют ранее не рассматривался в научной литературе.

Тип статьи – эмпирический.

Ключевые слова: календарные аномалии; сезонные эффекты; Гипотеза эффективного рынка; криптовалюты; биткоин.

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1. Introduction

Calendar anomalies (the Day of the Week Effect, the Turn of the Month Effect, the Month of the Year Effect, the January Effect, the Holiday Effect, the Halloween Effect etc.) is something that shouldn't exist according to the Efficient Market Hypothesis (EMH, *see Fama, 1965*). However there are many evidences that they exist in real life (*Fields, 1931; Cross, 1973; Jensen, 1978; French, 1980; Bildik, 2004; Mynhardt & Plastun, 2013; many others*).

The Month of the Year Effect (returns vary for different months in a year) is one of the most discussed calendar anomalies for the case of stock market (*Gultekin & Gultekin, 1983; Lakonishok & Smidt, 1988; Wilson & Jones, 1993; Wachtel, 1942; Giovanis, 2008; Zhang and Jacobsen, 2012; Compton et al, 2013; Caporale & Plastun, 2017*).

However to date no study has analysed such issues in the context of the cryptocurrency market.

Cryptocurrency market is rather new and might still be relatively inefficient and it might be a good basis for the Month of the Year Effect existence.

We focus in particular on the Month of the Year Effect, and apply a variety of statistical methods (average analysis, Student's t-test, ANOVA, the Kruskal-Wallis, and regression analysis with dummy variables) to examine whether or not it exists in the cryptocurrency market. The object of analysis is Bitcoin monthly returns over the period 2013-2019.

The paper is structured as follows: Section 2 briefly reviews the literature on the Month of the Year Effect; Section 3 outlines the methodology; Section 4 presents the empirical results; Section 5 offers some concluding remarks.

2. Theoretical background

Calendar anomalies (calendar effects, seasonal effects) are anomalies in returns, which depend on the calendar. The most important calendar anomalies are Day of the Week Effect; Turn of the Month Effect; Turn of the Year Effect; Month of the Year Effect; January Effect; Holiday Effect; Halloween Effect. According to the Month of the Year Effect returns vary for different months in a year.

For example, there are evidences that January show higher returns than any other month of the year (*Rozeff and Kinney, 1976; Wachtel, 1942*).

One of the calendar anomalies based from the "month of the Year Effect" family is so called Mark Twain effect. It claims that stock returns in October are lower than in other months.

Bildik (*2004*) use Turkish stock market as an object of analysis and also find that calendar anomalies existed in stock returns and trading volume.

Giovanis (*2008*) using GARCH estimation tested the month of the year effect using data from Athens Stock Exchange Market. They found evidences in favor of the January effect.

Tangjitprom (*2011*) analyzed Thai stock market (SET index) during 1988 to 2009. Using multiple regression techniques with dummy variables they show that returns are abnormally high during December and January.

Stoica and Diaconașu (*2011*) explored Central Europe stock markets over the period 2000 - 2010 and in the majority of the cases find evidences in favor of the existence of the month of the year effect and the existence of the January effect.

Compton et al (*2013*) analyzing monthly seasonality in the Russian stock market over the period 2000-2010 find strong evidence of a persistent monthly pattern (but no January effect).

Borowski (*2015*) analyzed Month of the Year Effect in the commodity market and provide evidences in favor of this anomaly.

Contrary to previous results *Ali et al* (*2009*) who analyzed Malaysian stock index over the period from 1994 to 2004 using GARCH (1 1)-M model can't find any clear pattern of January effect. Similar results are obtained by *Alshimmiri* (*2011*) for the case of Kuwait Stock Exchange over the period 1984-2000: no January effect was detected.

But at the same time returns during summer months (May-September) tend to be significantly higher than returns during other months of the year (October-April).

Wong et al (*2006*) based on Singapore stock market data over the period 1993-2005 reveals that the Month of the Year Effect has largely disappeared.

Silva (*2010*) explored Portuguese stock market during 1998-2008 and also find no evidences in favor or the January anomaly.

As can be seen the evidences are mixed. Possible explanation is market evolution – anomalies are fading in time (*Plastun et al., 2019*).

The cryptocurrency market represents a particularly interesting case being rather new, relatively unexplored and at the same time extremely vulnerable to anomalies, given its high volatility relative to the FOREX, stock and commodity markets etc. (*Cheung et al., 2015; Urquhart, 2016; Aalborg et al., 2019*).

Only few market anomalies are already discussed for the case of the cryptocurrency market. For example *Caporale and Plastun* (*2019*) explore overreactions in the cryptocurrency market and find evidence of price patterns after overreactions. *Chevapatrakul and Mascia* (*2019*) using the quantile autoregressive model show that days with extremely negative returns are likely to be followed by periods characterised by negative returns and weekly positive returns as Bitcoin prices continue to rise.

As for the calendar effects, *Kurihara and Fukushima* (*2017*) and *Caporale and Plastun* (*2018*) explored the day of the week effect in the cryptocurrency market and find evidences in its favor. But the Month of the Year Effect is still unexplored.

3. Problem statement

The purpose of this paper is to investigate the Month of the year effect in the cryptocurrency market.

4. Methods and Data

We use monthly data for Bitcoin. The sample covers the period from June 2010 (the first available observation) to the end May 2019.

The data source is *CoinMarketCap* (*https://coinmarketcap.com/coins/*). *CoinMarketCap* provides volume-weighted average prices reported for each crypto exchange (for example, BitCoin prices are the average of those from 400 markets). As the result this is the most reliable source of information about prices in the cryptocurrency market.

We use Bitcoin data because this cryptocurrency has the highest market capitalisation and longest span of data (*see Table 1*).

Table 1

Top cryptocurrencies by capitalisation (01.05.2019)*

№	Name	Market Cap	Price	Circulating Supply	Data start from
1	Bitcoin	$148 657 197 170	$8 267,84	17 980 175 BTC	28 Apr 2013
2	Ethereum	$19 674 550 330	$182,07	108 059 235 ETH	07 Aug 2015
3	Ripple	$12 017 970 035	$0,278408	43 166 787 298 XRP	04 Aug 2013
4	Bitcoin Cash	$4 236 366 686	$234,76	18 045 263 BCH	23 Jul 2017
5	Litecoin	$3 659 603 443	$57,70	63 420 942 LTC	28 Apr 2013

*Source: compiled by Authors based on (CoinMarketCap, 2019).

To explore the Month of the Year effect the following hypotheses are tested:

Hypothesis 1 (H1): Returns are different on different months of the year.
Hypothesis 2 (H2): Month of the Year effect provides opportunities for abnormal profits generation from trading in the cryptocurrency market.

To examine whether there is a Month of the Year effect we use the following techniques:

– average analysis;
– parametric tests (Student's t-tests, ANOVA);
– non-parametric tests (Kruskal -Wallis test);
– regression analysis with dummy variables.

Returns are computed as follows:

$$R_i = \left(\frac{Close_i}{Close_{i-1}} - 1\right) \times 100\%, \quad (1)$$

where R_i – returns on the *i-th* day in %;
$Close_i$ – close price on the *i-th* day;
$Close_{i-1}$ – close price on the *(i-1)-th* day.

Average analysis provides preliminary evidence on whether there are differences between returns on different months of the year.

A number of statistical tests, both parametric (in the case of normally distributed data) and non-parametric (in the case of non-normal distributions); they include Student's t-tests, ANOVA analysis, and Kruskal-Wallis tests are carried out for further evidences in favor or against differences between returns on different months of the year.

We test Null Hypothesis (*H0*): analyzed data sets (returns of specific month) belong to the same general population (the whole data set). In case of H0 rejection we get evidence in favor of anomaly. In other case (*H0* can not be rejected) no anomaly is observed.

We use Student's t-tests, ANOVA and Kruskal -Wallis test in two variants:

– overall testing – when all data is analyzed at once;
– separate testing – we compare data from the period "suspicious for being anomaly" (month of interest) with all the rest of the data, except the values which belong to the "anomaly data set" (month of interest returns).

We also run multiple regressions including a dummy variable to identify certain calendar anomaly:

$$Y_t = a_0 + a_1 D_{1t} + a_2 D_{2t} + \cdots + b_n Dn_t + \varepsilon_t, \quad (2)$$

where Y_t – return on the period t;
a_n – mean return for each month;
D_{nt} – dummy variable for each month, equal to 0 or 1. D_{nt} is 1 when mean return occurs on *n-th* month otherwise it is 0.
ε_t – random error term for month t.

The size, sign and statistical significance of the dummy coefficients provide information about possible anomalies.

4. Empirical results

Visual analysis (*Fig. 1*) gives clear signals in favor of this anomaly. Returns on March and October are 3-4 times higher than on other months. July, August and September look like the worth months for Bitcoin buyers. A "W" pattern is observed in Bitcoin monthly returns with peaks in March and October. As for the January effect and Mark Twain effect, there are no evidences of them in the Bitcoin returns.

Statistical tests show mixed results. According to t-test (*Table 2*) returns for some of the months statistically differ from the all other data. This evidences in favor of the anomaly and confirms the Month of the Year Effect.

ANOVA analysis (*Table 3*) overall does not confirm the anomaly. Overall data set analysis shows no statistically significant differences between different months and the whole data set. Nevertheless for the case of separate testing returns of August happened to be statistically different from the all other data excluding returns on August. So anomaly is only partially confirmed.

Non-parametric Kruskal-Wallis test (*Table 4*) for the case of overall data set does not confirm the anomaly. But separate testing results show the presence of statistically significant differences in returns on February, July and August which can be treated as evidence in favor of the Month of the Year Effect.

Regression analysis with dummy variables of the Month of the Year Effect finds no evidences in favor of this anomaly (*Table 5*). All the slopes are statistically insignificant (p-values are much higher than 0,05) as well as overall model (F is very low).

To summarize empirical results we form the following table (*See Table 6*).

As can be seen in general this anomaly is not observed in the cryptocurrency market (case of Bitcoin). But Bitcoin prices provide some anomalous evidences in dynamics of the July and August (abnormally lower than in other months of the year).

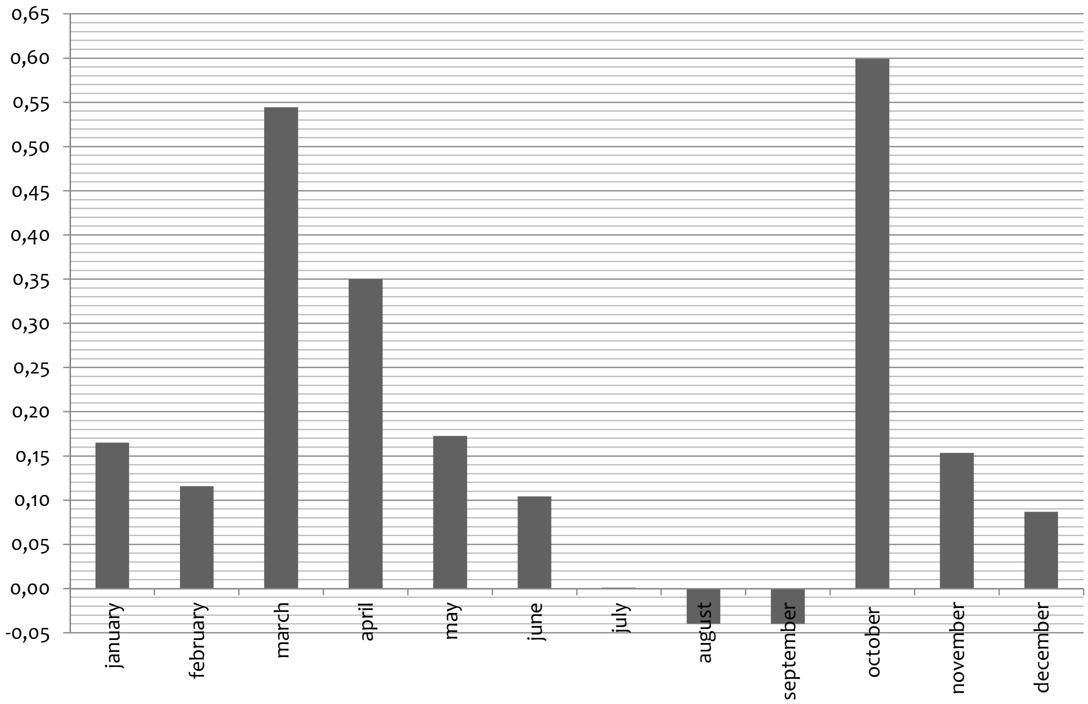

Fig. 1. Average analysis: case of Bitcoin returns*

*Source: compiled based on Author's calculations.

Table 2

T-test of the Month of the Year Effect (t-critical (p=0,95) = 2.15)*

Period	All data excluding specific month		Specific month		t-criterion	Null hypothesis	Anomaly status
	Average	Standard deviation	Average	Standard deviation			
	0,22	0,30	0,17	0,33	-0,78	Not rejected	Not confirmed
February	0,22	0,31	0,12	0,64	-0,83	Not rejected	Not confirmed
March	0,18	0,23	0,54	1,11	1,62	Not rejected	Not confirmed
April	0,20	0,27	0,35	0,53	1,38	Not rejected	Not confirmed
May	0,22	0,30	0,17	0,31	-0,71	Not rejected	Not confirmed
June	0,23	0,31	0,10	0,19	-2,90	Rejected	Confirmed
July	0,23	0,30	0,00	0,31	-3,58	Rejected	Confirmed
August	0,24	0,30	-0,04	0,17	-7,19	Rejected	Confirmed
September	0,20	0,25	-0,04	0,17	-6,58	Rejected	Confirmed
October	0,18	0,30	0,60	1,56	1,34	Not rejected	Not confirmed
November	0,22	0,31	0,15	0,30	-1,05	Not rejected	Not confirmed
December	0,23	0,28	0,09	0,35	-1,93	Not rejected	Not confirmed

*Source: compiled based on Author's calculations.

Table 3

ANOVA test of the Month of the Year Effect

Period	F	p-value	F critical	Null hypothesis	Anomaly status
Overall	0,80	0,64	1,89	Not rejected	Not confirmed
January	0,13	0,72	4,49	Not rejected	Not confirmed
February	0,21	0,65	4,49	Not rejected	Not confirmed
March	0,91	0,35	4,49	Not rejected	Not confirmed
April	0,55	0,47	4,49	Not rejected	Not confirmed
May	0,10	0,75	4,49	Not rejected	Not confirmed
June	1,06	0,32	4,49	Not rejected	Not confirmed
July	2,60	0,13	4,49	Not rejected	Not confirmed
August	5,88	0,03	4,49	Rejected	Confirmed
September	0,21	0,65	4,49	Not rejected	Not confirmed
October	0,63	0,44	4,49	Not rejected	Not confirmed
November	0,22	0,65	4,49	Not rejected	Not confirmed
December	0,87	0,37	4,49	Not rejected	Not confirmed

*Source: compiled based on Author's calculations.

Table 4

Kruskal-Wallis test of the Month of the Year Effect*

Period	Adjusted H	d.f.	P value	Critical value	Null hypothesis	Anomaly status
Overall	12,08	11	0,36	19,68	Not rejected	Not confirmed
January	0,00	1	0,96	3,84	Not rejected	Not confirmed
February	5,07	1	0,02	3,84	Rejected	Confirmed
March	0,16	1	0,69	3,84	Not rejected	Not confirmed
April	0,05	1	0,83	3,84	Not rejected	Not confirmed
May	0,05	1	0,83	3,84	Not rejected	Not confirmed
June	0,24	1	0,63	3,84	Not rejected	Not confirmed
July	4,31	1	0,04	3,84	Rejected	Confirmed
August	5,48	1	0,02	3,84	Rejected	Confirmed
September	0,05	1	0,83	3,84	Not rejected	Not confirmed
October	0,05	1	0,83	3,84	Not rejected	Not confirmed
November	0,10	1	0,76	3,84	Not rejected	Not confirmed
December	1,22	1	0,27	3,84	Not rejected	Not confirmed

*Source: compiled based on Author's calculations.

Table 5

Regression analysis with dummy variables of the Month of the Year Effect*

Parameter	Slope coefficient	p-value
January (a_0)	-0,165196	0,464480
February (a_1)	-0,020526	0,877017
March (a_2)	0,157744	0,236028
April (a_3)	0,076826	0,562771
May (a_4)	0,003030	0,981775
June (a_5)	-0,025402	0,848133
July (a_6)	-0,068313	0,606763
August (a_7)	-0,085275	0,520711
September (a_8)	0,065532	0,621468
October (a_9)	0,180435	0,175768
November (a_{10})	-0,004872	0,970697
December (a_{11})	-0,032599	0,805877
F-test	0,7965	0,643000
Multiple R	0,29	
Anomaly	not confirmed	

*Source: compiled based on Author's calculations.

Table 6

Overall results for the case of Bitcoin*

Month/Methodology	Average analysis	Student's t-test	ANOVA analysis	Kruskal -Wallis test	Regression analysis with dummies	Overall
January	-	-	-	-	-	0
February	-	-	-	+	-	1
March	+	-	-	-	-	1
April	-	-	-	-	-	0
May	-	-	-	-	-	0
June	+	+	-	-	-	2
July	+	+	-	+	-	3
August	+	+	+	+	-	4
September	-	-	-	-	-	0
October	+	-	-	-	-	1
November	-	-	-	-	-	0
December	-	-	-	-	-	0

*Source: compiled based on Author's calculations.

5. Conclusions

In this paper we have examined the Month of the Year Effect in the cryptocurrency market. To do this we have used different methodologies (average analysis, parametric tests (Student's t-tests, ANOVA), non-parametric tests (Kruskal -Wallis test) and regression analysis with dummy variables) applying to the Bitcoin monthly data over the period 2013-2019.

The following hypotheses of interest are tested. (*H1*): Returns are different on different months of the year; (*H2*): Month of the Year effect provides opportunities for abnormal profits generation from trading in the cryptocurrency market.

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