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Examining Day of the Week and Month of the Year Effects in Bitcoin and Litecoin Markets

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Abstract

Crypto currency technology works on a network that allows people to make payment all over the world without need of any intermediary. Since the development of this technology, it has get attention and price of crypto currencies has been rising fast and become very volatile. The paper examines the day of the week and month of the year effects in Bitcoin and Litecoin markets using GARCH (1,1) model. The sample period is from May 1, 2013 to December 21, 2017. Results indicated the validity of the day of the week and month of the year effects in Bitcoin and Litecoin returns. It is determined that Monday, Tuesday and Friday have significant positive effects on Bitcoin and negative Saturday effect on Litecoin returns. Also February, October and November have significant and positive effect on Bitcoin, significant and negative August effect on Litecoin returns in terms of month of the year effect.

Keywords: Crypto currency, Day of the Week Effect, Month of the Year Effect, GARCH
JEL Classification Codes: D53, O16

Bitcoin ve Litecoin Piyasasında Haftanın Günü ve Yılın Ayı Etkilerinin İncelenmesi

Öz

Kripto para teknolojisi, insanların herhangi bir aracıya ihtiyaç duymadan dünyanın dört bir yanında ödeme yapmalarını sağlar ve internet üzerinden çalışır. Bu teknolojinin ortaya çıkışı ile dikkatler bu paralara çevrilmiş, fiyatları hızla artmaya başlamış ve aynı zamanda oynak hale gelmişlerdir. Bu çalışmada GARCH (1,1) modeli kullanılarak Bitcoin ve Litecoin piyasalarında haftanın günü ve yılın ayı etkilerinin varlığı incelenmiştir. Çalışma dönemi 1 Mayıs 2013-21 Aralık 2017 arasını kapsamaktadır. Elde edilen sonuçlar Bitcoin ve Litecoin getirilerinde haftanın günü ve yılın ayı etkilerinin var olduğunu göstermektedir. Pazartesi, Salı ve Cuma günlerinin Bitcoin getirileri üzerinde pozitif ve anlamlı, Cumartesi'nin ise Litecoin getirileri üzerinde negatif ve anlamlı etkisi olduğu tespit edilmiştir. Ayrıca, yılın ayı etkisi açısından Şubat, Ekim ve Kasım aylarının Bitcoin üzerinde pozitif ve anlamlı, Litecoin getirilerinde ise Ağustos ayının negatif ve anlamlı etkisi olduğu belirlenmiştir.

Anahtar Kelimeler: Kripto paralar, Haftanın Günü Etkisi, Yılın Ayı Etkisi, GARCH
JEL Sınıflandırma Kodları: D53, O16

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1. Introduction

In the finance literature, Efficient Market Hypotheses (EMH) explains securities' price movements. The theory that is introduced by Fama (1965, 1970) suggests securities prices reflect available information and that investors trading on the market cannot gain abnormal returns using the information. However, researchers have found some evidences that are not consistent with EMH in financial markets. These evidences, called as anomalies, contradict with Random Walk Model that EMH is based on. Basic calendar anomalies are day of the week and the month of the year anomalies. However, the existence of these anomalies mostly has been examined for stock markets (Jaffe and Westerfield, 1985; Demirer and Karan, 2002; Dubois and Louvet, 1996; Lyroudi and Subeniotis, 2002; Li-Cheng, 2003; Ajayi, Mehdian and Perry, 2004; Atakan, 2008; Giovanis, 2009; Marrett and Worthington, 2011; Gonzalez-Perez and Guerrero, 2013; Onoh and Ndu-Okereke, 2016).

Today, the widespread uses of cryptography, internet and internet-based services have enabled new financial instruments to emerge. One notable example is the emergence of crypto currencies. Crypto currencies are a decentralized monetary system and currency that cannot be controlled by any government, company or authority, providing online payment to any person anywhere in the world. Since the introduction of the crypto currencies, they have get attention. The volumes of crypto currencies have been rising rapidly. Crypto currencies can be seen as a traditional currency like the dollar in terms of functioning; purchase and sale can be realized for any currency, and it is possible to buy and sell products and services in accepting establishments. Today, many investors use crypto currencies as an investment like stocks and bonds. Low transaction costs, international transferability, convertibility, protection from inflation, solving double payment and supply increase problems constitute some important advantages of crypto currencies (Yılmaz, 2016).

Dyhrberg (2016) stated that Bitcoin can be used financial markets and it can be categorized between gold and the American dollar. Also Chu, Chan, Nadarajah, and Osterrieder (2017) concluded that investors are trading into the crypto currencies for benefiting from the widespread use of this new technology in the long-term or making short-term profit by taking advantage of the sudden fluctuations in prices. Despite the risks involved and the lack of regulatory rules, crypto currency studies continue rapidly both in the academic world and in the banking and finance sectors. Nowadays, there are approximately 1600 crypto currencies in the market. Some of these are: Bitcoin, Litecoin, Ethereum, Ripple, Dash, Monero.

Crypto currency market is a growing market; it could be relatively inefficient. There is a vast literature that examines day of the week and month of the year anomalies. However, few studies (Kocoglu, Cevik and Tanrıoven, 2016; Caporale and Plastun, 2017; Latif and Azri, 2017; Kurihara and Fukushima, 2017; Kutlu, Sezer and Gümüş, 2017) have analyzed such calendar anomalies in the context of crypto currency market. This study examines the day of the week and month of the year effects in Bitcoin and Litecoin markets that have the highest market capitalization (as of December 19, 2017). The rest of the paper is organized as follows. Section 2 describes the history of crypto currencies (Bitcoin and Litecoin); section 3 explains the methodology employed in the study. Section 4 presents the empirical findings, section 5 concludes.

2. Evaluation of Bitcoin and Litecoin

Crypto currencies are different from any other traditional currencies that used around the world. They are independent from a central bank or an authority. In fact, crypto currencies are often limited[*] to a certain number that cannot be changed. Unlike traditional currencies or online payment systems, crypto currencies such as Bitcoin and Litecoin, decentralized peer-to-peer network without the need for an intermediary, such as a bank for money transfer. By removing the need for intermediary, digital currencies provide a more efficient infrastructure for money transfers, allowing cheaper and faster payments. Today, crypto currencies have become a global phenomenon that is known by many people (Kurihara and Fukushima, 2017, p. 57). The basic advantage of crypto currencies from traditional currencies is that they are not influenced by the economic situation of any country since they do not rely on central bank of any country. Also, it is not possible to freeze or seize accounts opened with crypto currency, since it is not known to whom it belongs and is not supervised by a central authority (Egilmez, 2017).

Crypto currency does not have a value derived from the value of metals like precious metals. The value is determined instantaneously in terms of supply and demand conditions in the market, just like in other traditional currencies or commodities (Egilmez, 2017). It can be converted into currencies of all countries through the dollar and other traditional currencies.

Bitcoin, which is announced in a study published by Nakamoto in 2008, is a crypto currency payment system, has been a pioneer in this field and still dominates the crypto currency market in the world (Nakamoto, 2008).

Bitcoin's price and market cap has increased from roughly \$139 and \$1.5 billion respectively on May 1, 2013 to all-time high of \$19475 price and \$326 billion market cap on December 17, 2017 (coinmarketcap.com, 2017, 22.12.2017).

[*] The total numbers of Bitcoin and Litecoin in circulation, currently around 16.5 million and 55 million, will never exceed 21 million and 84 million respectively as of December 21, 2017.

Bitcoin, which has the power to directly influence the real economy, has been aroused and used in a short time. Increasing use of Bitcoin and starting to be seen as an investment tool has led to the emergence of Bitcoin users, investors and stock exchanges (Kocoglu et al. 2016, 77). Virtual wallet (Bitcoin wallet) allows Bitcoin to send anyone has a wallet. When a Bitcoin is sent, a small amount of commission has to be paid, but when a Bitcoin is bought, no commission has to be paid. Buy-and-sell transactions take place instantly, unlike waiting for 2-3 days in a bank. In addition, it is impossible to break the software of crypto currency transactions. (Erdinc, 2017).

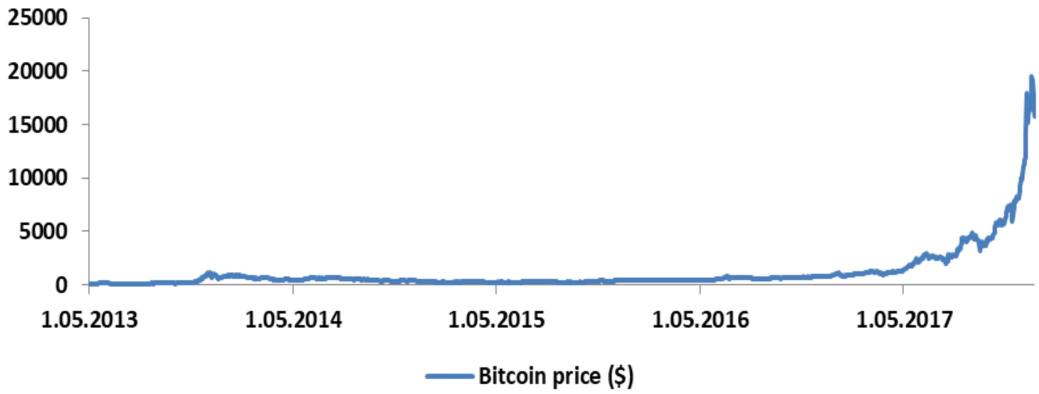
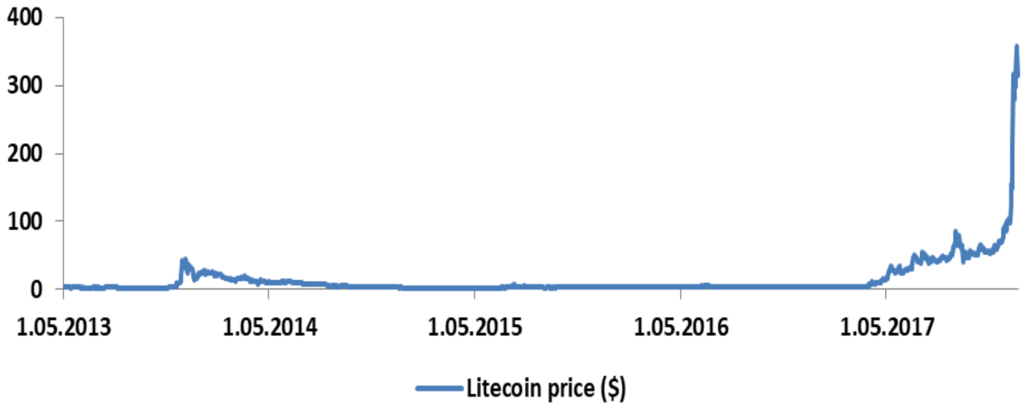


Figure 1: Historical Price of Bitcoin
Source: coinmarketcap.com, 22.12.2017

After great success of Bitcoin around the world, Litecoin which is developed by Bitcoin's open source software on October 7, has issued. It is the first example of alternative crypto currency, created by Charlie Lee, an ex-Google employee. Litecoin, the fastest growing crypto currency in recent times, is based on open source cryptographic protocol and does not work with a central or single administrator, similar to Bitcoin. Litecoin, technically similar to Bitcoin, trading costs around zero, and payments are four times faster than Bitcoin. In this respect, it is cheaper and more accessible than Bitcoin. It is also crypto currency, which is the highest market volume after Bitcoin (milliyet.com.tr/litecoin-nedir/, 25.12.2017).

Litecoin's price and market cap has increased from roughly $4.3 and $73.9 million respectively on May 1, 2013 to all-time high of $359 price and $19.5 billion market cap on December 19, 2017 (coinmarketcap.com, 2017).

Crypto currencies, despite its potential, have been adopted by a small number of consumers and businesses around the world. This is due to a number of factors, including the lack of a regulatory authority required to increase the credibility and legitimacy of crypto currencies. Another factor is the extreme fluctuations in their values.



Graph 2: Historical Price of Litecoin

Source: coinmarketcap.com, 22.12.2017

3. Literature Review

Despite the fact that the effects of the day of the week and the month of the year are examined in the stock markets (Solnik and Bousquet, 1990; Dubois and Louvet, 1996; Li-Cheng, 2003; Ajayi et al. 2004; Onyuma, 2009; Giovanis, 2009; Marrett and Worthington, 2011; Gonzalez-Perez and Guerrero, 2013; Chia, 2014; Onoh and Ndu-Okereke, 2016) and foreign exchange markets (Aydogan and Booth, 2003; Yamori and Kurihara, 2004; Ke, Chiang and Liao, 2007; Kumar, 2016), there are few studies investigating the existence of the these anomalies in the crypto currency market. For example; Kocoglu, et al. (2016) investigated the efficiency of the Bitcoin stock markets (Bitfinex, Bitstamp, Mt.Gox, Btce, Okcoin, Kraken, Anx, Coinfloor) cover the period from June 2, 2014 to June 2, 2015. The results showed that all stock markets (except Okcoin) move together in the long run. They also emphasized that although Okcoin appeared to be independent, it might also be the result of the fact that prices were not in American dollars, unlike other stock markets. So they concluded that Bitcoin market is still open to many risks and speculation.

Caporale and Plastun (2017) analyzed the day of the week effect in Bitcoin, Litecoin, Ripple and Dash markets cover the period 2013 to 2017. They used parametric and non-parametric methods and found Bitcoin market offers positive abnormal returns on Mondays.

Latif and Azri (2017) tested Bitcoin and Litecoin market efficiency using GARCH (1,1) model for the period of 2015 to 2016. The results showed that market efficiency of Bitcoin and Litecoin is inconsistent with weak form of efficiency. They concluded that crypto currency market has higher predictability power than stock market.

Kurihara and Fukushima (2017) investigated whether or not weekly price anomalies were valid in Bitcoin market for the period 7/17/2010 to 12/29/2016. They found the Bitcoin market is not efficient. They emphasized that Bitcoin transactions were getting more efficient day by day. They also suggested that Bitcoin returns could be efficient in the future.

Kutlu et al. (2017) examined the predictability of Bitcoin prices that based on Google searches cover the period 2011 to 2016 in USA and Turkey. Results showed that Bitcoin prices cannot be predicted by its past prices in Turkey. Also results revealed that when Bitcoin searches increased in Google, Bitcoin prices dropped in USA and Turkey searches had no effect on Bitcoin prices.

4. Data and Methodology

Daily data for two crypto currencies (Bitcoin and Litecoin) that have the highest market capitalizations are examined (as of December 19, 2017). Daily prices Bitcoin and Litecoin data were taken from coinmarketcap.com[†]. The sample period is from May 1, 2013 to December 21, 2017. Returns are calculated as follows:

$$y_t = \ln(\frac{P_t}{P_{t-1}})$$

where y_t is the return of crypto currency and $\ln(P_t)$ and $\ln(P_{t-1})$ are the natural logarithms of crypto currency at time t and t-1.

Before analyzing, it is mandatory to examine whether the crypto currency series are stationary within period. In time series analysis, using the non-stationary series in the equations can cause spurious relationships. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests are employed to test the stationary level.

In the literature several kinds of forming of conditional variances are used. Engle (1982) proposed a model that enables the forecast variance of return equation to change systematically over time. It is assumed that conditional variance, h_t, relies on the past squared residuals from the return$_t$, equation, ($h_t = V_c + \sum_{j=1}^{\alpha} V_j \in_{t-j}^2$), that is identified as Autoregressive Conditional Heteroskedastic Models (ARCH). Bollerslev (1986) then advanced the ARCH process by making h_t a function of lagged values of h_t likewise the lag values of ε_t^2.

[†] Price is calculated by taking the volume weighted average of all prices reported at crypto currency trading platform. Sources for the prices can be found on the markets section on each crypto currency page. For more information,https://coinmarketcap.com/currencies/bitcoin/#markets,https://coinmarketcap.com/currencies/litecoin/#markets, 09.03.2018.

($h_t = V_c + \sum_{j=1}^{\alpha} V_{Aj} h_{t-j} + \sum_{j=1}^{r} V_{\beta j} \in_{t-j}^{2}$) Such a modeling is known as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models (Berument and Kiymaz, 2001, p. 184).

The empirical examination is applied by using the GARCH model. In respect to GARCH (p,q) model the conditional variance of a time series contingent on the squared residuals of the process (Bollerslev, 1986). The GARCH model has the utility of including heteroskedasticity into the estimation procedure. The GARCH model ensures a more flexible framework in order to clutch several dynamic structures of conditional variance and it enables simultaneous estimation of various parameters of hypothesis (Choudhry, 2000, 237-238). After determining the GARCH model, the following equations (1 and 2) are created by dummy variables for the examination of the day of the week and month of the year effects respectively.

The GARCH (p, q) model that is employed for the day of the week effect on crypto currency returns is as follows (Choudhry, 2000, 238).

$$y_t = \delta_1 D_{1t} + \delta_2 D_{2t} + \delta_3 D_{3t} + \delta_4 D_{4t} + \delta_5 D_{5t} + \delta_6 D_{6t} + \delta_7 D_{7t} + y_{t-1} + \in_t \quad (1)$$

The dummy variables (D_{dt}) represent the days of the week. In other words, coefficients $\delta_1, \delta_2, \delta_3, \delta_4, \delta_5, \delta_6, \delta_7$ represent Monday, Tuesday, ….., and Sunday effects on crypto currency return respectively.

Month of the year effect GARCH (p, q) model on crypto currency returns is as follows: (Choudhry, 2000, 238).

$$y_t = \delta_1 D_{1t} + \delta_2 D_{2t} + \delta_3 D_{3t} + \delta_4 D_{4t} + \delta_5 D_{5t} + \delta_6 D_{6t} + \delta_7 D_{7t} + \delta_8 D_{8t} + \delta_9 D_{9t} + \delta_{10} D_{10t} + \delta_{11} D_{11t} + \delta_{12} D_{12t} + y_{t-1} + \in_t \quad (2)$$

The dummy variables (D_{dt}) in the returns represent the value of 1 if month is January and 0 otherwise and so on. y_t represents the return of crypto currency, D_1 is a dummy variable which takes the value of 1 if month is January and 0 otherwise and so on.

5. Findings

Table 1 indicates the descriptive statistics of the crypto currency returns. Series have positive mean return during the period. Also it is determined that the volatility is high in both crypto currencies. Two series are leptokurtic especially Litecoin, that is, all series have a thicker tail. Skewness coefficient of Bitcoin is skewed to the left and Litecoin is skewed to right respectively. Finally the crypto currency returns are found to be non-normal in the Jarque-Bera test.

Table 1: Descriptive Statistics of Crypto currency Returns

Crypto currency	Mean	Maximum	Minimum	Std. Deviation	Skewness	Kurtosis	Jarque Bera
Bitcoin	0.0028	0.3575	-0.2662	0.0436	-0.1353	12.24	6037[a]
Litecoin	0.0025	0.8290	-0.5139	0.0690	1.9065	30.08	52863[a]

[a], indicates significance at the 1% level.

In analysis, using the non-stationary series can cause spurious relationships. Table 2 reports ADF and PP unit root test results for Bitcoin and Litecoin returns. As shown Table 2 series are found stationary at their levels.

Table 2: Unit Root Test Results

	ADF		PP	
	Intercept	**Trend & Intercept**	**Intercept**	**Trend & Intercept**
Bitcoin	-40.73983[a]	-40.80146[a]	-40.89904[a]	-40.92574[a]
Litecoin	-39.70866[a]	-39.80029[a]	-40.05122[a]	-40.03954[a]

[a], indicates significance at the 1% level.

It is reasonable to consider the lagged interaction in the financial returns series normally for 1 to 5 days. In the study, autocorrelation is tested up to 36 lags and it is observed in the correlogram of residuals squared that there is 1 lagged autocorrelation.

Since the autocorrelation and partial autocorrelation coefficients of the first lag are important, first order AR, MA and ARMA models have been applied and it has been decided that AR (1), which is the optimal information criteria, is selected appropriate model (Atakan, 2008, s. 106). The equations and results for this model are shown at Table 3.

Table 3: Least Squares AR(1) Model for Bitcoin and Litecoin

	Coefficient	t-statistics	Prob.
	Bitcoin		
c	0.002854	2.699116	0.0070
Bitcoin(-1)	0.014260	2.689334	0.0057
	Litecoin		
c	0.002518	1.502377	0.1332
Litecoin(-1)	0.036528	2.505485	0.0124

The existence of the ARCH effect among the error terms of AR (1), which is the appropriate model for both crypto currency returns, is examined by the ARCH-LM test and the results are shown in Table 4.

In Table 4 the Obs * R-squared value of the predicted regression error squares are found 185.3864 for Bitcoin and 68.12808 for Litecoin. The probability values are also found significant at 1% level. Thus the null hypothesis, which expresses equal variance, will be rejected. In other words, there is an ARCH effect and this effect should be removed.

Table 4: ARCH-LM Test Results

	Bitcoin		
F-statistics	207.9219	Prob. F.	0.0000
Obs*R-squared	185.3864	Prob. Chi-Suare	0.0000
	Litecoin		
F-statistics	70.89901	Prob. F.	0.0000
Obs*R-squared	68.12808	Prob. Chi-Suare	0.0000

After the existence of the ARCH effect has been accepted, the appropriate ARCH model has been selected. The Akaike Information Criteria is used to determine the optimal ARCH-GARCH model in which the sum of squares of residual values should be minimum. Among them, GARCH (1,1) model which is the optimal model is preferred. Thus in order to test for day of the week and the month of the year effects in Bitcoin and Litecoin markets, GARCH (1,1) model are employed[‡]. The results of day of the week are shown in Table 5.

[‡] GARCH (1,1) models residual diagnostics (correlogram squared residuals, heteroskedasticity) are reported in appendix.

Table 5: Day of the Week Effect-GARCH (1,1)

	Coefficient	Prob.
Bitcoin		
D1	0.002041[c]	0.0869
D2	0.003547[a]	0.0023
D3	-0.001095	0.3721
D4	0.001894	0.1221
D5	0.003788[a]	0.0028
D6	0.000834	0.5129
D7	0.000624	0.5969
Litecoin		
D1	-0.000919	0.4880
D2	0.000107	0.9348
D3	-0.001969	0.1264
D4	0.001808	0.1757
D5	-0.000323	0.8083
D6	-0.002878[b]	0.0465
D7	-7.31E-05	0.9568

[a, b, c] indicates significance at the 1%, 5% and 10% level respectively.

The day of the week effect results show that returns of Bitcoin are affected by three days. Monday, Tuesday and Friday have significant positive effects on Bitcoin return. Investors can gain abnormal positive returns in these days. The return of Friday is higher than Monday and Tuesday. Of the seven days, only Wednesday imposes a negative effect in Bitcoin market but it is insignificant. Rest of the day’s effect is also insignificant effect.

In the Litecoin market, only Saturday returns found to be significant. In contrast to Bitcoin, the effect is negative. The returns of Monday, Wednesday, Friday and Sunday are also negative but the effects are insignificant.

Table 6 indicates month of the year effect in Bitcoin and Litecoin markets. The results show that three out of the twelve months (February, October and November) has significant positive effect on Bitcoin market. The returns are 0.005078, 0.003615 and 0.005664 respectively. February, October and November can be used in trading strategy for gaining abnormal returns. The rest of the year returns are also positive (except August) but they are insignificant.

Table 6: Month of Year Effect-GARCH (1,1)

	Coefficient	Prob.
Bitcoin		
D1	0.000137	0.9638
D2	0.005078[b]	0.0145
D3	0.000418	0.8112
D4	0.002983	0.0245
D5	0.001957	0.1923
D6	0.002300	0.1958
D7	-0.001417	0.3666
D8	-7.25E-05	0.9621
D9	0.000146	0.9156
D10	0.003615[a]	0.0060
D11	0.005664[a]	0.0056
D12	0.002715	0.1110
Litecoin		
D1	-0.001413	0.6266
D2	-0.000249	0.8844
D3	0.001222	0.3820
D4	-0.000469	0.7756
D5	0.001186	0.5513
D6	0.002535	0.2497
D7	-0.001895	0.4125
D8	-0.003636[b]	0.0261
D9	-0.000921	0.6229
D10	-0.000972	0.4353
D11	0.000225	0.9037
D12	-0.001470	0.4437

[a, b] indicates significance at the 1%, 5% level respectively.

In terms of Litecoin market, four months (March, May, June and November) have positive effect but they are insignificant. August has negative effect similarly Bitcoin market but also the effect is significant. In this month investors may take short position in Litecoin market.

5. Conclusion

Bitcoin and Litecoin are a revolution in the world with their technological infrastructure. They are crypto currencies that you can use all over the world. An important feature of these currencies is their ability to be converted into currencies of all countries via traditional currencies. The fact that there is no regulatory authority and their popularity makes crypto currencies a speculative currency. The functioning of the crypto currencies is not based on the central bank policy. Moreover, the weak definition of liquidity conditions of the crypto currency market and lack of certainty rules for investment makes them very volatile relative to traditional currencies and assets.

The study provides day of the week effect and month of the year effect in crypto currency markets using the GARCH (1,1) model. Bitcoin and Litecoin returns cover the period May 1, 2013 to December 21, 2017.

Results indicate significant presence of the day of the week in some of days on Bitcoin and Litecoin returns. For example Monday, Tuesday and Friday have significant positive effects on Bitcoin return. Thus investors can take long position on Monday and close it at the end of Tuesday and also on Friday for gaining abnormal returns. Also highest return is determined on Friday. This result is consistent with stock market literature (Jaffe & Westerfield, 1985; Lyroudi & Subeniotis, 2002; Demirer & Karan, 2002; Atakan, 2008) and also with Caporale & Plastun (2017) that found abnormal positive returns on Mondays in Bitcoin market.

In the Litecoin market, only Saturday returns found to be significant. Also unlike Bitcoin market, the effect is found negative. Thus investors can take short position on Saturday for trading strategy. The returns of Monday, Wednesday, Friday and Sunday are also negative but the effects are insignificant.

In terms of month of the year effect, February, October and November has significant and positive effect in Bitcoin market. In these months investor should take long position. There have been many events that have had a positive impact on the price of Bitcoin in these months. For example on October Chicago Mercantile Exchange Group announced to launch Bitcoin futures, Bitcoin covered Economist front page, EU announced no VAT in Bitcoin trades; on November People's Bank of China made supportive comments on Bitcoin markets. Further the rest of the year returns are also positive (except August) but they are insignificant. In the Litecoin market, August has only significant effect but it is negative. For the trading strategy investors can take short position. It can be concluded that Litecoin market seems to be relatively more efficient than Bitcoin market. On August some negative events had occurred. For example, Bitcoin XT Fork released, Bitfinex hacked. Furthermore, the presence of anomalies suggests that investors in the markets are not rational. Results also indicate that crypto currency market is not efficient. In the further studies it can be examined the validity of another anomalies in crypto currency markets.

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Appendix

ARCH-LM Test Results (Day of Week Effect)

Bitcoin			
F-statistics	0.109351	Prob. F.	0.7409
Obs*R-squared	0.109473	Prob. Chi-Suare	0.7407
Litecoin			
F-statistics	0.106340	Prob. F.	0.7444
Obs*R-squared	0.106459	Prob. Chi-Suare	0.7442

Correlogram of Standardized Residuals Squared (Bitcoin)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.008	-0.008	0.1097	0.740
		2	-0.017	-0.017	0.5816	0.748
		3	-0.017	-0.017	1.0821	0.781
		4	-0.034	-0.034	3.0255	0.554
		5	-0.010	-0.011	3.1931	0.670
		6	-0.014	-0.016	3.5505	0.737
		7	-0.013	-0.015	3.8376	0.798
		8	-0.010	-0.012	3.9938	0.858
		9	-0.019	-0.021	4.6287	0.865
		10	0.063	0.061	11.419	0.326
		11	-0.016	-0.017	11.842	0.376
		12	-0.018	-0.018	12.398	0.414
		13	-0.017	-0.018	12.889	0.456
		14	0.037	0.039	15.218	0.363
		15	-0.003	-0.004	15.232	0.435
		16	-0.020	-0.020	15.936	0.457
		17	-0.018	-0.018	16.507	0.488
		18	-0.009	-0.008	16.637	0.548
		19	-0.017	-0.016	17.108	0.583
		20	0.013	0.006	17.394	0.627
		21	-0.015	-0.015	17.760	0.664
		22	-0.026	-0.026	18.917	0.650
		23	-0.017	-0.017	19.425	0.676
		24	0.007	-0.002	19.503	0.725
		25	0.001	-0.002	19.506	0.772
		26	-0.006	-0.007	19.578	0.811
		27	-0.022	-0.022	20.392	0.814
		28	-0.006	-0.011	20.455	0.847
		29	-0.011	-0.012	20.648	0.872
		30	-0.013	-0.017	20.926	0.890
		31	0.002	0.001	20.936	0.914
		32	-0.022	-0.022	21.755	0.914
		33	-0.013	-0.014	22.032	0.927
		34	-0.005	-0.013	22.081	0.943
		35	0.023	0.019	23.023	0.940
		36	0.005	0.003	23.063	0.953

Correlogram of Standardized Residuals Squared (Litecoin)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
| |	| |	1	-0.008	-0.008	0.1067	0.744
| |	| |	2	-0.008	-0.008	0.2127	0.899
| |	| |	3	-0.009	-0.009	0.3417	0.952
| |	| |	4	-0.009	-0.009	0.4886	0.975
| |	| |	5	-0.009	-0.009	0.6153	0.987
| |	| |	6	-0.003	-0.003	0.6271	0.996
| |	| |	7	-0.008	-0.008	0.7304	0.998
| |	| |	8	-0.005	-0.006	0.7808	0.999
| |	| |	9	-0.006	-0.006	0.8362	0.976
| |	| |	10	-0.008	-0.009	0.9476	0.914
| |	| |	11	-0.004	-0.004	0.9695	0.786
| |	| |	12	-0.007	-0.008	1.0520	0.963
| |	| |	13	-0.002	-0.002	1.0568	0.938
| |	| |	14	-0.005	-0.006	1.1032	0.957
| |	| |	15	-0.007	-0.008	1.1901	0.988
| |	| |	16	-0.007	-0.008	1.2806	0.941
| |	| |	17	0.013	0.012	1.5581	0.988
| |	| |	18	0.020	0.019	2.2154	0.827
| |	| |	19	-0.004	-0.004	2.2415	0.764
| |	| |	20	-0.006	-0.006	2.2960	0.654
| |	| |	21	-0.005	-0.005	2.3403	0.776
| |	| |	22	-0.004	-0.004	2.3738	0.924
| |	| |	23	0.002	0.002	2.3794	0.774
| |	| |	24	-0.007	-0.007	2.4542	0.914
| |	| |	25	0.023	0.023	3.3448	0.914
| |	| |	26	0.000	0.000	3.3448	0.847
| |	| |	27	-0.006	-0.006	3.4081	0.976
| |	| |	28	-0.000	0.000	3.4081	0.914
| |	| |	29	-0.008	-0.007	3.5053	0.956
| |	| |	30	-0.003	-0.003	3.5198	0.963
| |	| |	31	-0.003	-0.003	3.5346	0.975
| |	| |	32	-0.008	-0.008	3.6511	0.957
| |	| |	33	-0.008	-0.008	3.7616	0.978
| |	| |	34	0.023	0.022	4.6509	0.948
| |	| |	35	-0.007	-0.008	4.7444	0.973
| |	| |	36	-0.005	-0.006	4.7926	0.924

ARCH-LM Test Results (Month of the Year Effect)

Bitcoin			
F-statistics	0.065442	Prob. F.	0.7981
Obs*R-squared	0.065517	Prob. Chi-Suare	0.7980
Litecoin			
F-statistics	0.098567	Prob. F.	0.7536
Obs*R-squared	0.098678	Prob. Chi-Suare	0.7534

Correlogram of Standardized Residuals Squared
(Bitcoin- Month of the Year Effect)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
| |	| |	1	-0.006	-0.006	0.0657	0.798
| |	| |	2	-0.017	-0.017	0.5617	0.755
| |	| |	3	-0.018	-0.018	1.1061	0.776
| |	| |	4	-0.035	-0.035	3.1796	0.528
| |	| |	5	-0.007	-0.008	3.2704	0.658
| |	| |	6	-0.015	-0.017	3.6784	0.720
| |	| |	7	-0.015	-0.017	4.0560	0.773
| |	| |	8	-0.009	-0.011	4.1917	0.839
| |	| |	9	-0.019	-0.021	4.8332	0.849
| |	| |	10	0.058	0.055	10.494	0.398
| |	| |	11	-0.016	-0.018	10.956	0.447
| |	| |	12	-0.020	-0.020	11.607	0.478
| |	| |	13	-0.017	-0.018	12.092	0.520
| |	| |	14	0.035	0.037	14.232	0.433
| |	| |	15	-0.003	-0.006	14.251	0.507
| |	| |	16	-0.020	-0.020	14.916	0.531
| |	| |	17	-0.018	-0.018	15.479	0.561
| |	| |	18	-0.011	-0.010	15.694	0.614
| |	| |	19	-0.016	-0.017	16.135	0.648
| |	| |	20	0.013	0.006	16.413	0.691
| |	| |	21	-0.015	-0.016	16.786	0.724
| |	| |	22	-0.025	-0.025	17.824	0.716
| |	| |	23	-0.018	-0.018	18.367	0.737
| |	| |	24	0.008	0.000	18.483	0.779
| |	| |	25	0.004	0.001	18.516	0.820
| |	| |	26	-0.008	-0.009	18.619	0.852
| |	| |	27	-0.022	-0.023	19.466	0.852
| |	| |	28	-0.006	-0.010	19.528	0.881
| |	| |	29	-0.011	-0.013	19.729	0.901
| |	| |	30	-0.011	-0.016	19.952	0.918
| |	| |	31	0.008	0.007	20.077	0.934
| |	| |	32	-0.023	-0.024	20.990	0.932
| |	| |	33	-0.013	-0.014	21.274	0.943
| |	| |	34	-0.008	-0.016	21.395	0.954
| |	| |	35	0.023	0.019	22.341	0.952
| |	| |	36	0.005	0.002	22.384	0.963

Correlogram of Standardized Residuals Squared
(Litecoin-Month of the Year Effect)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
| |	| |	1	-0.008	-0.008	0.0989	0.753
| |	| |	2	-0.008	-0.008	0.2036	0.903
| |	| |	3	-0.008	-0.009	0.3244	0.955
| |	| |	4	-0.009	-0.009	0.4597	0.977
| |	| |	5	-0.008	-0.009	0.5780	0.989
| |	| |	6	-0.003	-0.003	0.5894	0.997
| |	| |	7	-0.007	-0.008	0.6842	0.998
| |	| |	8	-0.005	-0.005	0.7270	0.999
| |	| |	9	-0.005	-0.006	0.7780	0.887
| |	| |	10	-0.008	-0.008	0.8838	0.996
| |	| |	11	-0.003	-0.004	0.9023	0.998
| |	| |	12	-0.007	-0.007	0.9767	0.999
| |	| |	13	-0.002	-0.002	0.9810	0.976
| |	| |	14	-0.005	-0.006	1.0250	0.984
| |	| |	15	-0.007	-0.008	1.1090	0.786
| |	| |	16	-0.007	-0.008	1.1921	0.963
| |	| |	17	0.012	0.011	1.4469	0.988
| |	| |	18	0.018	0.018	2.0142	0.937
| |	| |	19	-0.004	-0.005	2.0479	0.928
| |	| |	20	-0.005	-0.005	2.0950	0.941
| |	| |	21	-0.005	-0.005	2.1355	0.982
| |	| |	22	-0.004	-0.004	2.1630	0.827
| |	| |	23	0.002	0.002	2.1695	0.763
| |	| |	24	-0.007	-0.007	2.2426	0.653
| |	| |	25	0.020	0.020	2.9610	0.736
| |	| |	26	0.000	0.000	2.9610	0.923
| |	| |	27	-0.006	-0.006	3.0225	0.774
| |	| |	28	0.000	0.000	3.0226	0.922
| |	| |	29	-0.008	-0.007	3.1214	0.991
| |	| |	30	-0.003	-0.003	3.1390	0.838
| |	| |	31	-0.003	-0.003	3.1539	0.939
| |	| |	32	-0.008	-0.008	3.2676	0.876
| |	| |	33	-0.008	-0.008	3.3685	0.914
| |	| |	34	0.022	0.021	4.1939	0.986
| |	| |	35	-0.007	-0.007	4.2769	0.993
| |	| |	36	-0.005	-0.006	4.3275	0.964