Advances in Social Science, Education and Humanities Research, volume 585
Proceedings of the 1st UMGESHIC International Seminar on Health, Social Science and Humanities (UMGESHIC-ISHSSH 2020)

The Day of the Week Effect in Return of the Five Cryptocurrencies Market

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Abstract: Cryptocurrency works on a system that admits people to make payments all over the world without the requirement for any intermediary. Most digital currencies experience frequent periods of intense volatility. This paper examines the day of the week effects in return and volatility on Bitcoin, Ethereum, Ripple, Litecoin, and Tether currencies. To estimate volatile variance, this research uses five ARCH family models: ARCH, GARCH, EGARCH, TARCH and PARCH Models. The best models are derived based on Akaike Info Criterion and Schwarz Criterion. The sample periods vary based on the date of the initial release of each currency up to 31 December 2019. Results indicate the Power ARCH (PARCH) is the best model for Bitcoin and Litecoin, Threshold ARCH (TARCH) model is the best for Ethereum, Ripple, and Litecoin, and the EGARCH model is for Tether. Each model shows a different day of the week effects on each currency.

***Keywords**: Week Effect, Cryptocurrencies Market*

1. INTRODUCTION

Efficient Market Hypotheses (EMH), states that share prices reflect all available information and making it impossible for investors trading in the market, to gain abnormal returns. Therefore, it is aligned with the Random Walk theory stated that it's impossible to outperform the market without assuming additional risk. (E. Fama, 1970; E. F. Fama, 1965). Nevertheless, several scholars show some evidence, called anomalies that are not consistent with EMH and contradict the Random Walk Model. The existence of those anomalies commonly have been observed for stock market such as the calendar anomaly effect namely, the day of week effect ((Arora, 2018; Aziz & Ansari, 2015; Lu & Gao, 2016; Zilca, 2017)) and the month of the year anomalies ((Boudreaux, 1995; Mouselli & Al-Samman, 2016; Xiao, 2016).

The prevalent usage of cryptography, internet, and internet-based services have supported new ways of performing digital transfer mechanism. A remarkable illustration is the advent of cryptocurrencies. A cryptocurrency is a digital financial asset intended to function as an intermediary of exchange with supporting software that both authorize ownership and perform transfers, there is no condition for a 'trustworthy third party'(Giudici, Milne, & Vinogradov, 2020). Blockchain technology is used to validate the transaction data in digital money. Blockchain is a block of interconnected data so that it is visible like a chain, which will link users without going through any intermediaries. So that every user will save each block of data to other users. The system used on a blockchain can only add data so no data will be changed because each transaction will only add new blocks to each user's device in the form of data different encryption.

Investors trade cryptocurrency with the aim of earning both long and short-term profits, by gaining from sudden price volatility. Currently, there are approximately 1600 cryptocurrencies on the market (J Chu, Chan, Nadarajah, & Osterrieder, 2017); (Eyüboğlu, 2018). Some of them are Bitcoin, Etherium, Ripple, Litecoin, and Tether. (J Chu et al., 2017) have developed volatility models for cryptocurrency returns. While several other studies have analyzed the effect of the week of the day effect on cryptocurrency returns (Eyüboğlu, 2018),(Ma & Tanizaki, 2019),(Caporale & Plastun, 2019) and (Olaoluwa & Ephraim, 2019). The objectives of this research are to analyze the day of the week effect on 5 cryptocurrency returns (Bitcoin/BTC, Ethereum/ETC, Litecoin/LTC, Tether/USDT, and Ripple/XRP) and volatility, using the most fitted Arch family models. The rest of the paper is arranged as follows. Section 2 explains an overview of the cryptocurrency used in this research; Section 3. Explain the literature review; Section 4 describes the methodology applied in the research. Section 5 represents the empirical results, section 6 conclusions.

The Cryptocurrencies

1.1.Ethereum (ETH)

Ethereum is a distributed software platform that permits Smart Contracts and Decentralized Applications (DApps) to be improved with no obstacles, scams, control, or intervention from an intermediary. The applications on Ethereum are run on its platform-specific cryptographic token, ether. Ether is resembling a means for moving around on the Ethereum platform and is pursued by mostly developers looking to improve and run applications inside Ethereum. Ether, initiated in 2015, is the second-biggest digital currency by market capitalization after bitcoin. As of January 2020, ether's market capitalization is roughly 1/10 the size of bitcoin's (“Etherium,” n.d.).

1.2. Ripple (XRP)

Ripple is a real-time global settlement network that offers instant, certain, and low-cost international payments. initiated in 2012, Ripple enables banks to settle cross-border payments in real-time, with end-to-end transparency, and at lower costs. Ripple’s consensus ledger (its method of conformation) is unique in that it doesn’t require mining. Indeed, all of Ripple's XRP tokens were pre-mined before launch, meaning that there is no creation of XRP over time, only the introduction and removal of XRP from the market supply according to the network's guidelines. In this way, Ripple sets itself apart from bitcoin and many other altcoins. Since Ripple’s structure doesn't require mining, it reduces the usage of computing power and minimizes network latency(Ledger, n.d.).

1.3.Litecoin (LTC)

Litecoin, launched in 2011, was among the first cryptocurrencies to follow in the footsteps of bitcoin and has often been referred to as “silver to bitcoin’s gold.” It was created by Charlie Lee, an MIT graduate, and former Google engineer. Litecoin is based on an open-source global payment network that is not controlled by any central authority and uses "script" as a proof of work, which can be decoded with the help of CPUs of consumer-grade. Although Litecoin is like bitcoin in many ways, it has a faster block generation rate and hence offers a faster transaction confirmation time(Litecoin, n.d.)

1.4.Tether (USDT)

Tether was one of the first and most popular group cryptocurrencies which aim to peg their market value to a currency or other external reference point to reduce volatility. Because most digital currencies, even major ones like bitcoin, have experienced frequent periods of dramatic volatility, Tether attempt to smooth out price fluctuations to attract users who may otherwise be cautious. Launched in 2014, Tether describes itself as a blockchain-enabled platform designed to facilitate the use of fiat currencies digitally. Effectively, this cryptocurrency allows individuals to utilize a blockchain network and related technologies to transact in traditional currencies while minimizing the volatility and complexity often associated with digital currencies(Tether, n.d.).

1.5.Bitcoin Cash (BCH)

Bitcoin is a cryptocurrency invented in 2008 by an unknown person or group of people using the name Satoshi Nakamoto and started in 2009 when its implementation was released as open-source software. Bitcoin Cash (BCH) holds an important place in the history of altcoins because it is one of the earliest and most successful hard forks of the original bitcoin. In the cryptocurrency world, a fork takes place as the result of debates and arguments between developers and miners. Due to the decentralized nature of digital currencies, wholesale changes to the code underlying the token or coin at hand must be made due to consensus; the mechanism for this process varies according to the particular cryptocurrency(Bitcoin, n.d.).

2. LITERATURE REVIEW

Although the effects of the day of the week and the month of the year are examined in the stock markets;(Arora, 2018; Aziz & Ansari, 2015; Chiah & Zhong, 2019; X. Chu, Gu, & Zhou, 2019; Hassan & Kayser, 2019; Lu & Gao, 2016; Mouselli & Al-Samman, 2016; Reschenhofer, Mangat, Zwatz, & Guzmics, 2020; Xiao, 2016); Limited research analyzing the presence of these irregularities in the cryptocurrency market.

Kocoglu, et al. (2016) investigated the efficiency of the Bitcoin stock markets (Bitfinex, Bitstamp, Mt.Gox, Btce, Okcoin, Kraken, Anx, Coinfloor) include the period from June 2, 2014, to June 2, 2015. The findings proved that all stock markets (except Okcoin) shift jointly in the long run. They also highlighted that though Okcoin seemed to be independent, it may also be the effect of the fact that prices were not in American dollars, different from other stock markets. So they assumed that the Bitcoin market is still exposed to many risks and speculation

(Jeffrey Chu, Chan, Nadarajah, & Osterrieder, 2017) applied GARCH modeling of cryptocurrencies. They prepare GARCH modeling for the seven most prevalent cryptocurrencies. Twelve GARCH models are fitted to each cryptocurrency, and their fits are assessed in terms of five criteria.

(Eyüboğlu, 2018) analyzed the day of the week and month of the year impact in Bitcoin and Litecoin markets applying the GARCH (1,1) model. The outcome showed the existence of the day of the week and month of the year effects in Bitcoin and Litecoin returns. It is proved that Monday, Tuesday, and Friday positively significant influence Bitcoin return and Saturday negatively influenced Litecoin returns. Likewise in terms of month of the year effect, February, October, and November positively significant effects on Bitcoin return, and August negatively significant influenced Litecoin returns.

(Olaoluwa & Ephraim, 2019) examined the day-of-the-week effect in some prominent cryptocurrency in terms of pricing and market capitalizations. They performed the fractional integration regression method with dummies. They showed the day of the week effect is not significantly influenced cryptocurrency return, whereas there is likely evidence of Monday and Friday effects only in Bitcoin volatility. These evidence further sustains the existence of market efficiency of these cryptocurrency markets.

(Ma & Tanizaki, 2019) analyzed the day-of-the-week effect on both return and volatility of Bitcoin (BTC) from a period of 2013 to 2018. They used daily data obtained from CoinDesk Bitcoin Price Index. The research shows that t the day-of-the-week effect in the return equation differs with sample periods, while significantly high volatilities are experienced on Monday and Thursday. Hereafter, the significantly high mean return of Bitcoin on Monday is originated as a response to higher volatility. The day-of-the-week effect on both return and volatility persists robust after considering for stock market returns (S&P 500; SSEC; Nikkei 225) and foreign exchange market returns (USD/CNY; USD/JPY; EURO/USD). Lastly, no asymmetry effect on volatility is found here.

(Caporale & Plastun, 2019) investigate the day of the week effect in the cryptocurrency return applying a range of statistical techniques (average analysis, Student's t-test, ANOVA, the Kruskal–Wallis test, and regression analysis with dummy variables) as well as a trading simulation method. Most cryptocurrencies (LiteCoin, Ripple, Dash) are found not to show this anomaly. The only exception is BitCoin, for which returns on Mondays are significantly higher than those on the other days of the week. In this case, the trading simulation examination proves that there exist usable profit opportunities; however, most of these results are not significantly different from the random ones and therefore cannot be concluded as proof against market efficiency.

3. DATA AND METHODOLOGY

We examine daily data for 4 cryptocurrencies, choosing those with the highest market capitalization. The sample periods vary based on the date of the initial release of each currency up to 31 December 2019 (Bitcoin/BTC, Ethereum/ETC, Litecoin/LTC, Tether/USDT, and Ripple/XRP). The data source is CoinMarketCap (https://coinmarketcap.com/coins/). Return is computed as follows:

$$y_t = log\left(\frac{P_t}{P_{t-1}}\right) \qquad (1)$$

Y_t is the return of cryptocurrency and $\log(P_t)$ and $\log(P_{t-1})$ are the natural logarithms of cryptocurrency at time t and t-1

Before examining, we check whether the cryptocurrency data are stationary in the period. Using the non-stationary data in time series analysis triggers spurious relationships. The Augmented Dickey-Fuller (ADF) was used to test the stationary level (Ciucu, 2014); (Eyüboğlu, 2018). We also examine the ARCH test to analyze the existence of the ARCH effect. Residual Diagnostics/ARCH LM Test performed Lagrange multiplier tests to check whether the standard residuals show additional ARCH. The best model for each cryptocurrency was chosen based on the minimum value of the Akaike info criterion and the Schwarz criterion(Ciucu, 2014). Then the models: ARCH (autoregressive conditional heteroskedastic model); GARCH (generalized autoregressive conditional heteroskedastic model); EGARCH (exponential generalized autoregressive conditional heteroskedastic model); TARCH (Threshold GARCH); and PARCH (The Power Arch) are developed.

3.1. ARCH Family Models

ARCH family models are frequently used for time series data. Autoregressive Conditional Heteroskedasticity (ARCH) models are specifically developed to model and forecast conditional variances. The variance of the dependent variable is created as a function of past values of the dependent variable and independent, or exogenous variables. ARCH models were initiated by (Engle, 1982) and

generalized as GARCH (Generalized ARCH) by (Bollerslev, 1986) and Taylor (1986).
The ARCH(1) model can be extended to such that the conditional variance depends on more than on lagged realization. For instance :

$$ARCH(1): h_t = b_0 + b_0 u_{t-1}^2$$

$$ARCH(q): h_t = b_0 + b_0 u_{t-1}^2 + \cdots + b_0 u_{t-q}^2$$

$$ARCH(q): h_t = b_0 + \sum_{i=1}^{q} b_i u_{t-i}^2 \quad (2)$$

The ARCH(q) models show that the variance or volatility in a given period depends on the magnitude of the squared errors in the past q periods. Simultaneously examines the mean and variance of a variable. ARCH(q) model frequently yields negative coefficients of the lagged periods of the squared error
In elaborating an ARCH model, there are three distinct conditional arrangements: mean equation, variance, and error distribution.
The GARCH(1,1) Model
The specification of the GARCH (1,1) model :

$$Y_t = X_t'\theta + \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (3)$$

The mean equation is written as a function of exogenous variables with an error term, with σ_t^2 is conditional variance, which is a function of three terms :
A constant term: ω; news about volatility from the previous period, measured as the lag of the squared residuals from the mean equation : σ_{t-1}^2 , the ARCH term.

3.2. The Threshold GARCH (TARCH) Model
TARCH or Threshold ARCH and Threshold GARCH were presented by (Bollerslev, 1986). The generalized specification for the conditional variance is given by:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k \epsilon_{t-k}^2 \tau_{t-k} \quad (4)$$

There is a leverage effect, in this model, a negative correlation between past return and future volatility of returns. Negative news has more impact on the volatility of return than positive news.

3.3.EGARCH Model

The exponential GARCH model developed by (Nelson, 1991) is to capture the leverage effect of shocks (policies, information, news, incidents, and events) on the financial market. It allows for the testing of asymmetries. With good(bad) news, assets tend to enter a state of tranquillity (turbulence), and volatility decreases (increases). To do this, the log of the variance series is used.
The conditional variance for the EGARCH (p,1) model is specified as :

$$\log(h_t) = \varphi + \sum_{i=1}^{q} \eta_i \left| \frac{u_{t-1}}{\sqrt{h_{t-1}}} \right| + \sum_{i=1}^{q} \lambda_i \frac{u_{t-1}}{\sqrt{h_{t-1}}} + \sum_{k=1}^{p} \theta_k log(h_{t-k}) \quad (5)$$

At the left-hand side is the log of variance series (h_t), which makes the leverage effect exponential rather than quadratic. This ensures that the estimates are nonnegative.

$$\vartheta = constant;\ \eta = ARCH\ effect, \lambda = asymmetric\ effects\ and\ \theta = GARCH\ effect \quad (6)$$

If $\lambda_1 = \lambda_2 = \cdots = 0$ the model is symmetric. But if $\lambda_i < 0$ implies that bad news (negative shock) generates larger volatility of good news (positive shocks).

3.4. The Power ARCH (PARCH) Model

(Ding, Granger, & Engle, 1993) generalized the standard deviation GARCH model with the Power ARCH specification. In this model, the power parameter δ of standard deviation is estimated, and the optional parameter γ are added to capture asymmetry:

$$\sigma_t^\delta = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta + \sum_{i=1}^{p} \alpha_i (|\epsilon_{t-i}| - \gamma_i \epsilon_{t-1})^\delta \quad (7)$$

Some types of development of conditional variances are used. (Engle, 1982) suggested a model that allows the forecast variance of return equation to alter systematically over time. It is supposed that conditional variance, h_t, depends on the past squared residuals from the returns, equation, that $\left(h_t = V_c + \sum_{j=1}^{\alpha} V_j\, \epsilon_{t-j}^2\right)$ is classified as Autoregressive Conditional Heteroskedastic Models (ARCH).

(Bollerslev, 1986) then developed the ARCH process by creating ht a function of lagged values of h_t also the lag values of ε_t^2. $\left(h_t = V_c + \sum_{j=1}^{\alpha} V_{Aj} h_{t-j} + \sum_{j=1}^{r} p\, \epsilon_{t-j}^2\right)$.

After developing GARCH model, the following Equation is considered by dummy variables to examine the day of the week effect on Cyrptocurrecies returns.

$$y_t = \delta_1 D_{1t} + \delta_2 D_{2t} + \delta_3 D_{3t} + \delta_4 D_{4t} + \delta_5 D_{5t} + \delta_6 D_{6t} + \delta_7 D_{7t} + y_{t-1} + \epsilon_t \quad (8)$$

The dummy variables (Ddt) denote the days of the week. Coefficients δ_1 , δ_2, ….. δ_7 represent Monday, Tuesday, to Sunday impacts on cryptocurrency return respectively.

4. FINDINGS

The descriptive statistics of the cryptocurrency returns are shown in table 1. All of the currencies have a positive mean return throughout the period. Also it is showed that the volatility is high in all cryptocurrencies. All of those currencies is leptokurtic. Almost all cryptocurrency has positive skewness coefficient except Etherium. Finally, the cryptocurrency returns are non-normal in the Jarque-Bera test.

TABLE 1. Statistics Descriptive

Cryptocurrency	Mean	Median	Max	Min	SD	Skewness	Kurtosis	Jarque Bera	Obs
Bitcoin	0.0035	0.00151	0.07575	0.0000	0.00869	5.780387	40.3255	162291[a]	2551
Etherium	0.0011	-6.62E5	0.178206	-0.56583	0.03019	-3.45970	74.04937	4002397[a]	1885
LTC	0.00042	-0.0002	0.222106	-0.22347	0.02438	0.415100	17.69965	19987.9[a]	2113
USDT	0.00606	-0.00432	0.617069	-0.27185	0.08478	1.443377	10.19833	2085.174[a]	832
XRP	0.00075	-0.00098	0.446175	-0.26764	0.02769	2.790821	48.03039	189846.9[a]	2213

Working with the non-stationary series of data generate spurious relationships. Table 2 exhibits the results of the ADF and PP unit root test for all cryptocurrency returns. All data are stationary at levels and first difference and significant at 1% level.

TABLE 2. Unit Root Test

Cryptocurrency	Level		1st difference	
	Intercept	Trend & Intercept	Intercept	Trend & Intercept
Bitcoin	-8.644412	-9.823755	-6.505856	-6.283100
ETH	-46.62209	-46.68832	-19.13835	-19.13296
LTC	-47.33909	-47.33000	-20.56623	-20.56178
USDT	-28.50137	-28.50075	-14.41062	-14.40307
XRP	-29.85811[a]	-29.86158	-20.97503	-20.9701

The existence of the ARCH was analyzed by the ARCH- LM test and the results are shown in Table 4. Table 4 shows that the probability values are significant at 1% level. Thus the null hypothesis, which states equal variance, will be rejected. Then there is an ARCH effect and should be handled by developing ARCH family models namely ARCH, GARCH, EGARCH, TARCH, and PARCH.

Table 3. ARCH-LM test Result.

Cryptocurrency	Obs R-square	P-Value
Bitcoin	2407.418	0.0000
ETH	4.453399	0.0348
LTC	38.64278	0.0000
XRP	10.14006	0.0015
XRP	186.0652	0.0000

So we can develop ARCH family models,

The appropriate family ARCH model has been selected based on the minimum value of Akaike info criterion and the Schwarz criterion The AIC and AIC criteria are applied to decide the optimal ARCH-GARCH model in which the sum of squares of residual values should be minimum. To test for the day of the week in those 5 cryptocurrency market is derived from the best model. Day of the week result is shown in Table 5.- Table 9

TABLE 4. Day of the week effect
Bitcoin – PARCH Model

Variable	Coefficient	Prob
D1	0.387632***	0.0000
D2	0.045061	0.4004
D3	-0.021218	0.7055
D4	0.138310***	0.0191
D5	0.098557	0.1381
D6	0.117723	0.0554
D7	-0.084059	0.1895
Variance Equation		
C(8)	0.104366	0.0000
C(9)	0.151740	0.0000
C(10)	0.080467	0.0176
C(11)	0.826688	0.0000
C(12)	0.740031	0.0000

TABLE 5. Day of the week effect
Etherium (ETH) – PARCH Model

Variable	Coefficient	Prob
D1	-0.000116	0.9332
D2	0.002337	0.0565
D3	-0.002871	0.0335
D4	-0.002558	0.0381
D5	0.001624	0.2390
D6	0.002972	0.0837
D7	0.000744	0.6306
Variance Equation		
C(8)	0.003551	0.0609
C(9)	0.197232	0.0000
C(10)	-0.063292	0.1984
C(11)	0.744645	0.0000
C(12)	0.941854	0.0000

TABLE 6. Day of the week effect
Litecoin (LTC) – PARCH Model

Variable	Coefficient	Prob
D1	-0.003362	0.0000
D2	0.000295	0.4355
D3	-0.002805	0.0000
D4	0.000288	0.5161
D5	0.002906	0.0000
D6	0.001623	0.0364
D7	0.001753	0.0004
Variance Equation		
C(8)	0.009026	0.0000
C(9)	0.080798	0.0000
C(10)	-0.694627	0.0000
C(11)	0.896617	0.0000
C(12)	0.453957	0.0000

TABLE 7. Day of the week effect
Tether (USDT) – PARCH Model

Variable	Coefficient	Prob
D1	0.003593	0.3327
D2	0.011496	0.0000
D3	-0.002717	0.0000
D4	-0.005283	0.2022
D5	0.008099	0.0000
D6	0.000377	0.7359
D7	-0.002741	0.3231
Variance Equation		
C(8)	0.002375	0.3975
C(9)	0.071826	0.0000
C(10)	0.931612	0.0000
C(11)	0.146419	0.0725

TABLE 8. Day of the week effect
Ripple (XRP) – TARCH Model

Variable	Coefficient	Prob
D1	5.02E-05	0.9511
D2	0.000110	0.8993
D3	-0.003700	0.0000
D4	-0.001823	0.0538
D5	0.002193	0.0698
D6	-0.000194	0.8739
D7	-0.000738	0.5346
Variance Equation		
C	8.32E-05	0.0000
RESID(-1)^2	0.588382	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.313515	0.0000
GARCH(-1)	0.523809	0.0000

The day of the week effect results shows that the best model for Bitcoin is PARCH Model. Returns of Bitcoin are affected by three days. Monday, Thursday, and Friday have significant positive effects on Bitcoin return. Investors can gain abnormal positive returns by a trading strategy on these days. The return of Friday is higher than Monday and Tuesday. The rest of the day's effects is insignificant.

The best model for Litecoin was the PARCH model, return of Litecoin was affected by 5 days: Monday, Wednesday, Friday, Saturday, and Sunday. Two days namely Monday and Wednesday have a negative effect. The return on Wednesday is smaller than Monday.

The best model for the Etherium market is PARCH model, return of Etherium was affected by 3 days: Tuesday, Wednesday, and Thursday. Only Tuesday has a positive effect on return, and the other 2 days have a negative effect.

The best model for Tether is the PARCH model. Return of Tether was affected by 3 days: Tuesday (positive effect), Wednesday (negative effect), and Friday (positive effect).

The best model for Ripple was TARCH Model, and the return of Ripple was influenced by 2 days: Wednesday and Thursday.

5. CONCLUSION

This study aims to understand whether there are patterns in the cryptocurrency market, especially on Bitcoin, Etherium, Litecoin, Tether, and Ripple, or whether the market moves randomly. The results show that the cryptocurrency market does not move randomly, but there are phenomena of day-of-the-week. Therefore, the cryptocurrency market was not efficient because it had a certain pattern in the movement of the returns which made it followed a certain pattern and was not moving randomly because of the many requests and offers that occurred in the market. The pattern in the cryptocurrencies pattern could later be utilized by investors by buying the cryptocurrency before there was an increase in the return and selling them when the returns increased.

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