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A Study on Calendar Anomalies in the Cryptocurrency Market

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Abstract: Cryptocurrencies are sub-classes of digital currencies. Trading of these currencies have gained momentum during the past few years and have become new investment avenues for investors. An understanding on the market anomalies, which are patterns in asset prices would help the investors to adopt suitable strategies while trading in this asset class. This study aims to examine the presence of three calendar anomalies, day of the week, turn of the month, and year end effect in the cryptocurrencies. The top five cryptocurrencies which constitute a major share of the market capitalization value are selected for the study and the period of study is from July 23, 2017 to July 9, 2020. Dummy Variable Regression using GARCH (1,1) model was employed on the log value of returns of the cryptocurrencies. The study provides evidence on the existence of anomalies during Thursdays, the months March and April, and at the turn of the year.

Keywords: Cryptocurrency, Efficient Market Hypothesis, Calendar anomalies.

1 INTRODUCTION

Cryptocurrencies are subsets of the digital currencies [1] which gained prominence as an important type of digital currency during recent years. It has also become a new investment option for investors and trading in these cryptocurrencies have become colossal. There are more than 3500 types of cryptocurrencies being traded with an overall market capitalization of approximately \$350 billion as on August 5, 2020 (Source: Coinmarketcap.com). Among the cryptocurrencies, Bitcoin began operational in the year 2009 as the first decentralised cryptocurrency. It remains as the market leader in terms of trading with a market capitalization of \$208 billion as of August 5, 2020 constituting 60% of the total market share. Cryptocurrencies introduced subsequently are primarily clones of Bitcoin and other major cryptocurrencies and have novel features and certain fundamental differences. These cryptocurrencies have forayed into the market share of Bitcoin which has decreased from 86% (March 2015) to 60% (August 2020). While regulatory frameworks of cryptocurrencies are debated by policy makers across several countries, cryptocurrencies have also garnered interest of researchers. Several dimensions of the cryptocurrencies were studied by researchers, the asset class

of cryptocurrencies [2], volatility of cryptocurrencies [3], dynamic linkages of cryptocurrencies [4], investment options [5] and market anomalies [6]. The Efficient Market Hypothesis (EMH) laid on the foundations of the financial theories pertaining to market efficiency states that the asset prices reflect all available information. However, in real time situations the functioning of market deviates from the rules of EMH and these deviations are called anomalies. Anomalies may occur once and disappear or could occur repeatedly. Furthermore, these anomalies are categorized as fundamental anomalies, technical anomalies, and calendar anomalies. A calendar anomaly is a type of market anomaly that considers various stock markets behavior or economic effect related to the calendar, such as the day of the week, turn of the month and so on. Information on the calendar anomalies would be beneficial to investors and they can study these patterns and deploy suitable strategies to make profits. This study aims to investigate the presence of three calendar anomalies in the cryptocurrencies, the day of the week, turn of the month, and year end anomalies during the period July 23, 2017 to July 9, 2020.

2 LITERATURE REVIEW

A market anomaly refers to the difference in the performance of assets from its expected or assumed price path as defined by the EMH. Market anomalies and EMH are applicable to both stock and cryptocurrency market. Several studies have examined the presence of market anomalies in stock markets [7 - 11].

Studies related to calendar anomalies in the equity markets have revealed several patterns on the returns of indices and stock price movements at specific time frame owing to various reasons. Chandra [7] studied the calendar effect in the Indian Bombay Stock Exchange (BSE)-Sensex on basis of the turn of the month effect and timing of the month effect. Daily logarithmic market returns for ten years were analysed using the Dummy Variable Regression model. The analysis revealed that turn of the month effect as well as time of the month effect were present in the BSE-SENSEX. Market inefficiency was also established in this study. Deysappriya [8] examined the Colombo Stock Exchange (CSE) for the presence of day of the week effect and monthly effect market anomalies from January 1, 2004 to June 28, 2013 using daily and monthly return data and grouping in two sub-sample periods comprising of pre - war period and post-war period. Ordinary Least Square (OLS) and Generalized Auto Regressive Conditional Heteroskedasticity GARCH (1, 1) regression models were employed for analysis. The stock market anomalies, both day of the week effect and monthly effect were found to exist during the war period. Safeer & Kevin [9] investigated the presence of market anomalies on the five select companies of the BSE Sensex during the period January 2008 to December 2012. The anomalies included weekend effect, turn of the month effect, turn of the year effect in terms of price and volume and stock split effect. The presence of Monday effect was found to exist in the BSE indices from January 2008 to December 2012. However, the turn of the month effect was found to be insignificant. Shakila et al. [10] studied the semi-monthly effect in the BSE Sensex using the daily stock returns of five sectoral indices namely Standards and Poor (S&P) BSE

Auto Index, S&P BSE Bank Index, S&P BSE Consumer Durables Index, S&P BSE FMCG Index, and S&P BSE Health Care Index. The study found no evidence of semi-monthly effect in the selected sectoral indices from April 1, 2007 to March 31, 2017. Rossi & Gunardi [11] studied the presence of calendar anomalies, the January, and the weekdays' effects in the Stock Exchange Indices of France, Germany, Italy, and Spain. OLS and GARCH models were used to examine the Indices from 2001 to 2010 and the findings did not reveal existence of any significant calendar effect in these stock markets. The review from these studies showed mixed evidence on the presence of calendar anomalies on the stock markets.

The emergence of cryptocurrencies with novel features and the trading of these currencies which constitutes to very high market capitalization value has gained the attention of researchers to explore the presence of market anomalies in these currencies. Different facets of market anomalies studied by researchers in recent years include day of the week effect [6, 12], month of the year effect [11], persistence [13] and price over-reactions [14]. Cryptocurrency market constitute of more than three thousand cryptocurrencies but only a few top currencies contribute to major part of the market capitalization and the studies on market anomalies were focused either on Bitcoin or a particular type of calendar anomaly. Kurihara & Fukushima [15] investigated the market efficiency of Bitcoin concentrating on the weekly anomaly from July 17, 2010 to December 29, 2016 using OLS regression. This sample period was divided into two halves and the results showed that the Bitcoin market was inefficient for weekly anomaly. Caporalea & Plastunb [6] examined the presence of day of the week anomaly in the four cryptocurrencies Bitcoin, Ripple, Dash, and Litecoin for the period 2013 to 2017. Student's t-test, ANOVA, Kruskal–Wallis, Mann–Whitney, and OLS Dummy Variable Regression tests were used to analyse the entire sample period, and the sub-sample periods and evidence for Monday anomalies were found to exist only in Bitcoin currency. Kurihara & Fukushima [15] in their study found that the cryptocurrency market was inefficient but focused only on Bitcoin which was not necessarily representative of the entire cryptocurrency market and only the day of the week effect in the cryptocurrency market was examined. It can be observed from the literature review that only few studies have examined the calendar anomalies and only a particular type of calendar anomalies was studied in the cryptocurrency market. Hence this paper aims to fill this gap in the literature by examining the three calendar anomalies, the day of the week effect, month of the year effect, and turn of the year in the cryptocurrency market.

3 DATA AND METHODOLOGY

In this study the leading five cryptocurrencies Bitcoin, Ethereum, Tether, XRP, and Bitcoin cash were chosen for examination on the presence of calendar anomalies. These currencies constitute 80% of the total market capitalization value of the cryptocurrency market as of August 5, 2020 (coinmarket.com). The sample period considered for the study was three years from July 23, 2017 to July 9, 2020 based on the introduction of Bitcoin Cash on July 23, 2017. Data observations consisted of 1083 trading days the largest available data period for the chosen cryptocurrencies. Data relevant to the daily

closing prices for selected cryptocurrencies were sourced from the website coinmarketcap.com. In general, the time series data are generally portrayed by typical distributions which are used to examine its properties and to decide on the suitable statistical tests for analysis. The characteristics for the selected cryptocurrencies were examined for Normality using Jarque Bera Statistics, Stationarity using Augmented Dickey Fuller (ADF), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. The ADF test examines the null hypothesis as time series is not stationary. The KPSS test examines the null hypothesis as time series is stationary versus an alternative hypothesis that the series has a unit root. The unit root tests are examined without time series trend and intercept as the time series plot does not exhibit any specific trend (Figure 1). For longer sample periods the returns for the selected cryptocurrencies may not be normally distributed and regularly tend to show excess kurtosis and skewness which are basic with financial parameters [16] and hence, logarithmic returns of the time series data are used for further analysis.

In an efficient market the stock prices are expected to adjust to anomalies or new information very rapidly and the volatilities tend to return to its normal level [16]. Studies on calendar anomalies both in stock markets [7–9, 11] and cryptocurrencies market [6, 15, 17] have used Dummy Variable OLS Regression. In this study the Dummy Variable Regression is structured to analyse calendar anomalies by adopting the rationale of Caporale & Plastun [6] for the day of the week effect, Plastun et al. [17] for month of the year and turn of the year effects in the cryptocurrency market. The size, sign, and statistical significance of the dummy coefficients provide information about the respective calendar anomalies. Equation (1) presents the Dummy Variable Regression model to examine the day of the week effect on cryptocurrencies where $\ln(R_i)$ is the log of return of the daily closing prices of the select cryptocurrency computed using the formula $\ln(\text{Closing Price}/\text{Closing Price}-1)$, $\text{Constant}^{\text{Sunday}}$ is the constant value which captures the presence of Sunday anomaly, D_1 to D_n are the dummy variables that equals 1 for observations corresponding to a particular day of the week and 0 for the other days, β_1 to β_n are the mean return of the particular day of the week when the dummy variable equals to 1 and ε_t is the error term for the period t .

$$\ln(R_i) = \text{Constant}^{\text{Sunday}} + \beta_1 D_1 + \dots + \beta_n D_n + \varepsilon_t \quad (1)$$

The month of the year effect was examined using the Equation (2) where $\ln(R_i)$ represents the log of return of the daily closing prices of the select cryptocurrency computed using the formula $\ln(\text{Closing Price}/\text{Closing Price}-1)$, $\text{Constant}^{\text{December}}$ is the constant value that represents the anomaly pertaining to December month, D_1 to D_n are the dummy variables used for all days of the months January to November respectively, β_1 to β_n are the mean return of the days of the particular month when the dummy variable equals to 1 and ε_t is the error term for the period t .

$$\ln(R_i) = \text{Constant}^{\text{December}} + \beta_1 D_1 + \dots + \beta_n D_n + \varepsilon_t \quad (2)$$

The turn of the year effect is examined using Equation (3) where $\ln(R_i)$ is the log of return of the daily closing prices of the select cryptocurrency computed using the formula $\ln(\text{Closing Price}/\text{Closing Price}-1)$, Constant is the value that represents other days

of the year, D_1 is the dummy variable that is equal to 1 for the observations corresponding to all days of the last two weeks of December and first two weeks January, and 0 otherwise, β_1 are the mean return of the days of the last two and first two weeks of December and January when the dummy variable equals to 1 and ε_t is the error term for the period t .

$$\text{Ln}(R_t) = \text{Constant} + \beta_1 D_1 + \varepsilon_t \quad (3)$$

The residuals of the Dummy variable regression were verified for presence of autocorrelation using Ljung-Box (L-B) portmanteau test and heteroskedasticity using Lagrange's Multiplier (LM) test. The presence of ARCH effect was found in the residuals of the models for all cryptocurrencies and GARCH (1,1) regression model was used for the analysis of the anomalies. The results of Ljung-Box (L-B) portmanteau test exhibited the presence of autocorrelations in the residuals of the regression model pertaining to the cryptocurrency Tether and hence, Auto Regressive Moving Average (ARMA) model was used for further analysis.

4 FINDINGS AND DISCUSSIONS

The time series graphs and the descriptive statistics of the select cryptocurrencies provided preliminary evidence of the behaviour of the close price for the selected cryptocurrencies. From the visual analysis of the graph (Figure 1) it can be seen that all cryptocurrencies witnessed sharp increase in their prices during December 2017 and January 2018, however only Bitcoin and Ethereum showed increase during subsequent turn of the year time periods for the years 2019 and 2020. Based on the sample period, it can be observed that Bitcoin experienced a fall and subsequent rise in prices during the months March and April of all the years in the sample period, whereas it was not observed in other cryptocurrencies. Clustering of prices can be observed in Tether while other cryptocurrencies showed no specific trend in their price movements. It can be inferred from the values of skewness and kurtosis that the daily closing prices and log return of cryptocurrencies does not confirm to normal distribution. The log return of Bitcoin and Ethereum series showed that it was negatively skewed and the kurtosis value was much higher than 3 representing that the distribution is leptokurtic with fat tails indicating that the index posted negative returns during the sample period while other cryptocurrencies displayed positive returns. Normality of the cryptocurrencies was further statistically examined using Jarque - Bera statistics (Table 1). The statistic values for the cryptocurrencies were found to be significant at 5 % level of significance during the entire sample period implying that series does not meet the normality assumptions. In practice, a leptokurtic distribution is far more likely to characterize financial time series, and the residuals from a financial time series model. Brooks [18] recommends the usage of natural logarithmic transformations to meet the normality assumption as it can help to make a skewed distribution closer to a normal distribution. Hence, non-normal data series has been transformed into a normally distributed data series by applying the natural log transformation and used for further analysis.

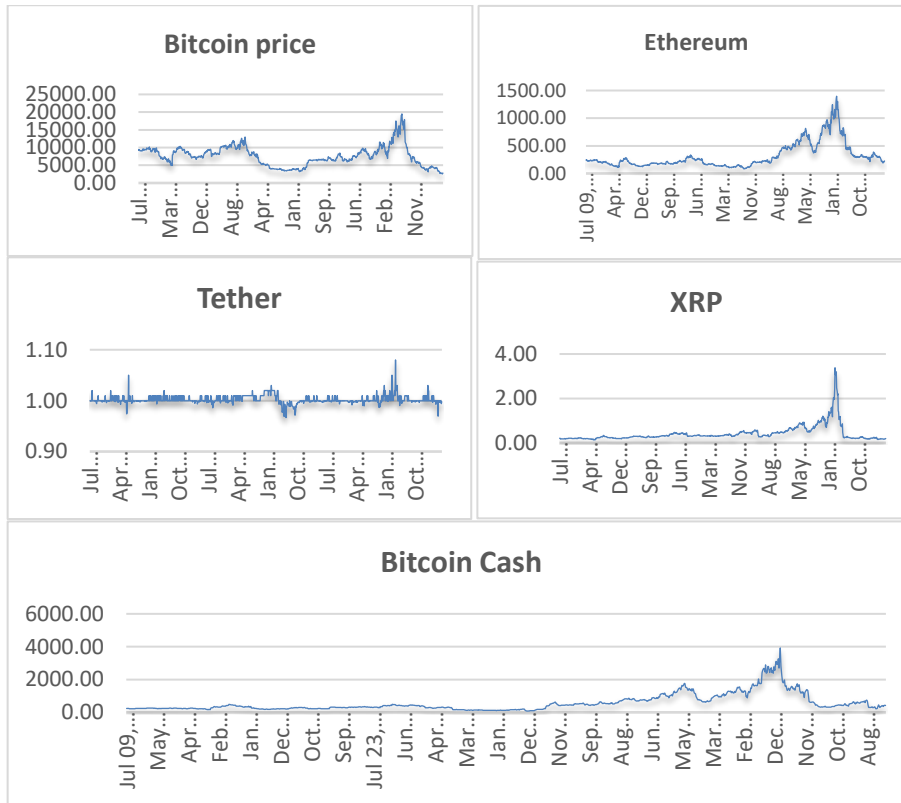


Fig. 1. Times series graphs of select cryptocurrencies

The stationarity of the closing prices of the crypto currencies were examined using unit root tests ADF and KPSS (Table 1). The critical values of the closing prices of the crypto currencies did not meet the criteria of the ADF and the KPSS test and were found to be non-stationary. The ADF results of the log returns of the cryptocurrencies showed that the t-statistic values were lesser than the critical values -1.9411 at 5% significance level. Results implied that the Null Hypothesis (H_0) was not accepted, and the series was stationary. The KPSS test statistic values were found to be lower than the critical value 0.463 at 5 % significance level. The Null Hypothesis (H_0) was not rejected, and the log returns of cryptocurrencies were found to be stationary. The stationarity of the log returns of cryptocurrencies were established and were used for further analysis.

	Bitcoin	ETH	Tether	XRP	Bitcoin Cash	Bitcoin	ETH	Tether	XRP	Bitcoin cash
	Daily Closing prices					Log normal values				
Mean	7597.8	314.38	1.002	0.414	561.54	0.0011	0.0001	0.000	0.000	-0.001
Median	7459.6	225.63	1.00	0.309	354.46	0.0013	-0.0001	0.000	-0.002	-0.003

Maximum	19497	1396.4	1.08	3.380	3923.1	0.2251	0.234	0.0572	0.607	0.432
Minimum	2529.4	84.310	0.967	0.140	77.37	-0.465	-0.551	-0.049	-0.399	-0.561
Std. Dev.	2796.3	231.1	0.008	0.357	534.7	0.044	0.053	0.007	0.062	0.077
Skewness	0.754	1.913	1.45	4.026	2.366	-1.032	-1.214	0.297	1.551	0.254
Kurtosis	4.406	6.48	15.31	24.96	9.62	16.94	15.659	14.804	21.739	12.48
Observations	1083	1083	1083	1083	1083	1082	1082	1082	1082	1082
Normality- Jarque Bera Statistics										
Jarque-Bera	191.76	1208	7216.1	2468.1	2987.6	8949.7	7490.8	6297.9	1625.8	4065.9
Stationarity – ADF Test results										
ADF t-Stat.	-0.44	-1.004	-0.90	-2.18	-1.434	-33.95	-34.88	-20.27	-20.88	-30.68
P. value	0.52	0.28	0.68	0.62	0.141	0	0	0.048	0	0
KPSS t-Stat.	0.3	1.77	0.08	1.02	1.02	0.146	0.106	0.106	0.105	0.07

*Bold indicates significance at 5% level

Table 1. Characteristics of cryptocurrencies

4.1 Day of the Week Anomaly

The day of the week anomalies were studied by assigning value 1 for the first dummy variable on all Mondays of the sample period and 0 for other days in Equation 1. Similarly, value 1 was assigned for all Tuesdays and 0 for other days. Sundays were not assigned values 1 since Sunday was taken as the reference variable and was represented by the constant term. The preliminary results of the Dummy Variable OLS regression equation revealed that the residuals were heteroskedastic and hence, GARCH (1,1) models were applied to examine the day of the week anomaly for all cryptocurrencies. Clustering effect of the closing prices of Tether was observed in the Figure 1 and the residuals of GARCH (1,1) model applied for Tether cryptocurrency also showed presence of autocorrelation. Hence, GARCH (1,1): ARMA (1,1) model was used to examine presence of day of the week anomaly in Tether cryptocurrency. The results of GARCH (1,1) models are provided in Table 2 and it can be observed that coefficients of Thursday were negative and significant for the cryptocurrencies Bitcoin (-0.008), Ethereum (-0.011), XRP (-0.010), Bitcoin Cash (0.017). The findings provided existence of Thursday anomalies for the four cryptocurrencies. Negative sign of the coefficient indicated that the cryptocurrencies had negative returns on Thursdays. In case of Tether, the day of the week anomaly was not significant for any of the weekdays. Adjusted r square values of GARCH (1,1) model improved from the OLS models suggested that the GARCH (1,1) model was a better fit model to study calendar anomalies. The Ljung-Box Q-statistics, LB (36) statistic tests the null hypothesis that autocorrelations up to lag 36 equals zero implying that the residuals and squared residuals are random and independent up to 36 lags. The values of Q (36) and $Q^2(36)$ of the Ljung-Box Q-statistics for the standardized and squared residuals were found to be insignifi-

cant and hence the residuals were uncorrelated. The ARCH LM test is a Lagrange multiplier test to assess the significance of ARCH effects or whether the residuals are exhibiting heteroskedasticity. The ARCH LM statistic was found to be insignificant at 5 % significance level, confirming the removal of heteroskedasticity in the residuals. The ARCH and GARCH terms in variance equation were positive and significant at 1% level, suggesting that once a shock has occurred, volatility tend to persist for longer periods. The findings differed from the studies by Caporale et al. [13] and Caporale & Plastun [6] who showed that Bitcoin exhibited Monday anomalies having abnormal positive returns. The difference may be accounted for the high market volatility on the cryptocurrency market from December 2019 owing to the COVID - 19 pandemic and the persistence of volatility due to shocks were statistically confirmed in the ARCH and GARCH terms of the GARCH(1,1) model.

	Bitcoin		Ethereum		Tether		XRP		BitcoinCash	
Mean Equation										
Variable	Co-eff.	Prob	Co-eff.	Prob	Co-eff.	Prob	Co-eff.	Prob	Co-eff.	Prob
C	0.00	0.335	0.00	0.98	0.00	0.47	-0.0	0.34	-0.0	0.75
Monday	0.00	0.726	0.00	0.73	0.00	0.83	0.01	0.07	0.01	0.35
Tuesday	-0.00	0.605	0.00	0.86	0.00	0.17	0.01	0.12	0.0	0.93
Wednesday	-0.00	0.562	-0.00	0.59	0.00	0.99	0.00	0.91	-0.0	0.82
Thursday	-0.01	0.032	-0.01	0.02	0.00	0.28	-0.01	0.02	-0.02	0.00
Friday	0.00	0.891	0.006	0.33	0.00	0.79	0.00	0.71	0.01	0.21
Saturday	0.00	0.764	0.008	0.21	0.00	0.29	0.01	0.25	0.01	0.19
AR (1)					0.08	0.15				
MA (1)					-0.8	0.0				
Variance Equation										
C	0.000	0.0	0.000	0.0	0.000	0.0	0.000	0.0	0.000	0.0
ARCH	0.133	0.0	0.101	0.0	0.150	0.0	0.145	0.0	0.120	0.0
GARCH	0.813	0.0	0.830	0.0	0.600	0.0	0.832	0.0	0.828	0.0
Adj R-sq.	-0.003		0.003		0.293		-0.012		0.002	
LB Q (36)	0.853		0.261		0.134		0.814		0.777	
LB Q ² (36)	1.000		0.721		0.901		0.975		1.000	
Arch effect	0.912		0.758		0.883		0.238		0.566	

Table 2. Results of Day of the Week anomaly of select cryptocurrencies

4.2 Month of the Year Anomaly

The month of the year anomaly was examined by assigning value 1 to dummy variable for January and 0 for other months and the process was repeated for subsequent months

in Equation 2. The month of December was used as the reference variable and was represented in the constant term. The results of GARCH (1,1) models applied for Bitcoin, XRP, Ethereum and Bitcoin cash cryptocurrencies and GARCH (1,1) ARMA model for Tether are provided in Table 3. As observed from the Table 3, Bitcoin was the only cryptocurrency that had positive significant values during the months March (0.016) and April (0.011) and therefore provided evidence for market anomalies during March and April. The positive value of the coefficient indicated that positive returns were earned in Bitcoin currencies and also confirmed the month anomaly during March and April. Plastun et al. [17] has found that Bitcoin had the lowest returns during the months of July and August. Other cryptocurrencies used in this study did not show any evidence for month anomalies. It can be surmised that Bitcoin which had higher risk return characteristics (Table 1) exhibited negative Thursday and positive March-April anomalies. Hence, market inefficiency for this cryptocurrency was evident. The traders can employ suitable trading strategies to generate abnormal profits in this asset class. Residual tests to examine the presence of ARCH effect was carried out and the insignificant values indicated the removal of ARCH effects. The statistics of Q(36) and $Q^2(36)$ of the Ljung-Box Q-statistics also confirmed the absence of autocorrelation in the residuals for the models of Bitcoin, XRP, Ethereum, and Bitcoin cash. The significant values of AR (1), MA (1) terms of Tether model GARCH (1,1): ARMA (1,1) confirmed the absence of autocorrelations in the residuals.

	Bitcoin		ETH		Tether		XRP		Bitcoin Cash	
	Mean Equation									
Variable	Co-eff.	Prob.	Co-eff.	Pro b.	Co-eff.	Pro b.	Co-eff.	Pro b.	Coeff.	Prob.
C	0.00	0.96	0.01	0.59	0.00	0.51	0.00	0.98	0.00	0.80
January	0.00	0.88	0.00	0.98	-0.00	0.13	0.00	0.80	0.00	0.82
February	0.00	0.62	0.00	0.81	0.00	0.94	0.00	0.86	0.00	0.78
March	0.02	0.00	-0.02	0.22	0.00	0.74	-0.00	0.61	-0.00	0.92
April	0.01	0.05	0.01	0.66	-0.00	0.38	0.01	0.42	0.02	0.15
May	0.00	0.81	-0.00	0.96	-0.00	0.69	-0.00	0.81	0.00	0.73
June	-0.00	0.71	-0.01	0.64	0.00	0.60	-0.01	0.27	-0.00	0.78
July	0.00	0.68	-0.01	0.56	-0.00	0.44	-0.00	0.71	0.00	0.82
August	0.00	0.64	-0.01	0.71	0.00	0.91	0.00	0.98	-0.00	0.78
September	-0.00	0.77	-0.01	0.49	-0.00	0.64	0.00	0.77	-0.00	0.95
October	0.00	0.62	-0.01	0.70	-0.00	0.60	0.00	0.96	0.00	0.95
November	-0.01	0.38	-0.01	0.54	0.00	0.82	-0.01	0.42	-0.00	0.82
AR (1)					0.06	0.28				
MA (1)					-0.77	0.00				
	Variance Equation									

C	0.00	0.0	0.00	0.0	0.00	0.0	0.00	0.0	0.00	0.00
ARCH	0.16	0.0	0.15	0.0	0.16	0.0	0.13	0.0	0.10	0.00
GARCH	0.80	0.0	0.60	0.0	0.81	0.0	0.84	0.0	0.85	0.00
Adj R-sq	-0.03		0.00		-0.00		-0.01		-0.01	
LB Q (36)			0.44		0.28		0.93		0.88	
LB Q ² (36)			0.91		1.00		0.99		1.00	
LM Arch			0.93		0.83		0.24		0.52	

Table 3. Results of Month of the Year anomaly of select cryptocurrencies

4.3 Turn of the Year Anomaly

The turn of the year anomaly on cryptocurrencies was analyzed using value 1 to dummy variables for the last two and first two weeks of December and January and 0 for other weeks of the year in Equation 3. Results of GARCH (1,1) models are provided in Table 4.

	Bitcoin		ETH		Tether		XRP		Bitcoin Cash	
Mean Equation										
Variable	Co-eff.	Prob.	Coeff.	Pro b.	Co-eff.	Pro b.	Co-eff.	Pr ob.	Coeff.	Prob .
C	0.00	0.297	-0.001	0.7	0.0	0.5	0.0	0.2	-0.002	0.46
Turn of the Year	0.01	0.414	0.01	0.0	0.0	0.8	0.01	0.1	0.018	0.03
AR (1)					0.03	0.0				
MA (1)					-0.7	0.0				
Variance Equation										
C	0.000	0.000	0.00	0.0	0.00	0.0	0.00	0.0	0.000	0.00
ARCH	0.136	0.000	0.09	0.0	0.14	0.0	0.13	0.0	0.100	0.00
GARCH	0.805	0.000	0.83	0.0	0.81	0.0	0.84	0.0	0.849	0.00
Adj R- sq.	-0.01		0.01		0.29		0.00		0.003	
LB Q (36)	0.884		0.45		0.46		0.89		0.872	
LB Q ² (36)	1.000		0.81		1.00		0.98		1.000	
LB Arch	0.904		0.79		0.83		0.23		0.518	

*Bold indicates significance at 5% level

Table 4. Results of Turn of the Year Effect

Results indicate that Ethereum (0.013) and Bitcoin Cash (0.018) are the two cryptocurrencies that have positive and significant values for turn of the year effect. The value of the ARCH LM statistic was found to be insignificant and the absence of ARCH

effects in the residuals was confirmed. The statistics of $Q(36)$ and $Q^2(36)$ of the Ljung-Box Q -statistics for the model standardized and squared standardized residuals were insignificant at 36 lags and hence the residuals were not serially correlated. Positive value of the coefficient indicates that there is a positive impact on the cryptocurrencies by the arrival of a new year. Other cryptocurrencies, namely Bitcoin, Tether and XRP were not affected by the turn of the year effect. Bitcoin cash and Ethereum were found to exhibit Thursday anomalies and turn of the year anomalies. Hence, the traders can employ trading strategy that involves short positions on Thursdays and close them at the end of this day. They can take long positions during the turn of the year except for Thursdays.

5 CONCLUSION

This paper examines the day of the week, month of the year and turn of the year calendar anomalies of the cryptocurrencies Bitcoin, Ethereum, Tether, XRP and Bitcoin Cash using Dummy variable GARCH regression. The study provides evidence for presence of the calendar anomalies during the sample period July 23, 2017 through July 9, 2020 and confirms market inefficiency in the cryptocurrency market. The findings of the study show that Bitcoin, Ethereum, XRP, Bitcoin Cash made negative returns on Thursdays. It may be attributed to the fact that Thursday falling in the middle of the week. Investors may have presumed that less volatility would result in less returns during this time and would have planned trading activities during the beginning and end of the week to make profits. Bitcoin also exhibited March and April month anomaly with positive returns. The months March and April are the end and start of a fiscal year and it may be suggested that investors can plan their investments especially in Bitcoin cryptocurrency for reaping more profits. Ethereum and Bitcoin were the only two cryptocurrencies effected by the turn of the year effect with positive returns caused by the change in the year. This may be due to the positive sentiment of the New Year. Tether was the only cryptocurrency that was not affected by any of the calendar anomalies examined in this paper and may be attributed to the clustering or persistence in price movements. Descriptive statistics of Bitcoin and Ethereum showed negative returns during the entire sample period. Thursday anomalies showed negative returns for these two cryptocurrencies, whereas turn of the month showed positive returns for Bitcoin and year end anomaly showed positive returns for Ethereum. It may be presumed that the occurrences of the negative returns on Thursdays were more frequent than the turn of the month and year end and hence, was reflected in the entire sample period. The findings would be beneficial to the investors and traders who can make use of these anomalies to adopt suitable trading strategies and achieve higher returns in the digital currency arena. The research in cryptocurrency is burgeoning and this study identifies the various calendar anomalies in this market and would benefit researchers by providing insights on market inefficiencies for developing models on volatility and forecasting. The cause of these anomalies may be due to volatility spill over from other global markets, political uncertainties, and news events or tweets and it can be taken into consideration for future scope of this study.

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