**Calendar effects in cryptocurrencies: not so straightforward**

**Introduction**

The exponential growth of cryptocurrencies is a phenomenon that has attracted considerable attention from investors, central banks and governments in recent years. Compared to traditional asset classes such as equity or debt, the cryptocurrencies are relatively young (The first cryptocurrency, BitCoin, was invented in 2009 but active trading started in 2013) and therefore fewer literatures are documented. Among these literatures, many researchers have been documenting about the existent of market anomalies in cryptocurrency market. Some evidences suggest that cryptocurrencies returns are much more volatile than other markets (Cheung *et al.* 2015, Dwyer 2015 and Carrick 2016), have persistence in its return and volatility series (Urquhart 2016, Caporale *et al.* 2018), have correlations with other cryptocurrencies (Yi *et al.* 2018, Ji *et al.* 2019) or have correlations with other asset classes (Dyhrberg 2016, Okorie and Lin 2020). In particular, some researchers have found seasonality cryptocurrency market, which potentially allow traders to earn abnormal profits (Aharon and Cadan 2019, Caporale and Plastun 2019, Kaiser 2019). These market anomalies make it questionable whether traditional market theory such as the efficient market hypothesis (EMH) can be used to correctly explain the abnormal behaviors of cryptocurrency markets. This theoretical background led to the key issue discussed in the present empirical research about the calendar effects in cryptocurrencies, which would be inconsistent with the Efficient Market Hypothesis (EMH), according to which, prices and returns should be unpredictable (see Fama, 1970 for the theoretical underpinnings).

This research is motivated by the number of stock market anomalies that have been identified in the literature to have significant market predictive ability, which is inconsistent with the EMH. One strand of these anomalies finds that stock returns are systematically lower or higher depending on the day of the week, the day of the month, or month of the year. The anomalies are commonly known as calendar effects (also referred as seasonalities). These include the well-known Monday effect (Cross 1973, Connolly 1979, French 1980, Maberly 1995 among others), January effect (Rozeff and Kinney 1976, Gultekin and Gultekin 1983, Keim 1987, Sun and Tong 2010 among others) and Halloween effect (Bouman and Jacobsen 2002, Lucey and Zhao 2008, Haggard and Witte 2010, Andrade et al. 2013 among others) which are the anomalies studied in this research.

Prior literatures about calendar effects in cryptocurrencies exists but there seems to be disagreement among scholars about the existence of such effects. Some researchers have documented that seasonality is not present in cryptocurrency (Baur *et al.* 2019, Caporale *et al. 2019,* Kinateder and Papavassiliou 2019), noting that cryptocurrency markets are indeed efficient (Bartos 2015, Nadarajah and Chu 2017, Tiwari *et al.* 2018). While others argue that Bitcoin show calendar effects (Aharon and Qadan 2019, Caporale and Plastun 2019, Kaiser 2019), noting the lack of government’s regulations and potentially inefficient cryptocurrency market (Urquhart and McGroarty 2014, Urquhart 2016, Kristoufek and Vosvrda 2019). Hence the existent of seasonality in cryptocurrencies warrants an empirical investigation as well as some theoretical background if such market anomalies were found[[1]](#footnote-1).

Unlike most prior literatures which either focus on Bitcoin (Urquhart 2016, Kurihara and Fukushima 2017, Baur *et al.* 2019) or focus on single calendar effect (Aharon and Qadan 2019, Caporale and Plastun 2019, Ma and Tanizaki 2019), this study carries out a more comprehensive analysis by considering five main cryptocurrencies and applying three different calendar effect tests over the period 2013–2020. In addition to academics, the contribution from this research is clear for traders and market participants who could generate abnormal profits as well as for market regulators to design the necessary regulations to prevent such arbitrage opportunities in the cryptocurrency markets.

The remainder of the paper is structured as follows. The following section presents a brief review of the literature regarding calendar anomalies. The next section describes the research hypotheses, data and methodology. The empirical results and robustness checks are then presented and discussed. Finally, the conclusions are given, along with suggestions for future research.

**2 Data**

As noted by Kaiser 2019 that sufficient market capitalization and liquidity are important criteria to be considered by investors and to qualify for the construction of a crypto fund under the regulation of the AIFM Directive by market regulators, the analysis, therefore focusses on the five largest cryptocurrencies by market capitalization (Bitcoin, Ethereum, Ripple, Tether and Litecoin) with a sufficiently long historical price series as to estimate seasonality patterns. The data source is Coinmarketcap.com. The application of daily returns, data source and a focus on the largest cryptocurrencies is in line with prior research (Urquhart 2016, Nadarajah and Chu 2017, Kaiser 2019) and therefore provides a solid basis for comparison. Table 1 report descriptive statistics of the data.

**Table 1:** Descriptive statistics

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Return |  |  |  | Size | Volume | Volatility | #Obs |
|  | mean | std | skew | kurt |  |  |  |  |
| BTC | 0.15 | 4.36 | -0.59 | 14.94 | 117,314.8 | 46,491.9 | 1.72 | 2520 |
| ETH | 0.23 | 7.19 | -3.45 | 71.11 | 14,770.1 | 11,396.3 | 2.73 | 1690 |
| XRP | 0.14 | 7.24 | 1.97 | 32.71 | 6,901.6 | 2,117.4 | 2.31 | 2423 |
| TET | 0.01 | 2.07 | -12.37 | 19.90 | 4,627.6 | 57,333.1 | 0.46 | 1845 |
| LTC | 0.01 | 6.49 | 1.51 | 27.98 | 2,494.6 | 3,598.2 | 2.39 | 2520 |

*Note*: This table presents the descriptive statistics for the five cryptocurrencies considered in this study. The coins considered are: Bitcoin (BTC), Ethereum (ETC), Ripple (XRP), Tether (TET) and Litecoin (LTC). The coins where selected on the basis of being the largest by market capitalization as of March 2020 and gathered from www.coinmarketcap.com. Statistics are provided for returns, market-capitalization (size), trading volume (volume) and volatility estimator.

**3 Methodology**

Urquhart and McGroarty (2014) and Kinateder and Papavassiliu (2019) argue that the method used to investigate calendar effects in cryptocurrency returns and volatilities should be generalized autoregressive conditional heteroscedasticity (GARCH) model with dummy variables because the model is capable of capturing volatility clustering and non-normality in cryptocurrency price series. This is particularly important when dealing with calendar effects, as these effects are sensitive to model specification. Ignoring the stylized facts can produce bias (see, for example, Bollerslev 1986, Connolly 1989, Auer and Rottmann 2014 for discussions). In addition, it is a consistent method for investigating not only how seasonality affect returns, but also how they impact volatility.

Since Engle (2001) show that GARCH(1,1) is the simplest and most robust of the family of volatility models, and is the most widely applicable used in the literature. Therefore, this research utilize GARCH(1,1) dummy regression following prior researches. In this regard, Auer and Rottmann (2014) recommend to use Bollerslev and Wooldridge's (1992) QML procedure for high-kurtosis data in order to correct standard errors. As shown in Table 1, Bitcoin returns (and all other coins under consideration) are characterized by excess kurtosis (k = 14.94) being far away from normal kurtosis (k = 3), therefore the QML estimation were used in the analysis throughout. All tests have the null hypothesizes of no calendar effect.

The returns are computed as:

; Where *Pi,t* are close price of a coin *i* on the *t*th day

As trading volume indicates the level of activity on the markets, as well as being a proxy for market liquidity, it is therefore included in the analysis. Finally, daily volatility estimator is estimated following Roger and Satchell (1991)’s methodology on the basis of high, low and closing prices. Accordingly, the volatility is estimated as follows:

Where *Hi,t* is the highest price, *Li,t* the lowest price, *Oi,t* the opening price and *Ci,t* the closing price of a coin *i* at day *t*. For robustness, this study also considers the squared daily return as an estimator for volatility. The results show no material differences from the main analysis.

**4. Results and discussion**

*4.1**January effect*

Since the 70’s when Rozeff and Kinney (1976) documented the higher average stock returns in January, scholars has been proposing potential reasons behind the phenomena. The literature generally links the stock market anomaly with tax-loss selling, window-dressing, omitted risk-factors, bid-ask bounce, information-release or a combination of all (see, for example Ritter 1988). Although many of the aforementioned appear to be unlikely reasons in the case of cryptocurrency, tax-loss selling (Starks *et. al.* 2006), appear to be reasonable because the US Internal Revenue Service (IRS) and similar authorities in many countries treated cryptocurrency as a property for tax purpose. In addition, the wash sale[[2]](#footnote-2) regulations, do not apply to cryptocurrency because it is classified as a property. This makes tax-loss selling even more likely to be present in cryptocurrency, and is also consistent with the observed empirical results of higher trading volume in January. Table 2 report the results on the January effect.

**Table 2:** January effect

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Return |  | Volume |  | Volatility |  |
|  | Coefficient | t-stat | Coefficient | t-stat | Coefficient | t-stat |
| BTC | -0.25 | -0.69 | 0.13 | 2.31\*\* | 0.15 | 0.03 |
| ETH | 1.12 | 2.20\*\* | 0.15 | 3.32\*\*\* | 0.30 | 0.21 |
| XRP | -0.28 | -0.66 | 0.74 | 9.33\*\*\* | 1.37 | 3.31\*\*\* |
| TET | -0.02 | 0.33 | 0.16 | 5.59\*\*\* | -0.93 | -0.01 |
| LTC | -0.01 | -0.02 | 0.41 | 5.89\*\*\* | 0.93 | 1.57 |

*Note*: This table reports the results for the January effect across the returns of each coin (Return), the trading volume of each coin (Volume) and the volatility estimator of each coin (Volatility). t-statistics reported are based on Bollerslev and Wooldridge's (1992) robust estimator. \*,\*\*,\*\*\* represent statistical significance at the 1%, 5%, and 10% levels, respectively. The coins considered are: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Tether (TET) and Litecoin (LTC). The coins were selected on the basis of being the largest by market capitalization as of March 2020, excluding recent bitcoin spin offs (Bitcoin cash and Bitcoin SV), and collected from www.coinmarketcap.com.

Overall, two main observations are observed. First, the returns of Ethereum in January are on average positive – implying a January effect is present in Ethereum returns. The result is consistent withKristoufek and Vosvrda (2019)’s posit that Ethereum and Litecoin are the least efficient cryptocurrency. Second, the trading volume of all coins under consideration are found to be higher in January month. This result is consistent with tax-loss selling hypothesis documented in prior literature, which predict that trading volume should be higher in January because investors buy back assets in the beginning of the year after a tax-loss selling at the previous year end (see, for example, Chang and Pinega 1986, Starks *et. al.* 2006, Chen *et al.* 2011) Finally, no consistent inference can be drawn from volatility series since only one out of five coins under considerations show significant relationship.

*4.2 Monday effect*

The Monday effect refers to the tendency of returns on Monday to be lower compared to the rest of the week. The weekend effect, often used interchangeably with the Monday effect in the stock market literature, is observed separately in this study on the basis of continues trading over the weekends in cryptocurrency markets. This allow the present study to investigate if trading patterns on Saturday and Sunday deviate from working days and thereby deviate from the classical specification of the weekend effect. Table 3 reports the results.

**Table 3:** Monday effect

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Return |  | Volume |  | Volatility |  |
| Panel A: Monday effect | Coefficient | t-stat | Coefficient | t-stat | Coefficient | t-stat |
| BTC | 0.09 | 0.32 | 0.19 | 3.84\*\*\* | 0.28 | 1.52 |
| ETH | -0.28 | -0.57 | 0.09 | 2.16\*\* | -0.17 | -0.43 |
| XRP | -0.12 | -0.28 | 0.33 | 4.86\*\*\* | 0.46 | 1.33 |
| TET | -0.00 | 0.87 | 0.08 | 2.15\*\* | -0.78 | -0.00 |
| LTC | -0.82 | -2.21\*\* | 0.12 | 1.87\* | 0.13 | 0.35 |
| Panel B: Weekend effect |  |  |  |  |  |  |
| BTC | 0.44 | 1.29 | -0.28 | -6.45\*\*\* | -0.20 | -1.03 |
| ETH | -0.20 | -0.46 | -0.14 | -4.64\*\*\* | 0.00 | 0.01 |
| XRP | 0.48 | 1.19 | -0.49 | -7.92\*\*\* | -0.01 | -0.22 |
| TET | -0.01 | -0.36 | -0.12 | -3.94\*\*\* | -0.00 | -0.11 |
| LTC | 0.71 | 1.60 | -0.20 | -3.62\*\*\* | -0.28 | -0.80 |

*Note*: This table reports the results for the Monday effect across the returns of each coin (Return), the trading volume of each coin (Volume) and the volatility estimator of each coin (Volatility). t-statistics reported are based on Bollerslev and Wooldridge's (1992) robust estimator. \*,\*\*,\*\*\* represent statistical significance at the 1%, 5%, and 10% levels, respectively. The coins considered are: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Tether (TET) and Litecoin (LTC). The coins were selected on the basis of being the largest by market capitalization as of March 2020, excluding recent bitcoin spin offs (Bitcoin cash and Bitcoin SV), and collected from www.coinmarketcap.com.

The null hypothesis if no Monday effect cannot be rejected for 4 out of 5 considered cryptocurrency returns. However, the coefficient of Monday dummy was found to be negative and statistically significant for Litecoin. This suggest the existent of Monday effect in Litecoin and is consistent with the stock market literatures (French 1980, Abraham and Ikenberry 1994, Ülkü and Rogers 2018 among others). Once again, the result confirms Kristoufek and Vosvrda (2019)’s posit that Ethereum and Litecoin are the least efficient cryptocurrency. All coin under consideration show higher trading volume in Monday, which is also in line with the stock market literature.

No evidence with respect to a difference in returns and volatility between weekend and non-weekend days were found. However, all considered coins have significantly lower trading volume during weekend. (all considered coefficients are negative and statistically significant at 1%). The result suggests, that trading activities, although possible on seven days a week, takes place primarily during working days, and are in line with Buar *et al.* 2019 and Kaiser 2019 using a different approach.

*4.3 Halloween effect*

Halloween effect (also known as “Sell in May” effect) refer to the market anomaly which returns from November to April are higher than for the other half of the year. The first empirical evidence was documented by Bouman and Jacobsen (2002), who detect the Halloween effect in 36 out of 37 considered equity markets. Most literature in the field posit that the Halloween effect are present in stock markets and the results are robust even after taken into considerations of outlier observations, transaction costs, compensation for risks or seasonality in news (for example, Bouman and Jacobsen 2002, Lucey and Zhao 2008, Haggard and Witte 2010, Andrade et al. 2013). Since Haggard and Witte (2010) and Kaiser (2019) argue that the Halloween effect does not driven by the January effect, it is therefore preferable to include the anomaly in the analysis. Table 4 report the results for the Halloween effect.

**Table 4:** Halloween effect

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Return |  | Volume |  | Volatility |  |
|  | Coefficient | t-stat | Coefficient | t-stat | Coefficient | t-stat |
| BTC | 0.04 | 0.31 | 0.29 | 15.38\*\*\* | 0.13 | 1.21 |
| ETH | 0.32 | 1.36 | 0.45 | 29.33\*\*\* | -0.24 | -1.15 |
| XRP | 0.00 | 0.03 | 0.61 | 21.07\*\*\* | 0.09 | 0.49 |
| TET | -0.02 | -0.68 | 2.90 | 68.81\*\*\* | -0.01 | -0.09 |
| LTC | 0.10 | -0.59 | 0.07 | 0.30 | -0.34 | -1.09 |

*Note*: This table reports the results for the Halloween effect across the returns of each coin (Return), the trading volume of each coin (Volume) and the volatility estimator of each coin (Volatility). t-statistics reported are based on Bollerslev and Wooldridge's (1992) robust estimator. \*,\*\*,\*\*\* represent statistical significance at the 1%, 5%, and 10% levels, respectively. The coins considered are: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Tether (TET) and Litecoin (LTC). The coins were selected on the basis of being the largest by market capitalization as of March 2020, excluding recent bitcoin spin offs (Bitcoin cash and Bitcoin SV), and collected from www.coinmarketcap.com.

Contrary to the results from equity market, it was found that return and volatility of cryptocurrency in non-summer months are not statistically different from return from the other half of the year, for all considered cryptocurrencies. Most considered coins show higher trading volume in non-summer months, in line with the stock market literature (Bouman and Jacobsen 2002, Hong and Yu 2019). The results reject the existent of Halloween effect in cryptocurrency and are consistent with Buar *et al.* 2019 using a different approach. No evidence of exploitable trading strategies, based on the Halloween effect, were found in all considered coins.

**5 Robustness checks**

For robustness, this study also utilizes non-parametric Kruskal–Wallis test (Kruskal and Wallis 1952) with respect to calendar effects in cryptocurrency returns in order to account for the non-normality, but find no material differences. In addition, to account for potential asymmetries, tests with respect to calendar effects in cryptocurrency returns based on a GLS-GARCH(1,1) approach (Glosten *et. al* 1993) are also conducted but no material differences were detected. Consistently, traditional OLS regression yield directionally identical results with lower significance.

This research also tests the Monday effect using 5-days a week system (excluding the weekend) to be consistent with the literature on stock markets, but observe no material differences. The test for the turn-of-the-month effect (Ariel 1987, Lakonishok and Smidt 1988, McConell and Xu 2008, Atanasova and Hudson 2010, among others) is also conducted but no statistically significant evidence was found across the set of the considered cryptocurrencies.

**6. Conclusion**

This study examines calendar anomalies in daily cryptocurrency return, trading volume and volatility in multiple cryptocurrencies. As calendar effects react sensitively to model specifications, the present research uses robust method and estimator that accounts for the stylized facts of cryptocurrency returns. Overall, the results differ from those documented in the stock market. In general, no consistent evidence of a Monday effect, January effect or Halloween effect in cryptocurrency returns were found (i.e. investors cannot earn abnormal profits on Mondays, in January or in non-summer months)

As the existence of calendar anomalies is not consistent with the Efficient Market Hypothesis (EMH), the findings from this research validate the view that cryptocurrency returns are mostly weak-form efficient with respect to calendar anomalies, which is in line with the findings of prior literature. (Nadarajah and Chu 2017, Baur et al. 2019 and Kinateder and Papavassiliou 2019). The absence of significant calendar effects in most cryptocurrencies under consideration indicates that there are generally no seasonal return patterns that could be exploited by arbitragers to generate abnormal profits.

However, two major exceptions were found in this study. First, it was found that Ethereum investors can generate abnormal returns in January. Second, abnormal profits can be generated from short-selling Litecoin in Monday. These results are robust after the considerations of volatility-clustering, non-normality and changes in methodologies to detect the anomalies. Although the anomalies are at odds with the rest of the conducted tests, it is consistent with the hypothesis that each cryptocurrency has different level of efficiency. In particular, the results are consistent with Kristoufek and Vosvrda (2019)’s posit that Ethereum and Litecoin are the least efficient cryptocurrency. Thus, future research about the cryptocurrencies efficiency ranking as well as the potential reasons behind the phenomena are highly encouraged.

Overall, this study contributes to the literature on cryptocurrency market efficiency and seasonality. Besides academics, this study may help Ethereum/Litecoin investors to improve their investment portfolio performance. Ultimately, the practical implications also extend to market regulators in order to design necessary regulations to promote fair trade and prevent arbitrage in the fast-growing cryptocurrency markets.

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1. Since EMH cannot be used to explain market anomalies such as the calendar effects, some researchers rely on alternative market hypothesizes to explain unusual market behaviors. Notable among the literatures is a study by Lo (2014) who proposed the Adaptive Market Hypothesis (AMH). A few studies support AMH in cryptocurrency market (For example, Khuntia and Pattanyak 2018 and Chu *et al.* 2019), hence, connected it to cryptocurrency. However, the true market model cannot be observed and are a matter of ongoing debates that lies outside the scope of this study. [↑](#footnote-ref-1)
2. A wash sale is a sale of a security (stocks, bonds, options) at a loss and repurchase of the same or substantially identical security shortly before or after. Losses from such sales are not tax deductible in most cases under the Internal Revenue Code in the United States. (See Section 1091 of the US Internal Revenue Code, “Loss from wash sales of stock or Securities”, for more details) [↑](#footnote-ref-2)