**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, cryptocurrencies are relatively young (the first, Bitcoin, was invented in 2009, but active trading did not begin until 2013) and the literature, therefore, is not extensive. Nevertheless, a considerable amount of research has addressed the existence of market anomalies in the cryptocurrency market. Some evidence suggests that cryptocurrency returns are much more volatile than other markets (Cheung *et al.*, 2015; Dwyer, 2015; and Carrick, 2016), exhibiting persistence and volatility in their return series (Urquhart, 2016; Caporale et al., 2018). It has also been documented that there is correlation between cryptocurrencies (Yi et al.*,* 2018; Ji et al.*,* 2019) and that they also show correlations with other asset classes (Dyhrberg, 2016; Okorie and Lin, 2020). In particular, some researchers have found seasonality in the cryptocurrency market, which potentially allows traders to earn abnormal profits (Aharon and Cadan, 2019; Caporale and Plastun, 2019; Kaiser, 2019). These market anomalies question whether traditional market theories such as the efficient market hypothesis (EMH) can explain the abnormal behaviors of cryptocurrency markets. This theoretical background forms a basis for the key issue discussed in the present empirical research, i.e. the question of whether there are calendar effects in cryptocurrencies, which would be inconsistent with the 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 as having significant market predictive ability, which contradicts the EMH. For example, it has been demonstrated 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. These anomalies are commonly known as calendar effects (also referred to as ‘seasonalities’). They include the well-known Monday effect (Cross, 1973; Connolly, 1979; French, 1980; Maberly, 1995 among others), the January effect (Rozeff and Kinney, 1976; Gultekin and Gultekin, 1983; Keim, 1987; Sun and Tong, 2010 among others) and the Halloween effect (Bouman and Jacobsen, 2002; Lucey and Zhao, 2008; Haggard and Witte, 2010; Andrade et al., 2013 among others). These anomalies are the focus of this research.

Prior literature has addressed the question of calendar effects in cryptocurrencies, but there seems to be disagreement among scholars about the actual 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). Others, however, argue that Bitcoin shows calendar effects (Aharon and Qadan, 2019; Caporale and Plastun, 2019; Kaiser, 2019), pointing to the lack of government regulations and a potentially inefficient cryptocurrency market (Urquhart and McGroarty, 2014; Urquhart, 2016; Kristoufek and Vosvrda, 2019). Hence, seasonality in cryptocurrencies warrants an empirical investigation as well as some theoretical background, if such market anomalies are found[[1]](#footnote-1).

Unlike most of the previous literature which either focuses on Bitcoin (Urquhart, 2016; Kurihara and Fukushima, 2017; Baur et al., 2019) or on a 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 of this research is clear for traders and market participants who could generate abnormal profits; it will also help to guide market regulators in designing the necessary regulations to prevent such arbitrage opportunities in cryptocurrency markets.

The remainder of the paper is structured as follows. The next section presents a brief review of the literature regarding calendar anomalies. Subsequent sections describe 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**

Kaiser (2019) notes that sufficient market capitalization and liquidity are important criteria to be considered by investors and to qualify for the construction of a crypto fund within the regulatory framework of the Alternative Investment Fund Managers (AIFM) Directive. The analysis, therefore, focuses on the five largest cryptocurrencies by market capitalization (Bitcoin, Ethereum, Ripple, Tether and Litecoin) with a sufficiently long historical price series so as to estimate seasonality patterns. The data set is extracted from CoinMarketCap.com. and the study is in line with previous research in terms of the application of daily returns, data sources and the focus on the largest cryptocurrencies (Urquhart, 2016; Nadarajah and Chu, 2017; Kaiser, 2019). Thus, the findings provide a solid basis for comparison. Table 1 reports the 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: Bitcoin (BTC), Ethereum (ETC), 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 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 as an 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 they are sensitive to model specification. Ignoring the stylized facts can produce biased results (see, for example, Bollerslev, 1986; Connolly, 1989; Auer and Rottmann, 2014 for discussions).

Engle (2001) shows that the GARCH(1,1) model is the simplest and most robust of the family of volatility models, and the most widely applied in the literature. Therefore, this research utilizes a GARCH(1,1) dummy regression, following prior research. In this regard, Auer and Rottmann (2014) recommend using 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, a QML estimator is used throughout the analysis. The null hypothesis for all tests is defined as no calendar effect.

The returns are computed as:

 where *Pi,t* is the closing price of a coin *i* on the *t*th day

 Besides being a proxy for market liquidity, trading volume indicates the level of activity on the markets and is therefore included in the analysis. Finally, the daily volatility estimator follows Roger and Satchell’s (1991) 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* on 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 1970s when Rozeff and Kinney (1976) documented higher average stock returns in January, scholars have been proposing potential reasons for the phenomenon. 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 of these (see, for example, Ritter, 1988). Although many of the aforementioned factors appear to be unlikely causes of anomaly in the case of cryptocurrency, tax-loss selling (Starks et. al*.,* 2006) may offer a reasonable explanation because the US Internal Revenue Service (IRS) and similar authorities in many countries treat cryptocurrency as property for tax purposes. In addition, wash sale[[2]](#footnote-2) regulations do not apply to cryptocurrency because it is classified as 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 reports 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 can be made. First, the returns of Ethereum in January are on average positive – implying that a January effect is indeed present in Ethereum returns. The result is consistent withKristoufek and Vosvrda (2019) who posit that Ethereum and Litecoin are the least efficient cryptocurrencies. Second, the trading volume of all coins under consideration is found to be higher in the month of January. This result is consistent with the tax-loss selling hypothesis documented in prior literature, which predicts that trading volume should be higher in January because investors buy back assets at the beginning of the year after tax-loss selling activities 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 the volatility series since only one out of five coins under consideration shows a significant relationship.

*4.2 Monday effect*

The Monday effect refers to the tendency of returns on Mondays 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 continued trading over the weekend in cryptocurrency markets. This allows the present study to investigate whether trading patterns on Saturday and Sunday deviate from working days and, consequently, 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 of no Monday effect cannot be rejected for 4 out of 5 of the cryptocurrency returns considered. However, the coefficient of the Monday dummy was found to be negative and statistically significant for Litecoin. This suggests the existence of a Monday effect in Litecoin and is consistent with the stock market literature (French, 1980; Abraham and Ikenberry, 1994; Ülkü and Rogers, 2018 among others). Once again, the result confirms Kristoufek and Vosvrda’s (2019) findings that Ethereum and Litecoin are the least efficient cryptocurrencies. All coins under consideration show a higher trading volume on Mondays, which is also in line with the stock market literature.

 No evidence was found to suggest a difference in returns and volatility between weekend and non-weekend days. However, all of the coins considered have significantly lower trading volumes at the weekend (all considered coefficients are negative and statistically significant at 1%). The results suggest that trading activities, although possible seven days a week, take place primarily on working days, and are in line with Kaiser (2019)’s study, using t-tests on a different set of cryptocurrencies ~~a different approach~~.

*4.3 Halloween effect*

The Halloween effect (also known as the “Sell in May” effect) refers to the market anomaly whereby 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 detected the Halloween effect in 36 out of 37 considered equity markets. Most literature in the field posits that the Halloween effect is present in stock markets and the results are robust even after taking into consideration 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 is not driven by the January effect, it is preferable to include the anomaly in the analysis. Table 4 reports 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 the equity market, it was found that the returns and volatility of cryptocurrency in non-summer months are not statistically different from the returns over the other half of the year, for all cryptocurrencies considered. Most show a 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 existence of the Halloween effect in cryptocurrency and are consistent with Baur et al., 2019, using Bitcoin intra-day dataset during 2011-2017. No evidence of exploitable trading strategies, based on the Halloween effect, were found in any of the coins considered.

**5 Robustness checks**

For robustness, this study also utilizes the 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 no material differences were found. 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) were also conducted, but again, no material differences were detected. Consistently, traditional OLS regression yields directionally identical results with lower significance.

This research also tested the Monday effect using a 5-day a week system (excluding the weekend) to be consistent with the literature on stock markets, but yet again, no material differences were observed. 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) was also conducted but no statistically significant evidence was found across the set of cryptocurrencies.

**6. Conclusion**

 This study examines calendar anomalies in daily cryptocurrency returns, along with trading volume and volatility in multiple cryptocurrencies. As calendar effects react sensitively to model specifications, the present research uses a robust method and an 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 was found of a Monday effect, January effect or Halloween effect in cryptocurrency returns (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 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 prior studies (Nadarajah and Chu, 2017; Baur et al., 2019; and Kinateder and Papavassiliou, 2019). The absence of significant calendar effects in most of the 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 discovered. First, it was found that Ethereum investors can generate abnormal returns in January. Second, abnormal profits can be generated from short-selling Litecoin on Mondays. These results are robust after the considerations of volatility-clustering, non-normality and changes in methodologies to detect anomalies. Although the anomalies are at odds with the rest of the conducted tests, it is consistent with the hypothesis that each cryptocurrency has a different level of efficiency. In particular, the results are in line with Kristoufek and Vosvrda (2019) who posit that Ethereum and Litecoin are the least efficient cryptocurrencies. Thus, future research about the efficiency ranking of cryptocurrencies, 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, offering guidance in designing the 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 calendar effects, some researchers rely on alternative market hypotheses to explain unusual market behaviors. Notable among the literature is a study by Lo (2014) who proposed the Adaptive Market Hypothesis (AMH). A few studies support the AMH in the cryptocurrency market (for example, Khuntia and Pattanyak, 2018 and Chu *et al.,* 2019). However, the true market model cannot be observed and is a matter of ongoing debate which lies outside the scope of this study. [↑](#footnote-ref-1)
2. A wash sale is a sale of a security at a loss and repurchase of the same security shortly after. Losses from such sales are not tax deductible 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)