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Calendar effects in Bitcoin returns and volatility

Harald Kinateder[a*] **Vassilios G. Papavassiliou**[b]

University of Passau University College Dublin

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Abstract

We use a GARCH dummy model to study the influence of calendar effects on daily conditional returns and volatility of Bitcoin during the period 2013 to 2019. The Halloween, day-of-the-week (DOW), and month-of-the-year (MOY) effects are analyzed. Our results reveal no evidence of a Halloween calendar anomaly. A classical DOW effect is not present in Bitcoin returns, however, we find significantly lower risk over the weekend whilst in the beginning of the week Bitcoin's volatility is more intense. Moreover, supporting evidence of a reverse January effect is detected. Our results also show that investors' risk drops substantially in September.

Keywords: Calendar anomalies; Bitcoin; GARCH dummy model; Efficient market hypothesis; Seasonalities

JEL codes: G11; G17

* Corresponding author: Tel: +49 (851) 509 – 3243

[a] School of Business, Economics and Information Systems, University of Passau, Germany. Email: harald.kinateder@uni-passau.de

[b] UCD Michael Smurfit Graduate Business School, Carysfort Avenue, Blackrock, Co Dublin, Ireland. Email: vassilios.papavassiliou@ucd.ie

1. Introduction

In recent years there has been an increased interest in the study of Bitcoin and its price formation process. A strand of literature focuses on the bubble behaviour of Bitcoin (Chaim and Laurini, 2019; Geuder et al., 2019; Fry, 2018) and other issues of market efficiency. Surprisingly, only a few papers have studied calendar anomalies in Bitcoin returns and volatility.[1] One would expect to find differences in seasonalities between Bitcoin and conventional assets, such as stocks, bonds, and commodities, due to Bitcoin's unique features as a cryptocurrency. We are also motivated by the fact that Bitcoin is the world's leading cryptocurrency by market capitalization.[2]

In this paper, we study several calendar anomalies in daily Bitcoin returns and volatility, including the Halloween, the day-of-the-week (DOW), and the month-of-the-year (MOY) calendar effects. We use a generalized autoregressive conditional heteroskedastic (GARCH) model with dummy variables which offers several advantages over other competing models. First, it is a consistent method for investigating not only how seasonalities affect returns, but also how they impact volatility (i.e. risk). Second, this model is capable of capturing volatility clustering and non-normalities in Bitcoin price series. This is particularly important when dealing with calendar effects, as these effects are very sensitive to model specification. Ignoring the stylized facts can produce bias at detecting a calendar anomaly which is not present in the data (see Auer and Rottmann, 2014 for a discussion). In this context, Boubaker

[1] Recent studies analyzing calendar anomalies in Bitcoin include those of Aharon and Qadan (2019), Baur et al. (2019), Kaiser (2019) and Ma and Tanizaki (2019), among others. The most extensively investigated seasonality in these papers is the day-of-the-week effect.

[2] On September 8, 2019, Bitcoin's market capitalization was $187.1 billion, whereas Ethereum, the second largest cryptocurrency, had a market capitalization of only $19.5 billion, which is about 10.43% of Bitcoin's market capitalization. Source: CoinMarketCap.com

et al. (2017) show that different error distributions in GARCH dummy models can produce different results for the dummy's *t*-statistic. Along these lines we robustly estimate Bitcoin calendar effects, offering fresh insights on Bitcoin seasonalities. We apply several model diagnostics to ensure that the GARCH dummy model is correctly specified and use the Bollerslev and Wooldridge's (1992) quasi-maximum likelihood (QML) estimator to get robust outcomes for the significance of the calendar dummies.

The rest of the paper is organized as follows. Section 2 presents the empirical methodology and describes the dataset. Section 3 discusses the empirical results. Finally, Section 4 concludes the paper.

2. Data and Methodology

This section describes the dataset employed and presents the methodological framework of the empirical analysis.

2.1. Data

The dataset contains daily Bitcoin closing prices, P_t, denominated in U.S. dollars from April 28, 2013 to September 8, 2019. It is extracted from CoinMarketCap.com and it is the longest historical Bitcoin price dataset currently available. We use daily continuously compounded returns in percentage terms, i.e. $R_t = [\ln(P_t) - \ln(P_{t-1})] \cdot 100$. In contrast to equities, Bitcoin is traded seven days a week, therefore data is collected for all available calendar days yielding a total of 2,325 observations. Table 1 reports key summary statistics. Bitcoin returns have a positive mean of 0.19 percent. In addition, we document mild negative skewness and excess kurtosis indicating a fat-tailed return distribution. The Jarque-Bera test indicates the presence of non-normality in Bitcoin returns, confirming earlier findings from other traditional asset classes. Finally, the Augmented-Dickey-Fuller (ADF) test shows that Bitcoin returns do not contain a unit root.

(Insert Table 1 about here)

2.2. Methodology

To study calendar effects, we apply the asymmetric GJR-GARCH(1,1) model proposed by Glosten et al. (1993) with additional external regressors (i.e. dummies). In addition, we include autoregressive (AR) terms in the mean equation yielding an AR(n)-GJR-GARCH(p,q) dummy model. The mean equation is

$$R_t = \nu + \sum_{i=1}^{n} \rho_i R_{t-i} + \lambda_{1,c} D_{t,c} + \varepsilon_t, \tag{1}$$

where the innovations $\varepsilon_t \sim F(0; h_t)$ are assumed to follow a stationary distribution F with unit mean and conditional variance h_t. The dummy $D_{t,c} \in \{D_{t,h}, D_{t,d}, D_{t,m}\}$ represents one of the three calendar dummies which are explained below. To avoid a potential dummy variable trap (see for example Kiymaz and Berument, 2003), we not only study each calendar effect, but also the DOW and MOY effects for each day or month separately. When estimating a GARCH dummy model, one has to be careful about the correct model specification. In this regard, Auer and Rottmann (2014) recommend to use Bollerslev and Wooldridge's (1992) QML procedure for high-kurtosis data in order to estimate covariances and correct standard errors for t-statistics. As shown in Table 1, Bitcoin returns are characterized by excess kurtosis ($\kappa = 10.60$) being far away from normal kurtosis ($\kappa = 3$), therefore we prefer to use the QML estimation in the analysis that follows.

Halloween dummy:

For the Halloween period from November to April, the dummy $M_{t,h}$ takes on the value of one in these months, and zero otherwise. This effect implies higher returns and/or different volatility in non-summer months, referring to the financial-world adage “sell in May and go away”.

DOW dummy:

The DOW dummy $D_{t,d}$ takes on the value of one on day d, and zero otherwise. We analyze the DOW effect for each weekday separately, i.e. from $d = 1$ (Monday) to $d = 7$ (Sunday). The DOW effect assumes that particular DOWs can generate abnormal returns or risk.

MOY dummy:

The MOY dummy $M_{t,m}$ takes on the value of one in month m, and zero otherwise. We study all months starting from January ($m = 1$) to December ($m = 12$). The MOY effect assumes that investors can earn abnormal returns in a particular month. In addition, there could exist different volatility levels across months.

Since we intend to examine not only calendar effects on returns but also on risk, we also include the aforementioned calendar dummies $D_{t,c}$ in the variance equation of the AR(n)-GJR-GARCH(p,q) dummy model:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \delta \varepsilon_{t-1}^2 I_{\{\varepsilon_{t-1}<0\}} + \sum_{i=1}^{q} \beta_i h_{t-i} + \lambda_{2,c} D_{t,c}, \quad (2)$$

where the term $\varepsilon_{t-1}^2 I_{\{\varepsilon_{t-1}<0\}}$ allows for a possible asymmetric response of conditional variance h_t to negative return innovations. Bitcoin’s volatility is simply given by $\sqrt{h_t}$, i.e. it is the square root of the conditional variance. The coefficient $\lambda_{2,c}$ measures the effect of our calendar dummies $D_{t,c}$ on Bitcoin's risk.

3. Empirical Results

In this section, we report the results of the GARCH dummy model on three different calendar anomalies, namely the Halloween, DOW, and MOY effect, and study the presence of seasonalities in Bitcoin returns and volatility.

Table 2 presents the estimation results on Bitcoin conditional returns R_t and conditional variance h_t using an AR(6)-GJR-GARCH(1,1) dummy model with a Halloween dummy. Reported are the model parameters of the mean and variance equation including their *t*-statistics and corresponding *p*-values. In addition, key model diagnostics such as the Ljung-Box test for standardized and squared standardized residuals as well as the Bayesian information criterion are provided.

(Insert Table 2 about here)

The model diagnostics indicate proper specification of the mean and variance equation as the Ljung-Box test reveals no significant autocorrelation for both specifications. In this context, our model selection procedure indicates that beyond AR(1) additional AR terms are necessary to ensure that standardized residuals are not autocorrelated. Despite the fact that Bitcoin returns exhibit mild skewness (see Table 1), there is no evidence for an asymmetric response of volatility to negative return innovations. However, the estimated coefficient of the one-day lagged variance h_{t-1} is highly significant and larger than 0.8, which suggests the presence of pronounced autocorrelation in the conditional volatility. As a result, Bitcoin's conditional volatility is highly persistent, i.e. days of high volatility tend to be followed by highly volatile days.

When it comes to the Halloween dummies in the mean and variance equation, we find no significant effect. This means that investors do not earn abnormal returns and face no abnormal risk during the Halloween period. This result is in line with that of Kaiser (2019), however, the author documents a significantly higher volatility during the Halloween period, using a different approach to model volatility.

(Insert Table 3 about here)

For the sake of space, we only report the results of the dummies for the remaining calendar effects as the rest of the results are similar to those provided in Table 2. In Table 3, we summarize the findings of the DOW effect. The results of the mean equation indicate that there is only a weak DOW effect on Wednesday's returns which is statistically significant at the 10 percent level. The dummy's negative coefficient implies that investors earn abnormal negative returns on Wednesdays. No anomaly can be detected in the remaining DOWs. In contrast to returns, volatility displays a pronounced DOW effect. Interestingly, in the beginning of the week, i.e. on Mondays and Tuesdays, Bitcoin exhibits significantly higher volatility than during the rest of the week. From Friday to Sunday there is also a DOW anomaly in volatility, however, Bitcoin's volatility is significantly lower during this period. This effect is only weakly significant on Fridays but it gains importance over the weekend. A possible explanation for this anomaly could be the fact that many traders do not trade Bitcoin over the weekend due to leisure activities or other reasons.

(Insert Table 4 about here)

Finally, Table 4 shows the findings of the MOY effect. The results of the mean equation do not show a pronounced MOY effect. We find a reversed January and March effect, which are only weakly significant at the 10 percent level. This indicates that Bitcoin returns in January and March are on average negative. The reversed January and March effects are the only anomalies that can be detected in the mean equation. Basically, there can be different reasons for the existence of a January effect, such as window dressing and tax-loss selling. The tax-loss selling hypothesis does not apply to all investors as there are countries that have different fiscal years, that is, the fiscal period does not end in December. A notable example is Australia, where the fiscal year ends in June. In addition, investors do not have to pay capital gains tax in certain countries. Bitcoin prices have increased substantially in the second half of 2017, so one reason for the existence of the inverse January effect might be the fact that investors have realized positive returns from their investments in other asset classes, such as stocks or bonds, and have simply deferred their tax liabilities due for the current period (Kaiser, 2019). Another possible reason could be the fact that Bitcoin investors have liquidated their positions in January due to Bitcoin's bubble between October 2017 and January 2018 (Geuder et al., 2019). In that regard, Griffin and Shams (2019) find that the price bubble of 2017 was mainly driven by one large player. It seems plausible to suggest that due to speculative activity in the Bitcoin market there have been distortive effects on Bitcoin prices that have led to negative MOY effects. The results of the variance equation reveal a pronounced MOY effect in September. In addition, there is a MOY anomaly in April and July which is only weakly statistically significant. It is apparent from these results that Bitcoin's volatility is reduced over the course of these three months compared to other months in our sample period.

4. Conclusion

This study examines calendar anomalies in daily Bitcoin returns and volatility. As seasonalities react very sensitively to model specifications, we use a robust estimator that accounts for the stylized facts of Bitcoin returns. Overall, our results differ from those documented in the equity market. There is no evidence of a classical DOW effect, i.e. investors do not earn abnormal returns on Mondays and Fridays. Our results underline that Wednesday is the only DOW that exhibits anomalous behaviour contrary to the evidence from equity markets where Wednesday is usually the less striking DOW. Moreover, we do not find a Halloween anomaly. This means that there is no significant return difference between the Halloween period and the non-winter period.

The existence of calendar anomalies is not consistent with the Efficient Market Hypothesis (EMH). Our findings validate the view that Bitcoin returns are mostly weak-form efficient, which is in line with the findings of Nadarajah and Chu (2017) and Baur et al. (2019), as the absence of significant calendar anomalies indicates that there are no seasonal patterns in returns that could be used by speculators to generate abnormal returns based on past Bitcoin price information. The implication of the EMH for investors is that speculation in the Bitcoin market is a loser’s game and a passive portfolio strategy is expected to beat an active management strategy (an interesting discussion can be found in Ang et al., 2010).

We find stronger evidence of calendar effects in Bitcoin’s conditional volatility than in the return series for both the DOW and MOY effects. Bitcoin is much less volatile in September and from Friday to Sunday, whereas volatility increases in the beginning of the week. Overall, our findings contribute to the ongoing research on Bitcoin’s market efficiency and seasonality and may help investors improve their investment portfolio performance. Market participants that would like to arbitrage away these calendar anomalies should bear in mind that these effects may disappear in the future. Once an anomaly is detected, arbitrageurs will try to exploit it and trading will increase but eventually the effects will subside or disappear completely.

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Table 1: Descriptive Statistics

This table presents key descriptive statistics for daily percentage Bitcoin returns. The results of the Jarque-Bera (JB) normality test and the Augmented-Dickey-Fuller (ADF) test are also reported. The sample period spans the dates from April, 28 2013 to September 8, 2019.

Mean	**Median**	**Std. dev.**	**Max**	**Min**	**Skewness**	**Kurtosis**	**JB**	**ADF**
0.1874	0.1944	4.3246	35.7451	-26.6198	-0.1757	10.5982	5,602.46	-48.33

Table 2: Halloween Effect

The table shows the results of the AR(6)-GJR-GARCH(1,1) dummy model for the Halloween effect. The mean equation contains a constant ν for up to a six period lagged Bitcoin returns, and the dummy $D_{t,h}$ of the Halloween period (i.e. November to April). The GARCH variance equation contains a constant ω, the term $\varepsilon_{t-1}^2 I_{\{\varepsilon_{t-1}<0\}}$ that accounts for a possible asymmetric response of conditional variance to negative news and the Halloween dummy. Measures of goodness of fit include the Bayesian Information Criterion (BIC) and the Ljung-Box (LB) test for lags 1 and 5 of standardized residuals and squared standardized residuals, respectively. *p*-values are based on Bollerslev and Wooldridge's (1992) robust estimator. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample period spans the dates from April 28, 2013 to September 8, 2019.

Variable	**Coefficient**	**Std. error**	***t*-statistic**	***p*-value**
Mean equation				
ν	0.1206	0.0733	1.6441	0.1002
R_{t-1}	0.0236	0.0257	0.9195	0.3578
R_{t-3}	0.0190	0.0241	0.7912	0.4289
R_{t-6}	0.0835	0.0239	3.4926	0.0005***
$D_{t,h}$	-0.0371	0.1224	-0.3027	0.7621
Variance equation				
ω	0.4859	0.1599	3.0381	0.0024***
ε_{t-1}^2	0.1430	0.0387	3.6992	0.0002***
$\varepsilon_{t-1}^2 I_{\{\varepsilon_{t-1}<0\}}$	-0.0123	0.0518	-0.2367	0.8129
h_{t-1}	0.8383	0.0250	33.5352	0.0000***
$D_{t,h}$	0.3238	0.2695	1.2014	0.2296
Diagnostics				
BIC			5.47	
LB(1)			2.51	
LB(5)			8.73	
$LB^2(1)$			0.83	
$LB^2(5)$			0.50	

Table 3: Day-of-the-week Effect

The table shows the results of the AR(6)-GJR-GARCH(1,1) dummy model for the DOW effect. Reported are the estimated coefficients $\lambda_{1,c}$ and $\lambda_{2,c}$ of the DOW dummies $D_{t,d}$ for $d = 1$ (Monday) to $d = 7$ (Sunday). To avoid a potential dummy variable trap, we study the DOW effect for each day separately. p-values are based on Bollerslev and Wooldridge's (1992) robust estimator. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample period spans the dates from April 28, 2013 to September 8, 2019.

Mean equation	**Coefficient**	**Std. error**	***t*-statistic**	***p*-value**
Monday	0.3277	0.2288	1.4321	0.1521
Tuesday	0.2343	0.2477	0.9458	0.3442
Wednesday	-0.4441	0.2351	-1.8893	0.0589*
Thursday	-0.2268	0.2002	-1.1330	0.2572
Friday	0.2421	0.1945	1.2451	0.2131
Saturday	0.1473	0.1935	0.7611	0.4466
Sunday	-0.2048	0.1590	-1.2881	0.1977
Variance equation				
Monday	6.4671	1.9792	3.2676	0.0011***
Tuesday	5.9142	2.0646	2.8646	0.0042***
Wednesday	0.6661	2.7939	0.2384	0.8116
Thursday	-1.7025	2.3644	-0.7201	0.4715
Friday	-3.5965	2.0987	-1.7137	0.0866*
Saturday	-4.5523	1.8078	-2.5182	0.0118**
Sunday	-3.8622	1.3049	-2.9597	0.0031***

Table 4: Month-of-the-year Effect

The table shows the results of the AR(6)-GJR-GARCH(1,1) dummy model for the MOY effect. Reported are the estimated coefficients $\lambda_{1,c}$ and $\lambda_{2,c}$ of the MOY dummies $D_{t,m}$ for $m = 1$ (January) to $m = 12$ (December). To avoid a potential dummy variable trap, we study the MOY effect for each month separately. p-values are based on Bollerslev and Wooldridge's (1992) robust estimator. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. The sample period spans the dates from April 28, 2013 to September 8, 2019.

Mean equation	**Coefficient**	**Std. error**	***t*-statistic**	***p*-value**
January	-0.6427	0.3713	-1.7311	0.0834*
February	0.3450	0.3134	1.1007	0.2710
March	-0.4515	0.2361	-1.9124	0.0558*
April	0.1896	0.2193	0.8647	0.3872
May	0.2809	0.1870	1.5025	0.1330
June	-0.0511	0.2223	-0.2297	0.8183
July	-0.1177	0.2043	-0.5762	0.5645
August	-0.1765	0.1686	-1.0468	0.2952
September	-0.0831	0.1533	-0.5423	0.5876
October	0.1779	0.1655	1.0748	0.2825
November	0.1391	0.2832	0.4910	0.6234
December	-0.0003	0.2302	-0.0011	0.9991
Variance equation				
January	1.1355	1.0479	1.0836	0.2785
February	-0.1538	0.2980	-0.5160	0.6058
March	0.4732	0.6806	0.6953	0.4869
April	-0.3467	0.1781	-1.9472	0.0515*
May	-0.0316	0.2801	-0.1128	0.9102
June	0.1129	0.3142	0.3594	0.7193
July	-0.3356	0.2021	-1.6606	0.0968*
August	0.2280	0.6424	0.3550	0.7226
September	-0.5007	0.1777	-2.8174	0.0048***
October	-0.3252	0.2173	-1.4966	0.1345
November	0.5317	0.5851	0.9088	0.3635
December	0.2385	0.3143	0.7589	0.4479