Should We Expect Bitcoin Markets to Be Efficient?*

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Abstract

We investigate whether Bitcoin markets demonstrate month-of-the-year effects, and whether such anomalies are present across markets that differ in terms of fees, trading requirements, size as well as the extent of legal support in their host countries. We use monthly return data for the period of 2015-2018 for Bitfinex, Bitstamp and Okcoin and find that returns were similar across the markets suggesting lack of internal frictions, and that all three Bitcoin markets showed a positive effect in December and a negative effect in January, followed by a positive effect in February. One explanation for the anomalies in the Bitcoin markets could be spillovers from the seasonal anomalies in broader markets, such as those posited by tax-loss or portfolio rebalancing hypotheses, which could result in some investors selling equity in December and repurchasing it in January and parking the proceeds in Bitcoin in the interim. If related to tax considerations, this situation could change as various jurisdictions start to enforce tax regulations for cryptocurrencies.

Keywords: *Bitcoin, Efficient Markets Theory, Month-of-the-Year Effect, Exchange Location, Calendar Anomaly, Cryptocurrency.*

***JEL Classification**: E42, G11, G12, G14, G15.*

1. Introduction

In an efficient market, asset returns should not exhibit any consistent patterns. Factors such as model misspecification, information asymmetry, behavioral issues, trading costs, and tax effects could all lead to markets inefficiencies (Fama, 1970, 1991). Even with markets increasingly utilizing technology to reduce frictions, patterns in asset-returns that go against market-efficiency have persisted. For example significant positive returns are observed before holidays due to behavioral issues (e.g., Lakonishok & Smidt,1988); while negative returns in December and positive returns in January arise due to trades induced by tax considerations, windows dressing, or information asymmetries (e.g., Rozeff & Kinney,1976; Haugen & Lakonishok, 1987; Ritter, 1988; Klock & Bacon, 2014). The Halloween Effect has been arise because people taking vacations during summer. Prior studies show that calendar-time

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market anomalies exist in traditional currency markets as well (e.g., Bollerslev & Domowitz, 1993; Akram et al., 2008; Aydoğan & Booth, 2010; Kaul & Sapp, 2009, Popovic & Durovic, 2014; Caporale & Plastun, 2017). With globalization, global trading facilitated by technology, liquidity and use of leveraged instruments assets have become more correlated, especially during downturns (Elkhamhi & Stefanova, 2015; Warren, 2015), implying issues in one market can increasingly impact other markets.

Negative returns in traditional markets in December if due to tax effects, followed by positive returns in January, could also lead to corresponding movements in and out of Bitcoins which could result in an opposite effect for Bitcoin markets, especially if Bitcoins are not taxed. Evidence for calendar-time market anomalies in the cryptocurrency markets such as the day-of-the-week effect (e.g., Decourt et al., 2017; Kurihara & Fukushima, 2017; Durai & Paul, 2018; Eyuboglu, 2018; Mbanga, 2018; Aharon & Qadan, 2019; Baur et al., 2019; Caporale & Plastun, 2019; Fraz et al., 2019; Kaiser, 2019; Yaya & Ogbonna, 2019), or the month-of-the-year effect (e.g., Eyuboglu, 2018; Baur et al.,2019; Fraz et al., 2019; Kaiser, 2019) is in general scarce, more so for the latter owing to the fact that crytocurrency markets have only been established starting 2009. Eyuboglu (2018), applying dummy variable regressions, finds significant positive Bitcoin returns for the months of February, October and November and insignificant positive returns for January during the period of 2013-2017 based on volume-averaged prices of all reported prices on the website Coinmarketcap.com. Fraz et al. (2019) applying a similar methodology find May, October and November to bring consistently higher Bitcoin returns than the other months, for the same period, based on price data from the cryptocurrency market capitalization website. Kaiser (2019), using similar data, examines month-of-the-year effect for 10 different cryptocurrencies using several methods during 2013- 2017 and 2013-2018 and finds that Bitcoin returns are significantly negative in January while other cryptocurrencies do not show any consistent patterns.

Inefficiencies could also arise in terms of differences across exchanges. Bitcoin is the first and the most popular cryptocurrency, trading on several exchanges around the world since 2009 (Nakamoto, 2008; Brandvold et al., 2015). As of September 5, 2019, there were more than 200 cryptocurrency exchanges and Bitcoin had reached a market capitalization of about $194 Billion (Crypto-Compare, 2019a). To account for exchange-to-exchange differences, we examine the month-of-the-year effect in the three largest Bitcoin/U.S.Dollar (USD) exchanges: Bitfinex, Bitstamp and Okcoin. Bitcoin markets are not completely frictionless and Briere et al. (2015) find prices change based on the exchange. There are fee-differentials across exchanges with Bitstamp having the highest fees and Okcoin the lowest. Unlike Bitfinex and Okcoin, Bitstamp does not allow margin trading. On the other hand, Okcoin is the only exchange that requires ID verification for trading fiat currencies for Bitcoin (Bitfinex Exchange Review, 2019). Bitstamp has about 14 active markets and trading pairs and offers various payment methods, including credit cards. Bitfinex has around 128 active trading pairs and accepts only wire transfers. Okcoin has about 32 active trading pairs, and until June 2019, no credit card payments were accepted (Huillet, 2019). Daily trading volumes are highly volatile, with sharp peaks, but overall Bitfinex is larger than Bitstamp, which in turn is significantly larger than Okcoin (Crypto-Compare, 2019b). The exchanges are also based in countries with different attitudes towards cryptocurrencies. Luxembourg, the base country for the Bitstamp exchange, supports the use of cryptocurrency as a means for investment and financing activities; Hong Kong, the headquarter for Bitfinex, is classified as a "fence sitter"; while China, the base country for Okcoin, is a strong opponent of the cryptocurrency markets (Thomson Reuters Report, 2017; Law Library of Congress Report, 2018). Bitstamp, Bitfinex and Okcoin have been active since 2011, 2012 and 2013 respectively. Bitstamp had changed its home country to the UK, another country supportive of Bitcoin, for about three years starting 2013 but has since moved back to Luxembourg. Baur et al. (2019) is the only prior study that examines the month-of-the-year effect in several Bitcoin exchanges. It uses heat maps to identity consistent patterns across time and exchanges and do not find any consistent month-of-the-year effect anomaly during 2011-2017 in Bitcoin returns for any exchange.

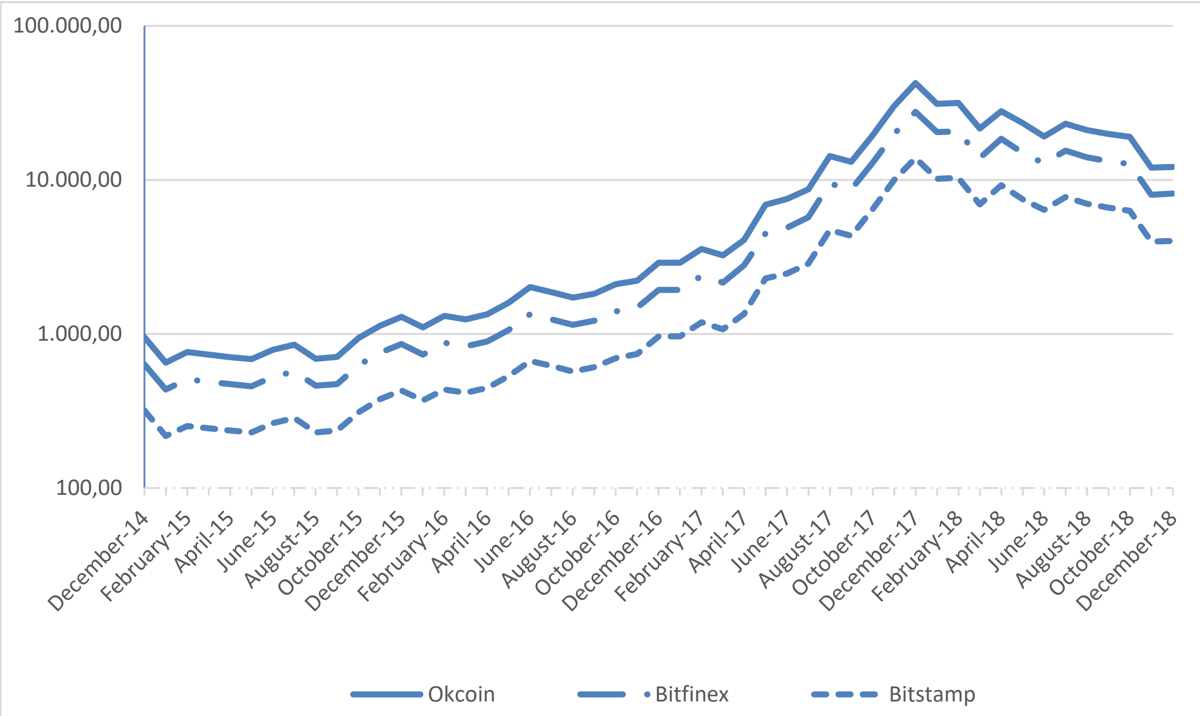
We find a strong month-of-the-year effect anomaly in the Bitcoin markets during the period of our study. The results from our analyses across exchanges are broadly similar, and we find only minor differences with respect to the month-of-the-year effect anomaly among the three Bitcoin exchanges considered. The remainder of the work is organized as follows: Section 2 describes the data and methodology; Section 3 presents the results of our analyses; and Section 4 presents the conclusions.

2. Data and Methodology

We collect the monthly closing price data for Bitcoin/USD from the Bitfinex, Bitstamp and Okcoin exchanges for 2015-2018 from Financial Contents (markets.financialcontents.com) and Crypto Data Download (cryptodatadownload.com) websites.

Figure 1 shows the closing prices of the Bitstamp, Bitfinex and Okcoin exchanges for the period 12/2014-12/2018, and shows some differences in price across exchanges. The average daily closing price for Bitcoin during the sample period is $3,230.07 for Okcoin, $3,164.69 for Bitfinex and $3,075.87 for Bitstamp. The maximum price achieved during the sample period is $19,943.30 for Okcoin while it is $19,187.50 for both Bitstamp and Bitfinex. Okcoin always has the highest closing price while the Bitstamp exchange has the lowest one. During our sample period, Bitcoin prices have higher volatility in the Okcoin exchange with a standard deviation of above $4,000, compared to the Bitstamp and Bitfinex exchanges where the standard deviation of prices is around $3,700.

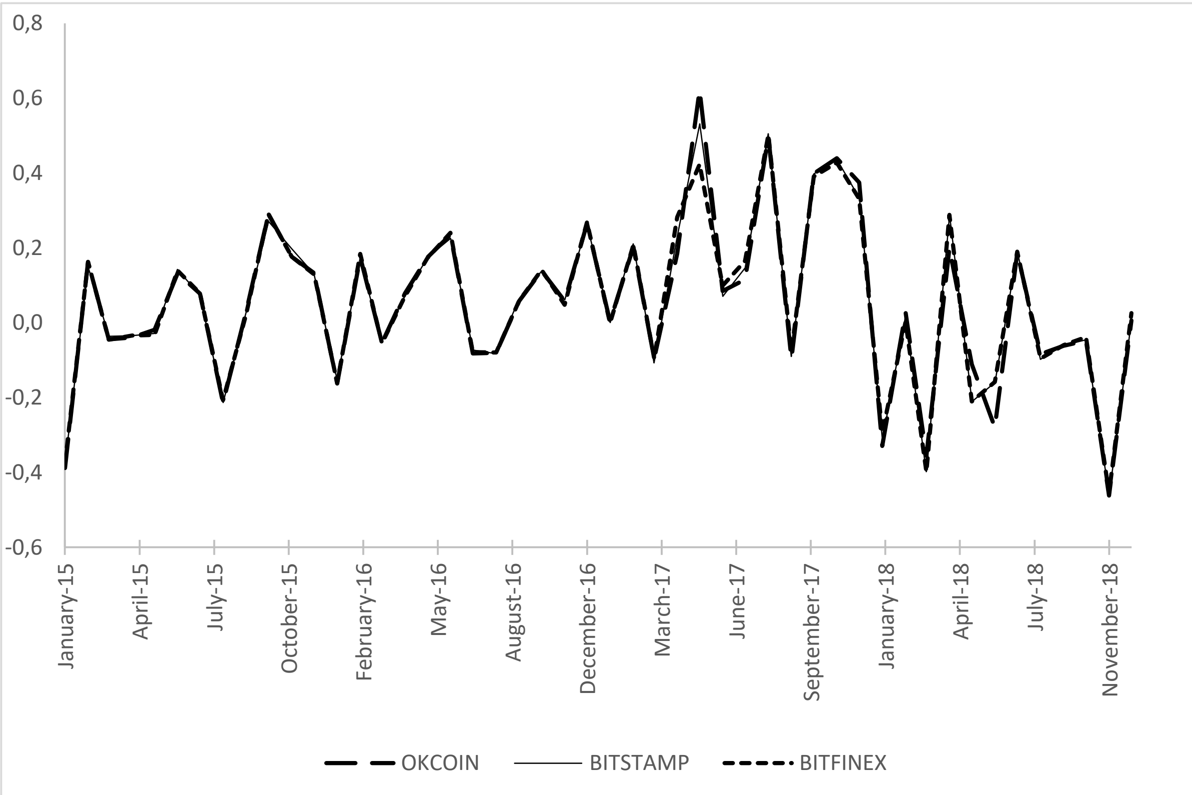
Figure 1: Bitcoin/USD Prices - Bitstamp, Bitfinex & Okcoin Exchanges, 12/2014-12/2018



Notes: Prices are on logarithmic scale. Price data is from markets.financialcontents.com and cryptodatadownload.com

We examine whether the Bitcoin markets are efficient by searching for the presence of the month-of-the-year effect anomaly in Bitcoin prices and whether any potential anomaly present in the market exhibits different characteristics across the three different exchanges. To ensure the stationarity of the variables used in our analyses, we apply the Augmented Dickey-Fuller (1979, 1981) unit root test of stationarity. Our results, which are not reported here to save space, show that the natural logarithm of Bitcoin prices are integrated of order 1 indicating that the series are stationary in first differences.

Figure 2: Monthly Bitcoin Returns - Bitstamp, Bitfinex & Okcoin Exchanges, 2015 - 2018



Notes: Underlying price data is from markets.financialcontents.com and cryptodatadownload.com

We use monthly Bitcoin returns for our analyses estimated by the following equation:

$$R_t = ln\left(\frac{B_t}{B_{t-1}}\right) \quad ...(1)$$

where R_t is the monthly Bitcoin return and B_t is the Bitcoin price for Month t. We take the closing price in the last trading day at the end of Month t as the Bitcoin price for Month t. As shown in Figure 2, Bitcoin monthly returns across the three different cryptocurrency exchanges during the same time frame are essentially identical.

We examine the month-of-the year effect using:

$$R_t = \beta_{Jan}(D_{Jan})_t + \beta_{Feb}(D_{Feb})_t + \beta_{Mar}(D_{Mar})_t + \beta_{Apr}(D_{Apr})_t + \beta_{May}(D_{May})_t + \beta_{June}(D_{June})_t + \beta_{July}(D_{July})_t + \beta_{Aug}(D_{Aug})_t + \beta_{Sep}(D_{Sep})_t + \beta_{Oct}(D_{Oct})_t + \beta_{Nov}(D_{Nov})_t + \beta_{Dec}(D_{Dec})_t + e_t \quad ...(2)$$

where t is the month of the sample period; the dummy $(D_i)_t$, where i represents the calendar month is 1 if *t* is i, zero otherwise; R_t is the monthly Bitcoin return; β_i represents the average return for Month i; and e_t is the error term at month t. A nonzero coefficient for a calendar month dummy indicates a month-of-the-year anomaly for that month.

The absence of the month-of-the-year effect anomaly requires the finding that none of the calendar month dummy variables in Eq. 2 is statistically significant. If any calendar month shows significance in Eq. 2, we further test whether the observed differences in average returns between a significant month and the remaining 11 months are statistically meaningful. For instance, if the dummy variable representing January is statistically significant in Eq. 2, we examine whether the difference between January returns those of other months are significantly different from zero, using:

$$R_t = c + \beta_{Feb}(D_{Feb})_t + \beta_{Mar}(D_{Mar})_t + \beta_{Apr}(D_{Apr})_t + \beta_{May}(D_{May})_t + \beta_{June}(D_{June})_t \\ +\beta_{July}(D_{July})_t + \beta_{Aug}(D_{Aug})_t + \beta_{Sep}(D_{Sep})_t + \beta_{Oct}(D_{Oct})_t + \beta_{Nov}(D_{Nov})_t \\ +\beta_{Dec}(D_{Dec})_t + e_t \qquad ...(3)$$

Here the constant term, c, in Eq. 3 represents the average return on January and the coefficients (β_i) represent the difference in average returns between the month i and January. The remaining variables are as defined in Eq. 2.

All regressions use HAC standard errors and covariance estimators based on Newey and West (1987) that adjust for autocorrelation and heteroscedasticity. We also report Wald F test statistics for all regressions, which is commonly used for regressions with multiple dummy variables (Davidson & MacKinnon, 2004; Stata FAQ).

3. Results

Table 1 shows the results from regressions based on Eq. 2. It shows that the month-of-the-year effect anomaly exists for January, February and December in all of the three cryptocurrency exchanges. February and December have significant positive returns while January has significant negative returns for all markets. For the Bitfinex exchange only, October also has the month-of-the-year effect anomaly with significantly positive returns, with results being only marginally significant for Bitstamp and Okcoin. Marginally-significant negative returns were observed across the exchanges for March, followed by marginally-significant positive returns for April.

Table 1. The Month of the Year Effect Anomaly for Bitcoin Returns, 2015 - 2018

	BITFINEX	BITSTAMP	OKCOIN
	β_i	β_i	β_i
D_{Jan}	-0.207959**	-0.211302**	-0.218873**
D_{Feb}	0.139105***	0.135190***	0.142209***
D_{Mar}	-0.148174*	-0.147677*	-0.137116*
D_{Apr}	0.151960*	0.139664*	0.105865*
D_{May}	0.088382	0.116887	0.166571
D_{June}	0.080189	0.069706	0.043079
D_{July}	0.088925	0.084686	0.074553
D_{Aug}	0.030136	0.028065	0.030197
D_{Sep}	-0.014070	-0.014459	-0.017527
D_{Oct}	0.196078**	0.189732*	0.195249*
D_{Nov}	0.049232	0.058348	0.053093
D_{Dec}	0.188917***	0.183765**	0.194400**
R^2 / Adjusted R^2	0.313227 / 0.103400	0.296794 / 0.081900	0.302630 / 0.089600
Wald F-stat.	13.7706***	11.9857***	12.9691***

Notes: The table reports regression results for Eq. (2) using Bitcoin returns from the Bitfinex, Bitstamp and Okcoin exchanges during 2015-2018. Each D_i represents a dummy variable for calendar month i with a value of 1 when the month is i and 0 otherwise. It includes the coefficient of each dummy variable. The monthly Bitcoin return data is the dependent variable estimated using the Bitcoin closing price in the last trading day of the month. There are 48 monthly observations. Bitcoin prices are obtained from the websites markets.financialcontents.com & cryptodatadownload.com. R-squared and Adjusted R-squared values are reported at the end of the table. Regressions use HAC estimators adjusted for autocorrelation and heteroscedasticity (Newey & West, 1987). Wald F test statistics are reported in the last row. *, **, *** denote significance at 10%, 5% and 1%, respectively

Results for differences in returns between months which show month-of-the-year effect anomaly (i.e., January, February, October and December), and the remaining months, based on Eq. (3), are in Table 2. The table has 4 panels, Panels A, B, C and D, reporting January, February, October and December effects, respectively. For each panel we report only months with statistically significant coefficients to save space. Overall, the results show the existence of significant differences for these months relative to others, as well as the uniformity of the results across exchanges.

For January, Panel A of Table 2 shows that January returns appear smaller than all other months; significantly so relative to February, April, July, September, October and December. The only inter-exchange differences appear in relative significance. For May, the differences are only marginally significant for Bitfinex and Bitstamp while being significant for Okcoin, and for June the results are significant for Bitfinex and Bitstamp while being only marginally significant for Okcoin.

Table 2. Significant Monthly Effect Anomalies for Bitcoin Returns, 2015-2018

	BITFINEX	BITSTAMP	OKCOI N
	β_i	β_i	β_i
Panel A. January Effect			
D_{Feb}	0.347064***	0.346491***	(0.361081***
D_{Apr}	0.359919***	0.350966**	0.324737***
D_{May}	0.296341*	0.328189*	0.385443**
D_{June}	0.288148**	0.281008**	0.261952*
D_{July}	0.296884***	0.295988***	0.293425***
D_{Sep}	0.193889**	0.196843**	0.201345**
D_{Oct}	0.404037***	0.401034***	0.414122***
D_{Dec}	0.396877***	0.395067***	0.413272***
R^2 / Adjusted R^2	0.313227 / 0.037600	0.296794 / 0.081900	0.302630 / 0.035200
Wald F-stat.	9.175000***	8.231900***	7.988800***
Panel B. February Effect			
D_{Jan}	-0.347060***	-0.346491***	-0.361081***
D_{Mar}	-0.287280***	-0.282867***	-0.279324***
D_{Sep}	-0.153180**	-0.149648**	-0.159736***
R^2 / Adjusted R^2	0.313227 / 0.103380	0.296794 / 0.081925	0.302630 / 0.089545
Wald F-stat.	12.327270***	11.985740***	12.969140***
Panel C. October Effect			
D_{Jan}	-0.404037***	-0.401034***	-0.414122***
D_{Mar}	-0.344252***	-0.337409**	-0.332365***
D_{Sep}	-0.210147**	-0.204191*	-0.212776*
R^2 / Adjusted R^2	0.313227 / 0.103380	0.296794 / 0.081925	0.302630 / 0.089545
Wald F-stat.	12.327270***	11.985740***	12.969140***
Panel D. December Effect			
D_{Jan}	-0.396877***	-0.395067***	-0.413272***
D_{Mar}	-0.337091***	-0.331442***	-0.331516***
D_{Sep}	-0.202987**	-0.198224**	-0.211927**
R^2 / Adjusted R^2	0.313227 / 0.103380	0.296794 / 0.081925	0.302630 / 0.089545
Wald F-stat.	12.327270***	11.985740***	12.969140***

Notes: The regression results for Eq. (3) for January, February, October and December anomalies are reported in Panels A, B, C and D, respectively. The dependent variable, the monthly Bitcoin returns, are the same as explained in Table 1. Each D_i represents a dummy variable for calendar month i with a value of 1 when the month is i and 0 otherwise. For each panel, only the months with significant coefficients are shown for space sake. R-squared, Adjusted R-squared and Wald F test statistics are reported for each panel. Regressions use HAC estimators adjusted for autocorrelation and heteroscedasticity (Newey & West, 1987). *, **, *** denote significance at 10%, 5% and 1%, respectively.

For all three exchanges, February returns shown in Panel B of Table 2 are significantly higher than the January, March and September returns.

As Panel C of Table 2 indicates, October returns are October returns are significantly higher than the January and March returns. The October effect appears only in Bitfinex in Table 1, and is marginally significant for Bitstamp and Okcoin. In Panel C of Table 2, October returns for Bitfinex are also significantly different from September returns, but only marginally so for Bitstamp and Okcoin.

Finally, Panel D of Table 2 shows that the December effect is consistent across the three exchanges with December returns being significantly higher than the January, March and September returns.

4. Conclusions

We examine if the month-of-the-year effect anomaly is present in the Bitcoin markets during the period of 2015-2018, and whether the nature of this anomaly changes based on the market. We apply autocorrelation and heteroscedasticity adjusted robust least squares regressions with dummy variables for Bitcoin/USD returns in three different Bitcoin exchanges, Bitfinex, Bitstamp and Okcoin which have different fees, trading requirements as well as levels of support for cryptocurrency in the countries in which the exchanges are based.

Overall, our results support the findings of the studies claiming that the Bitcoin markets are not efficient because of various anomalies (e.g., Urquhart, 2016; Kurihara & Fukushima, 2017; Makarov & Schoar, 2018; Reynolds et al., 2018; Fraz et al., 2019), and in line with Kaiser (2019) who suggests a reverse January effect based on cryptocurrency market characteristics such as uncertainty related to market fundamentals and informational inefficiencies; and contradict prior findings of weak efficiency such as Nadarajah and Chu (2017) and Yaya and Ogbonna (2019). In contrast to Baur et al. (2019), we confirm that month-of-the-year effects hold when different exchanges are considered separately.

One reason for our observed positive December effect and negative January effect, that are the opposite in direction to the effects seen in traditional markets, could be that more money may flow into Bitcoins in December and may flow back out in January. Bauer (2019) suggests, based on trading patterns through the day and after-hours, as well as for different days as well as months, that institutional investors are a significant component of Bitcoin trades, especially USD-Bitcoin or Euro-Bitcoin trades. We do not seek evidence for trading for tax-effects in trading volume patterns as it has been estimated that up to 80% of the volumes may be wash trading (BlockChain Transparency Institute, 2018). Given that the Halloween Effect, which has been hypothesized as arising due to people taking vacations in summer needing to pay for them and not wanting to be invested in the stock market out of a fear of sudden downturns (Jacobson & Zhang, 2018), we would not expect a significant positive return for Bitcoins over summer months either as Bitcoins are considered highly risky. Table 1 shows none of the results for summer months to be significantly different from zero, although March has marginally significant negative returns across exchanges while April shows marginally-significant positive returns.

We would note that Bitcoins, as well as other cryptocurrencies, are relatively new and even regulatory attitudes have yet to be finalized. The supply of Bitcoins is limited, and ultimately finite. Events such as forks and halving also impact prices. The volatility in prices, and the lack of a determinant of value except for comparison with the dollar, suggests potentially less of a role as currency and more as a virtual commodity. In this regard, the US Internal Revenue Service has been increasingly active in informing taxpayers of their reporting requirements with regard to their cryptocurrency trades (Green, 2019). If jurisdictions start to enforce taxation related to Bitcoins to a significant extent, it would be of interest to repeat the analyses and determine if the December-January effects observed for our sample period persist.

The Bitcoin market is the largest cryptocurrency market, and the most well-known. Even so it is relatively small in that there are companies on stock exchanges that have higher valuations than the entire market capitalization of Bitcoin. It is also a relatively new market with greater underlying risks. The concept of a virtual commodity itself is relatively new, and it is not entirely clear how the use of Bitcoin as a full-fledged currency will evolve. From a broader perspective, if such a market is part of a larger set of markets, any inefficiencies that exist in the wider markets could lead to corresponding patterns in return, even if that market itself has fewer inherent sources of inefficiency as money can always flow from one market to others.

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