Bachelor Thesis [programme: IBEB]

The seasonal effect of Chinese New Year in cryptocurrency market

Author: Krivosheev Eduard, 453271

Supervisor: Vitalie Spinu

Second supervisor: Chen Li

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Abstract

Considering the time-series data of Bitcoin for the last 7 years, we test for the existence of seasonal effect of Chinese New Year corresponding to Bitcoin`s price, return, volume and volatility. By using OLS and ARDL models we did not observe any seasonal effect except small negative movement of price (return) in the period of 30 days after the CNY period. Besides, the results show that our variables of interest exhibit high persistence, meaning that it is the persistence of BTC that determines its price, return, volume and volatility rather than some seasonal effects.

Contents

Introduction

There are some existing patterns about stock returns in financial markets. People have started studying the possible trends that could be used in order to make a profit since the financial market was invented. We will focus on findings when the weak form of the efficient market hypothesis (EMH) is violated. This weak form, also known as a random walk model, suggests that price changes are random, meaning that it is impossible to predict the future price and take advantage of it (Malkiel, 1973).

But is this theory supported with the empirical evidence? It seems that the answer is no. The existence of the seasonal effect has been proven by many scientists from all over the World. The most famous work about the seasonality of the capital market was published in 1976 by Michael Rozeff and William Kinney (Michael S Rozeff, 1976). The uniqueness of this paper is that it was one of the first published works that has proved the seasonal effects. Their research has revealed the pattern that is known now as a "January effect". The idea is that the highest mean of return is experiencing during the first month of the year. Prices for all kinds of stocks, especially for small-cap stocks, tend to increase in this period of time. This pattern was lately discussed by Reinganum (REINGANUM, 1983). His explanation is connected with a term known as tax loss sales, tendency to decrease the capital gain before the end of the year. The main aim of this action is to lower the taxes on capital gain by selling stocks at a loss. It allows people to decrease the amount of taxes that should be paid by the end of the financial year. Moreover, it is also legal to buy these stocks back after 30 days, what makes this hypothesis even more powerful.

Another important research about the day-of-the-week effect was conducted by French (R.French, 1980). The paper has studied the return of stocks of 500 largest firms on New York Stock Exchange from 1953 to 1977. The conclusion that there is a permanent negative return on Monday was made by using the regression model. One of the possible explanations for this pattern is that there is a tendency for negative information to be revealed during the weekend.

We mentioned some calendar and seasonal patterns in the financial market. But most of them have been studied so many times. That is why the main aim of this research is to examine these patterns but in crypto-market. Market capitalization in cryptocurrency has increased from 10$ billion in 2014 to 172$ billion in 2019 ("CoinMarketCap", 2019). The blockchain system was invented recently, meaning that the sample size is not big enough to examine all the seasonal and calendar effects in this particular area. In relation to the massive power of the US in the financial market, China has got a comparable impact, but in the cryptocurrency market. According to the group of scientist from the University of Florida (Ben Kaiser, 2018) more than 50% of total network hash power is concentrated among Chinese people. Moreover, it can be seen from the Table1 that Chinese Yuan is the most frequent currency that is exchanged for Bitcoin (BTC) for the time period between 2014 and 2019("Bitcoinity.org", 2019).

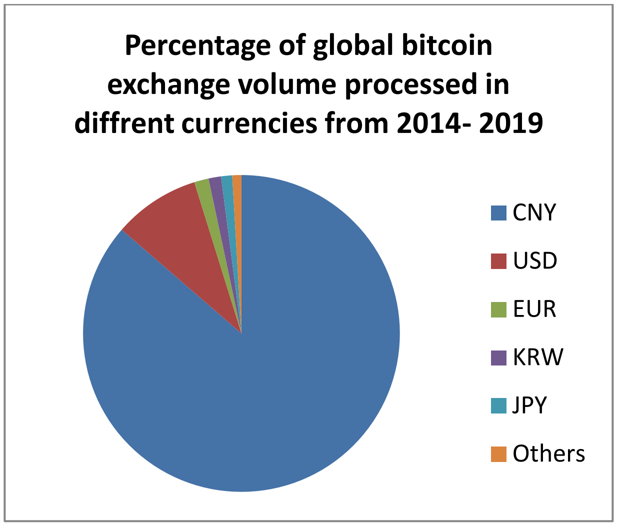
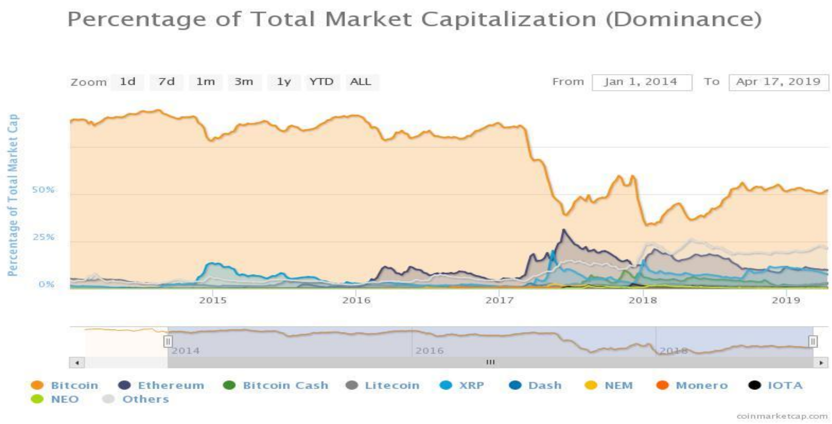


Table 1

Bitcoin was the first example of an asset that refers to the class of 'digital assets'. It was invented in 2009 by a group of people in order to present the first decentralized digital currency. Now Bitcoin is considered as the dominant cryptocurrency all over the World. According to ("CoinMarketCap", 2019) market capitalization of BTC is almost 93 billion dollars what represents more than 50% of the whole market. As we can see from the graph1, Bitcoin's dominance rate is above 50 percent ("CoinMarketCap", 2019). Moreover, (Pavel Ciaiana, 2018) have examined the relationship between BTC and other altcoins (the name for all digital currencies, except Bitcoin). In his research he used the autoregressive distributed lagged model (ARDL) in order to test whether the Bitcoin and altcoin markets are interdependent. The main finding of his work is that there is a price relation between currencies, especially in the short run. Also, it can be explained by the fact that most altcoins have trading pairs only with BTC. The price of most altcoins is based on Bitcoin exchange rate rather than USD rate. That is the second reason why prices for Bitcoin and altcoin markets are connected. From the facts mentioned above, it is possible to conclude that Bitcoin can be considered as a good representative of all digital currencies. And all the findings that will be made from this research, based on data for BTC, could be applicable for other types of altcoins.



Graph 1

Combining the facts about China's impact in the cryptocurrency market and the price relationship between Bitcoin and other digital currencies, we decided to focus on the following research question:

How Chinese New Year (CNY) influence the cryptocurrency market and to what extent?

The main aim of this research is to analyze whether this effect really exists. And if it does, then try to understand the underlying reasons that drive the market in this period. Although this market has become very popular among individuals from different countries, there is a lack of research on trends and patterns in this area. This paper will provide the working principles of this market and contribute the new empirical evidence of seasonality to the scientific World. All results will be compared with other works within the same area of study. The implication of the research could result in creating some possible trading strategies for obtaining an abnormal return in the crypto market.

Hypothesis

Our hypotheses are mainly based on a fact that cryptocurrencies are traded among private investors rather than institutional. This idea was confirmed by (Shaen Corbet, 2018) in their research about the introduction of futures contract on Bitcoin. They found that 97% of information that affects BTC price is represented in the spot market. At the same time they came to the conclusions that price discovery is mostly driven by unsophisticated investors. It is very important findings because we suppose that anticipative "sell off" event occurs due to people sentiments when they want to exchange cryptocurrency on fiat money in order to buy presents, going on a vacation etc. This judgment was supported by (Mei Hui, 2019) in her work about the CNY effect on BTC market. By using the decomposition method it was found there is a relation between drop in BTC price and willingness of Chinese people to exchange BTC on fiat money 3-4 weeks before CNY. Moreover, there is some difference between financial and cryptocurrency markets that have forced us to study this particular event instead of more familiar events such as day-of-the-week effect, January effect, year end rally effect. Firstly, crypto market works 7 days a week, 24 hours a day opposite to financial market. Secondly, as it was already stated above crypto market is more influenced by private investors in contrast to the financial market. Therefore it seems more plausible to study CNY effect, especially taking into account the impact of this country on crypto market. Moreover, the typical seasonal effects that occur in financial market were tested in cryptocurrency area by (Kaiser, 2018) in his paper about the seasonality in cryptocurrencies. He studied top 10 currencies in terms of market capitalization to see whether they experience a) Monday effect b) Weekend effect c) January effect or d) Halloween effect. But the results showed that there were not any statistically significant seasonal effects, except reverse January effect for BTC.

Therefore, the first hypothesis is:

H1: The price (return) of BTC decreases during Chinese New Year.

In order to obtain more precise results it was decided to use return as the second dependent variable for this hypothesis. We are going to divide this hypothesis by two sub hypothesis that measures the effect before and after this particular event. We will apply the same plan for all hypotheses, because results for 2 periods may differ. And we find it necessary to study the period after CNY because it can be the case that CNY effect spreads even for the longer period than just 1 month before the event.

Volatility of an asset is defined as the average magnitude of fluctuations measured over a specific time period (Opschoor, 2013). It helps to define the risk of an asset. There is a relation between volatility and performance of the market. Lawrence has proved this fact by using the modified GARCH-M model (Lawrence R. Glosten, 1993). The paper suggests that there is a negative relation between volatility and expected return. The findings of this research are also consistent with other studies (John, 1987) and (Fama, 1977). Moreover, from the first hypothesis it follows that prices fluctuate sharply in the period of CNY. So it should influence the volatility by the definition of this term. Therefore, the second hypothesis is:

H2: The volatility of cryptocurrency is increased due to Chinese New Year.

The proxy for independent variable in this model is a price volatility that is calculated as an average of hourly standard deviations (that is, the standard deviation of raw trades calculated for each hour and then averaged).

Our research question implies the existence of a cyclical mechanism that is repeated every year. This cycle starts with an increasing number of selling positions 3-4 weeks before CNY (Mei Hui, 2019). In this period of time, people are eager to exchange cryptocurrency into fiat money which they are willing to spend on presents and vacations. All market is influenced by these actions because China is a major player in this area. These sell-off events lead to a drop in BTC price and an increase in the trading volume. Therefore, it was decided to formulate the third hypothesis as:

H3: The trading volume is significantly increased because of Chinese New Year.

Data

In order to study the CNY effect on cryptocurrency market it was decided to use the time series data. This kind of dataset allows detecting seasonal fluctuations patterns.

Our dataset was obtained from multiple sources. The large part of the information was gotten from ("Bitcoinity.org", 2019) and contains the data for variables such as: price, volume, volatility, number of trades per minute. The daily return was computed manually by simply dividing today`s price by yesterday one minus 1. It was decided to choose BitFinex exchange as a major source of info because it has held the 1st place in terms of trading volume for the last 2 years, making external validity relatively high. Moreover, it contains the historical data of BTC for the last 7 years that is the longest period among all exchanges. This exchange applies US dollar as the only source of currency that could be used in order to buy cryptocurrency. This fact is very important to mention, because of the Chinese regulations in cryptocurrency market on September 2017. The Central Bank of China decided to ban trading of cryptocurrency on domestic exchanges such as Okcoin, Huobi and Btcchina which were the leaders in this area in terms of trading volume. These regulations forced them to move on Over-The-Counter market, making impossible to obtain the data from 2017.

The data of the historical value of VIX Index was retrieved from the Federal Bank of St.Louis. The Wikipedia database was used in order to obtain the data for number of search queries for “bitcoin” word in Wiki website. Finally, the Quandl resources allowed getting the historical price of gold. All the data is presented on the daily basis. The observation period starts in March 10th, 2013 and lasts till May 8th, 2019. We also constructed three dummy variables that would help us to measure the necessary effects. CNY dummy takes value of 1 throughout 2 months: 1 month before CNY and 1 month after. Similarly, CNY_before indicates 1 month before CNY takes place and CNY after states for 1 month after. Here is the list of all variables that we are going to use:

Name of the variable	Description
price	Price of Bitcoin, USD
volume	Trading volume of Bitcoin, USD
volatility	Volatility of Bitcoin, average of hourly standard deviations
vix	Volatility index, % points of volatility to be expected
gold_price	Price of gold, USD
bit_search	Number of search queries for “Bitcoin” word
return	Daily return of BTC, %
CNY	Dummy variable, takes value of 1 when there is a month before CNY and a month after
CNY_before	Dummy variable, takes value of 1 when there is a month before CNY
CNY_ after	Dummy variable, takes value of 1 when there is a month after CNY

Methodology

To answer the research question we proposed hypothesis that would help to understand the behavior of the market. In order to test hypothesis it was decided to use three different OLS models.

Firstly, we used simple static OLS model without any transformations in the dataset.

$$BTC_t = \alpha + \beta_1 CNY + \beta_2 X + \varepsilon$$

Where BTC is a proxy for particular specification (depends on the hypothesis), CNY is a dummy for Chinese New Year, X is the factor of other controls, and ε is the error term.

Some control variables are included in our ARDL model because BTC proxies could be influenced by other factors. VIX- index reflects the volatility of S&P 500 and is a good control for macro environment. In order to control for interest-driven impact, the Wikipedia data will be applied, namely, number of search queries for “bitcoin” word. Also BTC was called as a safe haven investment in a period of Cypriot financial crisis.
Therefore, it was decided to use the gold price as another control variable. It should be mentioned that the strong effect of these controls was proven by Poyser in his research about the determinants of Bitcoin’s price (Poyser, 2017). . Moreover, the logarithmic scale was applied price, volume and volatility, because we

are interested mostly in a change of variables measures on the basis of a ratio rather than a difference between values.

It was also necessary to make robustness check in order to see whether the effect has the same magnitude and significance in a narrower time frame because when we take the large time frames it could be the case that other conditions influence the BTC specification.

There are two major problems that could arise because we are working with financial data with high frequencies and long timespans.

Firstly, the unit roots problem that could lead to spurious regression (obtaining high R^2 values even if the variables are not correlated). This might lead us to erroneously conclude that there is some relationship between variables, whereas in reality this relationship is spurious due to random-walk of both variables which have a stationary trend. In order to deal with it we determined the appropriate amount of lags for unit-root test, as autocorrelation might bias the test results.

Then Dickey-Fuller test for unit roots was applied to define whether our variables contain unit roots. It was determined that variable: price of BTC, vix index and gold price possess unit roots. In order to deal with this problem, we took the first difference of these variables. These predictors are differentiated to deal with spurious correlation that arises due to stochastic trends in such data. Therefore, first-differences are used purely to address the statistical issue that might lead us to erroneous conclusions about our key predictors. Therefore, the second OLS model looks like:

$$\Delta BTC_t = \alpha + \beta_1 CNY + \beta_2 \Delta X + \varepsilon$$

Secondly, we are working with the daily data and this most likely leads to the autocorrelation problem as, usually, contemporaneous (today) value of high-frequency financial data is highly predictable by its own lags. Thus, in order to solve this problem it was decided to define the appropriate amount of lags that should be used to deal with autocorrelation problem. It was done by using Akaike (AIC) and Schwarz (SIC) information criterion. Therefore, we used Autoregressive Distributed Lag Model (ARDL) model as robustness check specification because it was useful to check whether delayed (lagged) effects of certain explanatory variable on the state of crypto market change the conclusions of static OLS model. In other words, how fast certain BTC proxy reacts to changes in the world financial markets. This model can be considered as the most internally valid one and written as:

$$BTC_t = \alpha + \beta_1 CNY + \sum_{s=0}^{m} \beta_2 \Delta X_{t,t-s} + \sum_{s=1}^{e} \beta_3 \, BTC_{t,t-s} + \varepsilon_t$$

Where BTC is a proxy for particular specification (depends on the hypothesis), CNY is Chinese New Year, X is the factor of other controls, t is the time period, t-s is the time leg, $BTC_{t,t-s}$ is the lag of dependent variable.

In order to compare the CNY period and the entire year we use Table 2 that includes information for some years. The table for each year could be found in the appendix (Table 1). It can be seen that during cny period the average return is lower for 5 out of the 6 years of observations. Also volatility experiences higher values in this period, especially in 2018. Moreover, we can observe that average volume is higher for 4 out of 6 years of observations.

Table 2: Descriptive statistics

CNY	mean	p50	sd	min	max	count
2014						
0						
price	482.0766	474.847	107.3903	312.1411	678.9111	303
return	-.0018031	-.0029104	.0280125	-.0898038	.1138123	303
volatility	1.298188	1.09145	.7153808	.3226655	4.124418	303
volume	6703042	4596134	6326723	345542	6.22e+	303
1						
price	737.0541	792.463	106.2125	497.7926	937.5439	62
return	-.0019255	-.0034788	.0436315	-.1296756	.1537	62
volatility	3.198183	2.629309	1.9254	1.182478	12.6754	62
volume	1.07e+07	8461006	8992477	1760951	4.57e+07	62
2018						
0						
price	7059.093	6612.709	2243.672	3275.559	16689.85	302
return	-.0019278	-.0005732	.0304384	-.1095711	.0887498	302
volatility	18.07818	13.96425	15.27318	3.112017	114.0275	302
volume	2.09e+08	1.58e+08	1.64e+08	2.10e+07	9.65e+08	302
1						
price	9915.368	10022.33	1309.968	6849.868	12428.35	63
return	-.0062038	-.003631	.0587014	-.1323068	.1488947	63
volatility	54.49646	49.07794	24.27827	25.43783	156.7213	63
volume	6.00e+08	5.63e+08	2.64e+08	2.26e+08	1.53e+09	63

Table 2A represents the comparison for periods before and after CNY (1 month before and 1 after). We can see that the average return and price are lower in the period before, but the standard deviations are higher. Furthermore, the results show that average volatility and volume experience higher values in the period before with respectively higher values of standard deviation.

Table 2A: Descriptive statistics (All periods)

CNY before	mean	p50	sd	min	max	count
1						
price	2661.27	840.9296	3507.349	206.8714	12428.35	192
return	-.0009679	.0013567	.0416692	-.1323068	.1488947	192
volatility	13.11675	2.120957	26.42297	.3014827	156.7213	192
volume	1.26e+08	1.55e+07	2.67e+08	2305924	1.53e+09	192

CNY after	mean	p50	sd	min	max	count
1						
price	2700.25	916.7568	3492.236	236.7476	11525.59	185
return	.0011977	.0008675	.0326208	-.1296756	.1537217	185
volatility	9.109168	2.053689	15.70987	.231103	67.34837	185
volume	1.08e+08	1.70e+07	2.14e+08	1760951	9.84e+	185

Finally, descriptive statistics do not reveal any anomalies or outliers in the data that might lead to erroneous conclusion in our empirical analysis.

Results and Discussion

From this point onwards we use HAC standard errors in every specification in order to correct for potential autocorrelation and heteroscedasticity in the error term. Each hypothesis starts with an examination of the aggregate dummy indicating the period of CNY and then moves to disaggregated dummy with selected period before CNY and after CNY.

Price

H1: The price of BTC decreases during Chinese New Year.

Table 3: The effect of CNY on price (aggregate dummy)

Table 3: Regression output: Price (aggregate dummy)

	(1) price	(2) price	(3) price	(4) Δprice	(5) Δprice
CNY	379.7*	-144.7	-356.7***	-29.29	-14.48
	(1.95)	(-0.97)	(-3.53)	(-1.62)	(-0.91)
Linear trend		3.528***	2.340***	0.0104	
		(47.41)	(25.79)	(0.75)	
volatility			84.84***	-5.009	-5.562
			(4.18)	(-1.24)	(-1.58)
vix			-8.482		
			(-0.81)		
gold_price			4.836***		
			(11.73)		
trade_n			11.84	1.591	2.086
			(1.42)	(0.93)	(1.48)
Δvix				-0.468	-2.381
				(-0.10)	(-0.61)
Δgold_price				0.294	0.284
				(0.95)	(0.96)
L.Δprice					0.362***
					(4.60)
L2.Δprice					-0.0246
					(-0.21)
L3.Δprice					0.0872
					(1.11)
_cons	2300.7***	-1571.8***	-7125.3***	-1.035	0.780
	(30.63)	(-25.41)	(-12.02)	(-0.17)	(0.10)
N	2244	2244	1547	1210	1208
adj. R^2	0.001	0.481	0.825	0.055	0.180

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We start the analysis with the simple static OLS model and, for the illustrative purposes, outline why such results might be misleading and gradually move the more robust static OLS models further supported by the results from the dynamic ARDL model (Table 3). In the specification (1) we simply regress our key variable on price. It can be seen that CNY dummy is significant at 10% level and the magnitude is equal to 379, meaning that in the period of CNY BTC price increases, on average, by 379$. However, this result is not in line with our hypothesis, as we might be capturing positive trend in BTC price across time. To deal with this issue, we include linear trend in our regression. After de-trending we observe that sign is switched, but CNY dummy is no longer significant. Besides, it appears that BTC is, on average, increasing by 3.5$ per day. The problem of such regression is that it might still suffer from omitted variable bias.

For the regression (3) we, therefore, add our controls variables[1]. CNY dummy is, surprisingly, significant again. It might be explained by the fact that some of, previously omitted, variables exert positive effect on BTC price, which reduces absolute magnitude of our coefficient rendering it insignificant. The magnitude of the coefficient is substantially higher, indicating that seasonal effect results in a decrease of BTC price of 357$. In addition, linear trend is still significant, but it is of lower magnitude due to inclusion of controls. Additional controls, gold price and volatility, are significant at 1% level. Namely, 1$ increase in a gold price leads to 4.83$ increase in a price of BTC. Similarly, 1 point increase in volatility leads to 85$ increase in BTC price.

As we can see, after de-trending, R^2 is still relatively high (model explains 82% of variation in price), which is suspicious and might be an indication of some problems with our key variables. It might appear that our time series is not trend-stationary and contains a unit root and in the presence of a shock, unit-root processes do not revert to mean. We, therefore, conduct a unit root test on our key variables and controls. It appears, that price variable indeed contains a unit root, even when controlling for the trend in a Dickey-Fuller test.

By using the Dickey-Fuller, we uncover that price of BTC, VIX index and gold price contain unit roots. For the regression (4) we, therefore, first difference problematic variables (price, gold price and vix index). Neither CNY dummy nor any of our controls are significant, which indicates that previously obtained results are spurious due to stochastic trend and there is no seasonal effect of CNY dummy on BTC price. Finally, for the purpose of testing robustness of our results to serial correlation contained in the dependent variable, we estimate the model that includes lags of the dependent variable in specification (5). Our hypothesis about the relatively high R^2 value was confirmed because after the unit roots test it became much smaller with a value of 0.055. ARDL model indicates that coefficient is still insignificant, which means that autocorrelation is an unlikely cause of the results that we have previously obtained.

[1] *We might add one more control – bitcoin search. Although our key relationship is significant, this regression cannot be considered as valid, because the number of observations is cut in half from 1547 to 965 due to bitcoin search variable. The data for this variable is available only from the middle of 2015, which might exclude some important developments in the early stages of BTC development. However, other results are robust to the exclusion of this variable, that is why I decide not include this control in further specifications*

Table 4: The effect of CNY on price (Before/After dummy)

Table 4: Regression output: Price (Before/after dummy)

	(1)	(2)	(3)	(4)	(5)
	price	price	price	Δprice	Δprice
CNY_before	360.6	-104.5	-493.7***	-13.24	7.048
	(1.37)	(-0.51)	(-3.27)	(-0.47)	(0.29)
CNY_after	399.6	-186.6	-223.1*	-45.46**	-35.63*
	(1.50)	(-0.92)	(-1.90)	(-2.21)	(-1.76)
Linear trend		3.529***	2.334***	0.0110	
		(47.40)	(25.96)	(0.78)	
volatility			85.03***	-5.017	-5.584
			(4.17)	(-1.25)	(-1.59)
vix			-7.413		
			(-0.70)		
gold_price			4.794***		
			(11.49)		
trade_n			11.92	1.579	2.082
			(1.43)	(0.93)	(1.48)
Δvix				-0.483	-2.406
				(-0.10)	(-0.61)
Δgold_price				0.307	0.302
				(0.99)	(1.01)
L.Δprice					0.363***
					(4.61)
L2.Δprice					-0.0226
					(-0.19)
L3.Δprice					0.0908
					(1.15)
_cons	2300.7***	-1572.1***	-7084.3***	-1.282	0.975
	(30.62)	(-25.41)	(-11.91)	(-0.21)	(0.13)
N	2244	2244	1547	1210	1208
adj. R^2	0.001	0.480	0.825	0.055	0.182

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In order to test the effect before and after CNY, we include separate dummies in our regression – CNY before and CNY after (Table 4). We ran the the regressions for both dummies separately, but the results do not differ from the case where we include the dummies in one regression (see appendix 2). Therefore, for the sake of the complete model, it was decided to include both in the same regression. And as it can be observed in the regression (1) without controls, our keys dummies are not significant. Neither they are significant after accounting for a positive trend in price (yet magnitude and significance of trend is preserved).

However, after the inclusion of controls we observe that dummy CNY before becomes statistically significant at 1% level with magnitude of -493.7, meaning that 1 month before the CNY the price of BTC decreases by 498$. Coefficient for CNY after dummy is only significant at 10% level and magnitude is two times lower than in period prior to CNY. Similarly, to aggregate dummy models, both volatility and gold price are statistically significant. Yet, after accounting for unit roots, only period after is significant at 5% level and no other variable are. It indicates that during the period after CNY, price decreases by approximately 45$ on average. After including lags of the dependent variable, coefficient is somewhat reduced but is still significant at 10% level. The first lag of the price suggests that 1$ positive change in yesterday`s price leads to 0.36$ increase in a price of the next day.

We see that there are some differences in obtained results depend on a model we use. Firstly, we see that CNY before effect becomes insignificant when we switch to the first-difference model. It might be due to the fact that we lose some variation that could potentially lead to different results.

Yet, we can observe that period after does not lose its significance so it is possible to conclude that price before CNY is less responsive to the seasonal effect than price after. Most importantly is why BTC price declines only after CNY but not before. The most appropriate explanation for these findings is that the price effects originate only after the CNY due to price stickiness (situation when the price does not react immediately to the changes in the market). Such effect is not observed for the aggregated CNY, due to the fact that we partially loose significance due to aggregation issue, with effect being insignificant prior to CNY and barely significant after CNY.

In addition, when including lags of the dependent variable we see that price/return of BTC yesterday is a significant predictor of the price/return of BTC today, which either makes our key variable insignificant or reduces its magnitude. This is due to the high persistence of Bitcoin, meaning that even if the seasonal effect of CNY is present, it the BTC price in the previous day that largely determines the price of BTC today.

Return

H1a: The return on BTC decreases during Chinese New Year.

Now we use return as alternative proxy in order to see whether we obtain the same result (Table 5).

Specification (1) shows that during CNY period there is no statistically significant effect on the return. Only after adding both trend and controls in our regression, it can be observed that CNY dummy is significant at 10% level. The coefficient for CNY dummy is - 0.53%. Surprisingly, after accounting for a stochastic trend, it can be seen that our CNY dummy becomes highly significant at 1% level, with the coefficient being equal to

-0.008, meaning that period of CNY leads to negative change in return by 0.8%. Results are robust to the inclusion of dependent variable lags.

Table 5: The effect of CNY on return (aggregate dummy)

Table 5: Regression output: Return (aggregate dummy)

	(1) return	(2) return	(3) return	(4) return	(5) return
CNY	-0.00346	-0.00321	-0.00528*	-0.00792***	-0.00616**
	(-1.61)	(-1.52)	(-1.91)	(-2.62)	(-2.03)
Linear trend		-0.00000168	-0.000000827	2.24e-08	
		(-1.05)	(-0.36)	(0.01)	
volatility			-0.000359	-0.000265	-0.000375
			(-1.17)	(-0.79)	(-1.28)
vix			-0.000517*		
			(-1.88)		
gold_price			0.0000251		
			(1.11)		
trade_n			0.000109	0.0000586	0.000131
			(0.68)	(0.33)	(0.89)
Δvix				0.000982	0.00108
				(0.89)	(1.02)
Δgold_price				0.000220*	0.000182
				(1.73)	(1.63)
L.return					0.340***
					(4.44)
L2.return					-0.0751
					(-1.14)
L3.return					-0.124
					(-1.34)
_cons	0.00355***	0.00540**	-0.0180	0.00464	0.00308*
	(3.79)	(2.32)	(-0.63)	(1.26)	(1.67)
N	2243	2243	1547	1210	1208
adj. R^2	0.001	0.001	0.010	0.010	0.128

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As for the second regression that includes CNY before and CNY after dummies (Table 6), we can observe that CNY after is significant at 10% level and implies that after the period of CNY the return is reduced by 0.66%. CNY before dummy is really close to the significance level of 5% and shows magnitude of 0.84% after accounting for unit roots in our control variable. Yet, ARDL model renders our CNY dummies insignificant again. But it can be seen that the lagged effect of our dependent variable is significant at 1% level. The first lag of return suggests that 1% positive change in yesterday`s return leads to 0.34% increase in return of the next day.

Table 6: The effect of CNY on return (Before/After dummy)

Table 6: Regression output: Return (Before/after dummy)

	(1)	(2)	(3)	(4)	(5)
	return	return	return	return	return
CNY_before	-0.00452	-0.00430	-0.00656*	-0.00837*	-0.00689
	(-1.44)	(-1.38)	(-1.65)	(-1.93)	(-1.59)
CNY_after	-0.00235	-0.00207	-0.00403	-0.00746**	-0.00543
	(-0.92)	(-0.81)	(-1.16)	(-1.99)	(-1.41)
Linear trend		-0.00000169	-0.000000883	7.92e-09	
		(-1.05)	(-0.39)	(0.00)	
volatility			-0.000357	-0.000264	-0.000374
			(-1.16)	(-0.79)	(-1.28)
vix			-0.000507*		
			(-1.86)		
gold_price			0.0000247		
			(1.09)		
trade_n			0.000109	0.0000589	0.000131
			(0.68)	(0.33)	(0.88)
Δvix				0.000982	0.00108
				(0.89)	(1.02)
Δgold_price				0.000220*	0.000181
				(1.73)	(1.62)
L.return					0.340***
					(4.44)
L2.return					-0.0753
					(-1.14)
L3.return					-0.124
					(-1.34)
_cons	0.00355***	0.00541**	-0.0176	0.00465	0.00307*
	(3.79)	(2.32)	(-0.61)	(1.26)	(1.67)
N	2243	2243	1547	1210	1208
adj. R^2	0.000	0.001	0.010	0.009	0.128

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Overall, our most robust specifications (with controls and first differences) both for return and price proxies confirm our main hypothesis, there is a pronounced effect on price and return after CNY. Certain discrepancies between the obtained results for price and return can be explained by the fact that price suffers from unit root problem and by taking the first difference we lose some variation of these variable that could potentially lead to this output. Effect of the return is consistent with the effect of price proxy which is in line with our explanation of price stickiness. After accounting for the lagged, BTC price significance of disaggregated dummy disappears, meaning that it is the persistence of BTC price that determines its price or return rather than some seasonal effects.

Moreover, it should be mentioned that although we find some significant negative effect in return for this time period, the magnitude is not big enough in order to make an abnormal profit due to the transaction costs.

Volatility

H2: The volatility of cryptocurrency is increased due to Chinese New Year.

Table 7: The effect of CNY on volatility (aggregate dummy)

Table 7: Regression output: Volatility (aggregate dummy)

	(1) volatility	(2) volatility	(3) volatility	(4) volatility	(5) volatility
CNY	3.668***	2.034*	3.615***	1.479	-1.061*
	(3.07)	(1.85)	(4.49)	(0.94)	(-1.76)
Linear trend		0.0110***	-0.00984***	0.0114***	
		(20.47)	(-9.56)	(15.01)	
price			0.00591***		
			(16.61)		
vix			-0.144		
			(-1.54)		
gold_price			-0.0138***		
			(-4.01)		
Δprice				-0.0192	-0.00903
				(-1.26)	(-1.14)
Δvix				-0.208	-0.105
				(-0.58)	(-0.94)
Δgold_price				-0.00947	0.00284
				(-0.33)	(0.25)
L.volatility					0.819***
					(4.90)
L2.volatility					0.0193
					(0.09)
L3.volatility					0.176
					(1.32)
_cons	7.482***	-4.585***	24.32***	-4.687***	0.390*
	(18.68)	(-12.81)	(4.24)	(-9.22)	(1.82)
N	2244	2244	1547	1210	1209
adj. R^2	0.005	0.157	0.690	0.192	0.864

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Again, firstly we simply regress our dummy on volatility (Table 7). Although the coefficient is statistically significant and is in line with our hypothesis, R^2 of this model is really small and equal to 0.0057. Besides inclusion of trend reduces the coefficient`s significance substantially. For further specifications we change a set of our controls in a way that now we include price because it could influence volatility and volume (for the next hypothesis) and exclude trade_n because it is essentially the same as our volume variable (we would encounter multicollinearity in this case as there is 93% correlation between two).

As a result of controls inclusion, R^2 becomes much higher (0.69). It also can be observed that CNY dummy is again significant at 1% level. Volatility increases in this period of time by 3.615. Also we can see that both BTC price and gold prices are significant at 1% level. After accounting for unit roots in prices and vix index, we do not observe any statistically significant results for our key variables for the whole period of CNY. As for the lagged effects of our dependent variable, the significance and magnitude are quietly the same in both (4) and (5) speciciations. It can be seen that 1 point rise in volatility of the previous day leads to increase in volatility of the following day by 0.82. This result is significant at 1% level.

Table 8: The effect of CNY on volatility (Before/After dummy)

Table 8: Regression output: Volatility (Before/after dummy)

	(1) volatility	(2) volatility	(3) volatility	(4) volatility	(5) volatility
CNY_before	5.635***	4.184**	5.914***	4.754*	-1.547*
	(2.90)	(2.33)	(4.10)	(1.90)	(-1.89)
CNY_after	1.627	-0.201	1.335**	-1.852	-0.576
	(1.33)	(-0.18)	(2.33)	(-1.20)	(-1.03)
Linear trend		0.0110***	-0.00974***	0.0114***	
		(20.44)	(-9.49)	(15.02)	
price			0.00588***		
			(16.66)		
vix			-0.162*		
			(-1.77)		
gold_price			-0.0131***		
			(-3.76)		
Δprice				-0.0193	-0.00901
				(-1.27)	(-1.14)
Δvix				-0.209	-0.105
				(-0.60)	(-0.93)
Δgold_price				-0.00663	0.00240
				(-0.23)	(0.21)
L.volatility					0.819***
					(4.90)
L2.volatility					0.0198
					(0.09)
L3.volatility					0.176
					(1.33)
_cons	7.482***	-4.602***	23.65***	-4.705***	0.382*
	(18.67)	(-12.77)	(4.11)	(-9.24)	(1.78)
N	2244	2244	1547	1210	1209
adj. R^2	0.007	0.159	0.693	0.197	0.864

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For the next regression we combine two dummies again in order to see whether volatility is different for the periods before and after CNY (Table 8). This approach provides us with a set of interesting results. Firstly, CNY before dummy remains unambiguously significant across all specifications (although it only significant at 10% in the last two), indicating that volatility is more pronounced in the period before CNY. CNY is important in a sense that it brings an additional volatility to crypto market. Seasonal effect is important in terms that it brings some fluctuations in price volume and volatility. However, high persistence of BTC overshadows the seasonal period itself meaning that high persistence of BTC is also inherent to its volatility. It goes in line with results of Urquhart (2016) that came to the conclusion that BTC is an inefficient market. In other words, BTC is susceptible to self-fulfilling prophecy if people expect BTC to be more volatile today it would be more volatile tomorrow.

Volume

H3: The trading volume is significantly increased because of Chinese New Year.

Table 9: The effect of CNY on volume (aggregate dummy)

Table 9: Regression output: Volume (aggregate dummy)

	(1) volume	(2) volume	(3) volume	(4) volume	(5) volume
CNY	38330182.4***	19415110.9	29834402.5***	14299653.8	-6821622.8
	(2.90)	(1.61)	(3.38)	(0.84)	(-0.89)
Linear trend		127255.1***	-98952.9***	138375.8***	
		(21.69)	(-9.86)	(15.71)	
price			65900.9***		
			(18.92)		
vix			20462.5		
			(0.02)		
gold_price			-149868.3***		
			(-4.16)		
Δprice				-125176.2	-63567.5
				(-0.77)	(-0.75)
Δvix				-3305280.7	-775275.4
				(-0.67)	(-0.33)
Δgold_price				-273283.6	-55613.2
				(-0.83)	(-0.35)
L.volume					0.671***
					(6.80)
L2.volume					0.00444
					(0.04)
L3.volume					0.353***
					(3.86)
_cons	78766482.6***	-60899583.5***	229897197.3***	-65759769.1***	5115116.5*
	(18.21)	(-15.56)	(3.76)	(-11.20)	(1.85)
N	2244	2244	1547	1210	1209
adj. R^2	0.005	0.177	0.693	0.187	0.811

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For the first regression without any controls, we get significance of 1% for our key variable. Although it goes in line with our hypothesis, R^2 value is relatively small 0.0053. The magnitude is 38.3 mln, meaning that in the period of CNY volume increases by 38.3 mln of $.

After addition of trend and controls we can see that our key variable is still significant but at 1% level with a magnitude of 29.8 mln. Moreover, our prices variable shows significance of 1% level. When testing the regressions after taking the first difference of our key variable, surprisingly both CNY and the price of BTC lose their significance. Results hold in the ARDL model.

Quantitatively similar results are observed after disaggregating our CNY dummy (Table 10). Volume of BTC does not change and all variation is mostly accounted by a linear trend, which is logical as only low amounts of BTC are mined during holidays and considering the size of the Chinese BTC market, the biggest chunk of its production stems from this country in usual periods. Besides, the volume of BTC exhibit high persistence that confirms the findings of (Halvor Aarhus Aalborg, 2018) about BTC characteristics of (Rui, 2005) about the relation between stock returns, trading volume and volatility. Therefore, it is not the period which predicts our dependent variable but the volume/price/volatility of BTC in the previous day.

Table 10: The effect of CNY on volume (Before/After dummy)

Table 10: Regression output: Volume (Before/after dummy)

	(1) volume	(2) volume	(3) volume	(4) volume	(5) volume
CNY_before	46812578.0**	30029821.7*	40945189.1***	36295401.4	-12740840.3
	(2.37)	(1.66)	(2.75)	(1.41)	(-1.09)
CNY_after	29526831.3*	8376082.7	18816181.1**	-8075226.4	-871665.8
	(1.81)	(0.56)	(2.00)	(-0.39)	(-0.10)
Linear trend		127330.0***	-98451.1***	138492.6***	
		(21.67)	(-9.82)	(15.72)	
price			65796.2***		
			(18.94)		
vix			-63816.2		
			(-0.06)		
gold_price			-146561.5***		
			(-4.00)		
Δprice				-126034.6	-63294.1
				(-0.77)	(-0.75)
Δvix				-3315564.8	-771065.5
				(-0.68)	(-0.33)
Δgold_price				-254174.1	-60841.7
				(-0.77)	(-0.38)
L.volume					0.671***
					(6.80)
L2.volume					0.00477
					(0.05)
L3.volume					0.354***
					(3.88)
_cons	78766482.6***	-60981760.8***	226642678.1***	-65876109.0***	5054035.2*
	(18.20)	(-15.52)	(3.67)	(-11.21)	(1.84)
N	2244	2244	1547	1210	1209
adj. R^2	0.005	0.177	0.694	0.189	0.811

t statistics in parentheses
All specifications utilize HAC errors
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Conclusion

Our research contributes to the discussion of efficiency of crypto market by studying the seasonal effect of Chinese New Year.

We found that BTC price declines only after CNY but not before. It happens due to price stickiness of BTC. The results for return proxy are consistent with the results for price. We did not observe any seasonal effects that influence the BTC price/return. But we detect that price and return experience high persistence meaning that its price/return of the previous day determines the present price/return rather than seasonal effect.

As for volatility and volume we did not find any calendar effects but we observed these variables also exhibit high persistence. It might be the case that high persistence of volume/volatility overshadows the seasonal period itself meaning that BTC would most likely to be determined by its previous value and it essentially follow the random walk model.

We can conclude that persistence of BTC is a very important concept in our context. The results suggest that trends and macro shocks influence the indicators of BTC rather than fundamental variables or seasonal effects. It means that it is difficult to predict the BTC exchange rate, even more difficult than predicting exchange rate of fiat money.

References

Andrea Erossa, F. M. (2019). The intraday dynamics of bitcoin. *Research in International Business and Finance* , 71-81.

Ben Kaiser, M. J. (2018). The Looming Threat of China: An Analysis of Chinese Influence on Bitcoin.

Fama, E. F. (1977). Asset returns and inflation. *Journal of Financial Economics*, 115-146.

John, C. (1987). Stock returns and the term structur. *Journal of Financial Economics*, 373-399.

Halvor Aarhus Aalborg, P. M. (2018). What can explain the price, volatility and trading volume of Bitcoin? *Finance Research Letters* .

Kaiser, L. (2018). Seasonality in cryptocurrencies. *Finance Research Letters* .

Lawrence R. Glosten, R. J. (1993). On the Relation between the Expected. *THE JOURNAL OF FINANCE*, 1779-1801.

Malkiel, B. G. (1973). *A Random Walk Down Wall Street: The Time-Tested Strategy for Successful Investing .* Ww Norton & Co.

Mei Hui, P. (2019). 'Chinese New Year Effect' in BTC Market. Retrieved from https://medium.com/tech4she/chinese-new-year-effect-in-btc-market-ab4bd3136199

Michael S Rozeff, W. R. (1976). Capital market seasonality: The case of stock returns. *Journal of Financial Economics* , 379-402.

Opschoor, A. (2013). *Understanding Financial Market Volatility.* Tinbergen Institute Research Series.

Pavel Ciaiana, M. R. (2018). Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money*, 173-195.

Poyser, O. (2017). Exploring the determinants of Bitcoin's price: an application of Bayesian Structural.

R.French, K. (1980). Stock returns and the weekend effect. *Journal of Financial Economics*, 55-69.

REINGANUM. (1983). THE ANOMALOUS STOCK MARKET BEHAVIOR OF SMALL FIRMS IN JANUARY. *Journal of Financial Economics*, 89-104.

Rui, G.-m. C. (2005). The Dynamic Relation Between Stock Returns, Trading Volume, and Volatility. *The Financial Review* , 153-174.

Shaen Corbet, B. M. (2018). Bitcoin Futures—What use are they? *Economics Letters* , 23-27.

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters* , 80-82.

Bitcoinity.org. (2019). Retrieved from https://data.bitcoinity.org/markets/volume/30d?c=e&t=b

Cryptocurrency Market Capitalizations | CoinMarketCap. (2019). Retrieved from https://coinmarketcap.com/

Appendix

Table 1: Descriptive statistics

CNY	mean	p50	sd	min	max	count
2014						
0						
price	482.0766	474.847	107.3903	312.1411	678.9111	303
return	-.0018031	-.0029104	.0280125	-.0898038	.1138123	303
volatility	1.298188	1.09145	.7153808	.3226655	4.124418	303
volume	6703042	4596134	6326723	345542	6.22e+	303
1						
price	737.0541	792.463	106.2125	497.7926	937.5439	62
return	-.0019255	-.0034788	.0436315	-.1296756	.1537	62
volatility	3.198183	2.629309	1.9254	1.182478	12.6754	62
volume	1.07e+07	8461006	8992477	1760951	4.57e+07	62
2015						
0						
price	277.8412	252.0265	62.56166	199.0961	462.555	303
return	.0005442	.0008436	.0288932	-.1738044	.1649015	303
volatility	.6130016	.4083934	.6442128	.0942602	6.507286	303
volume	8280643	4887904	1.12e+07	499574.6	1.23e+	303
1						
price	248.7447	240.6782	25.17529	206.8714	295.081	62
return	.0049682	.0011873	.0372965	-.0833037	.1349688	62
volatility	.7805404	.723104	.4156562	.231103	2.93640	62
volume	1.20e+07	1.03e+07	8415685	3219857	5.837	62
2016						
0						
price	597.0817	611.4623	123.1102	406.9885	921.8093	292
return	.0031277	.0016749	.0191501	-.0897547	.1021713	292
volatility	.834072	.5632745	.7574193	.1635613	5.085665	292
volume	9721951	4557548	1.37e+07	569303.4	9.17e+07	292
1						
price	438.6212	403.814	134.6971	370.9095	971.4603	67
return	-.0004196	.000022	.0226847	-.0748499	.0515023	67
volatility	.8129393	.6850529	.4192448	.3346888	2.1982	67
volume	1.07e+07	8325440	7923965	3367414	4.91e+07	67
2017						
0						
price	4508.888	2800.375	4033.85	932.4121	19270.7	306
return	.0088086	.0096202	.0428515	-.1722699	.1701078	306
volatility	21.84953	10.64317	33.29159	1.069743	246.1874	306
volume	2.36e+08	9.25e+07	3.53e+08	5435051	2.25e+09	306
1						
price	981.0347	990.4587	101.8214	784.788	1193.343	59
return	.0042203	.0088346	.030617	-.1112712	.0591302	59
volatility	2.280217	1.818786	1.831193	.452718	12.17626	59
volume	1.96e+07	1.48e+07	1.67e+07	2476031	9.26e+0	59
2018						
0						
price	7059.093	6612.709	2243.672	3275.559	16689.85	302
return	-.0019278	-.0005732	.0304384	-.1095711	.0887498	302
volatility	18.07818	13.96425	15.27318	3.112017	114.0275	302
volume	2.09e+08	1.58e+08	1.64e+08	2.10e+07	9.65e+08	302

	mean	p50	sd	min	max	count
1						
price	9915.368	10022.33	1309.968	6849.868	12428.35	63
return	-.0062038	-.003631	.0587014	-.1323068	.1488947	63
volatility	54.49646	49.07794	24.27827	25.43783	156.7213	63
volume	6.00e+08	5.63e+08	2.64e+08	2.26e+08	1.53e+09	63

2019

	mean	p50	sd	min	max	count
0						
price	4813.401	5076.184	735.5481	3847.756	6211.079	65
return	.0070329	.0029157	.0218331	-.0316789	.1242112	65
volatility	8.087264	7.14688	4.837626	1.809321	22.9533	65
volume	5.26e+07	4.26e+07	4.31e+07	9467144	2.58e+08	65
1						
price	3757.551	3694.773	194.4885	3447.236	4133.332	63
return	.0003812	.0000765	.0177888	-.0542459	.0478035	63
volatility	5.279553	4.79809	2.102592	1.793054	11.98201	63
volume	4.85e+07	4.17e+07	2.96e+07	1.12e+07	1.46e+08	63

Table 2: The effect of CNY on price (Before/After dummy)

Variable	(1) price	(2) price
CNY after	163.5	
	(1.04)	
volatility	30.43	31.58
	(1.28)	(1.30)
vix	-28.58*	-20.49
	(-1.88)	(-1.39)
gold_price	1.536***	1.479***
	(2.99)	(2.78)
trade_n	62.49***	62.43***
	(6.07)	(6.02)
CNY_before		-511.1**
		(-2.57)
_cons	-763.1	-763.5
	(-0.99)	(-0.99)
N	1547	1547
adj. R-sq	0.687	0.689

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01