BITCOIN IN CHINA

Master thesis in Finance

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ΤΜΗΜΑ ΛΟΓΙΣΤΙΚΗΣ

ΚΑΙ ΧΡΗΜΑΤΟΟΙΚΟΝΟΜΙΚΗΣ

7 Ιανουαρίου 2021

Συντονιστή Μεταπτυχιακών Προγραμμάτων

Τμήματος Λογιστικής και Χρηματοοικονομικής

Β Ε Β Α Ι Ω Σ Η

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Η εξεταστική επιτροπή,

________________________ ____________________

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Abstract

The aim of this study is to investigate and show how the Chinese stock market affects bidirectional or unidirectional the Cryptocurrency market and in particular, Bitcoin. To carry this project, we have retrieved daily historical daily data for BTC / CNY from Bitcoinity and DataStream databases. Using the ban of the bitcoin in China on October of 2017 as a possibly exogenous shock to the Bitcoin market (Event 1) we examine the relationship between the stock market and the bitcoin market in China and US before and after this event. Before the event, the Chinese stock market and specifically Shanghai Index returns Granger cause BTC / CNY returns. In addition, in the US market we do not observe any association BTC / USD to US stock market. But after the event took place, we observe a unidirectional association from BTC / USD to US stock market. Additionally, we examine the relationship between arbitrage and bitcoin bid-ask spreads before and after the People's Bank of China applied fixed trading transactions of 0.2% per trade (Event 2). Before this event, analysis suggests a unidirectional positive relationship between bid-ask spreads in US and the arbitrage. Post this event we find a unidirectional positive relationship of bid-ask spreads in China and arbitrage. Theoretical literature supports these event changes that we find.

1. Introduction

Bitcoin is the most well-known digital currency and the first cryptocurrency created. Nakamoto (2009) was the first to introduced bitcoin in his paper and marked the beginning of trading and cryptocurrency mining by a lot of investors. From that point onwards, bitcoin and other cryptocurrencies popularity exploded. In contrast to fiat currencies that are using central banking systems, cryptocurrencies use decentralized control and blockchain. The bitcoin is a digital currency created to work as a tool of exchange of cryptocurrency possession record. Each transaction is kept using a solid cryptography in a database.

Due to its unique attributes, cryptocurrency market and specifically bitcoin is the optimal cryptocurrency to examine arbitrage opportunities and discover price differences between markets e.g., gold, equity and cryptocurrencies. Worldwide there are many cryptocurrency exchanges in different continent and countries that are not at all integrated. Most of the cryptocurrency exchanges work as a traditional stock market. Namely, investors place an order to buy or sell and the cryptocurrency exchanges clear up the trades on a centralized book. However, the traditional stock market operated under regulations in contrast to the cryptocurrency market which is not regulated market. This means that no one can ensure best execution for trades.

Traders are generally interested in bitcoin's unique features. However, they find more interest in bitcoin during economic uncertainties and capital controls. First, bitcoin is not stable due to the fact is not connected to fundamental based cash flows, although the main risk for bitcoin is coming from countries internal issues. Second and most important is that bitcoin is decentralized. Restrictions by an individual regulator will not affect the whole cryptocurrency market but only one country as it happened in China in 2017. In this study, we examine two unique events. First event, in January 2017 the Chinese exchanges applied fixed trading transactions of 0.2% per trade and second event that took place in China in October 2017 when Chinese Government decided to ban the bitcoin pairs in all Chinese exchanges. Third, the bitcoin is protected from inflation by design due to the prefixed and limited supply, which is determined by algorithms. Furthermore, if an individual country chooses to increase inflation by the monetary policy bitcoin still not be that much affected.

Yu and Zhang (2020) demonstrate that traders prefer to trade in Bitcoin during economic or political uncertainty in a country because of the large spreads and volatility. In our empirical study, we examine whether the change of equity market returns in China affect the cryptocurrency market. More specific we investigate whether there is a bidirectional or unidirectional relationship from Chinese stock market to BTC / CNY before the ban and after the ban. For the same event, we also investigate whether there is a Granger Causality effect from BTC / USD to US stock market. To identify this association, we use daily returns of the biggest index in China, Shanghai Index which represents 1542 China-based companies, the BTC / CNY pair (yuan is the currency in China) and the vector autoregressive (VAR) methodology. Additionally, we examine the relationship between BTC / USD and the largest US indices which are Nasdaq, S&p500 and Dow Jones. We focus on the period post the bitcoin ban by Chinese Government from the Chinese exchanges.

We also examine the increase of transaction costs in China (a second event), and whether it might lead to an increase the bitcoin price arbitrage. In other words, we investigate whether the increase of spreads can increase the arbitrage after the People's Bank of China started applying friction on bitcoin trades. Due to the large volatility in bitcoin, there is high possibility for speculators to find arbitrage opportunities across the countries and continents. To derive results, we use one main econometric model, the Vector Autoregression (VAR) Granger causality and we apply it on both event studies. In our research the arbitrage (gap) depending on fiat currency USD / CNY, BTC / USD and BTC / CNY, we will explain in detail in the next sections.

Literature Review

Chapter 1

In the literature, there are papers that compare different markets (such as stock market, bond market, bitcoin market) within a country (or economic zone), and other papers that compare markets (such as stock markets) across countries. Wanat, Papież, and Śmiech (2015), Vazakidis and Adamopoulos (2012) and Bouoijour and Selmi (2015) are three papers that demonstrate a similar work with what we do in Chapter 1 of this study.

Wanat, Papież, and Śmiech (2015) investigates the dynamic linkages between main European stock markets and two commodities: the crude oil and gold. The authors investigate two hypotheses: (a) whether the relationship between stock markets and commodity prices is stable over time, (b) whether gold and oil prices (Granger) cause the European stock market. The study focuses on the European market, which is the second largest economy in the world with GDP of 12,715,823 million USD. The authors choose the largest European indices: the DAX from Frankfurt Stock Exchange and FTSE100 from London Stock Exchange. For crude oil, they use the spot prices of Europe Brent (BRENT).

The study uses daily data from January 2, 1998 to June 30, 2014 and the period is divided in 13 sub-samples and investigate the relationship between commodity market and European stock market using the methodology of Granger Causality. They compare the following pairs German stock index (DAX) and crude oil prices (Brent), German stock index (DAX) and gold, UK stock market (FTSE100) and crude oil, UK stock market (FTSE100) and gold.

Generally, in literature the authors use Granger causality aiming to investigate both the existence of a relationship between markets and direction of this relationship, which is very important for financial investors. Wanat, Papież, and Śmiech (2015) examine in 13 sub-samples the four pairs DAX-GOLD, DAX-BRENT, FTSE100-GOLD, FTSE100-BRENT. They suggest that at 5% statistical significance level, DAX granger causes gold after the 5th sub-period and FTSE100 Granger causes the gold after the 2nd sub period. In general, the results indicate that past information of DAX and FTSE100 can forecast the gold prices. In opposite direction, they found that GOLD and BRENT do no Granger cause DAX and FTSE100 indicating that past information does not improve the prices forecasting. In Chapter 1 we follow the paper's idea to examine different markets using the Granger methodology. In particular, we examine the relationship between the bitcoin in China and the biggest index in China, the Shanghai Composite index which represents 1542 China-based companies in the stock exchanges of China.

Moreover, in the literature there are papers that use Granger Causality to compare markets with economic data. For example, the study of Vazakidis and Adamopoulos (2012) which examines the relationship between stock markets, economic growth and interest rates. Using the method of Granger causality, they find a unidirectional causal relationship from economic growth to stock market, a unidirectional causal relationship from interest rate to stock market and a unidirectional causal relationship from economic growth to interest rate. Our study follows a same Vector Autoregressive methodology.

Bouoijour and Selmi (2015) examine the relationship between bitcoin, Shanghai Index, gold and Hash rate. Hash rate is an indicator of the processing power of the Bitcoin Network. The authors examine the event of Chinese trading bankruptcy in 2013. They used data from 2010 to 2014, similar period with our study and found a positive relationship between Shanghai Index and Bitcoin. Also, they found unclear evidence if bitcoin can be safe heaven as gold. So, the aforementioned paper supports our Hypothesis 1 that there is positive relationship from the biggest Chinese index to the BTC / CNY.

Chapter 1 is contributing in the literature important and interesting results on the relationship between Bitcoin market and stock markets in China and in US. By employing the full data history from June of 2011 to October of 2017 of pair BTC / CNY (yuan), we examine the Granger causality between bitcoin and the stock market in China. In literature, other research relies on data of BTC / USD or bitcoin index and we do not find there is no similar comparison using the same approach of vector autoregression (VAR). Moreover, we examine the unique event that took place in China in October 2017 when Chinese Government decided to ban the bitcoin pairs in all Chinese exchanges. There are available data of BTC / CNY for six years period before the event. We used six years of US data pre the event and three years post the event. Our results suggest that before this event there is no evidence of Granger Causality between US stock market and BTC / USD but there is evidence of Granger Causality between Stock market in China and BTC / CNY. However, post this event Granger Causality seems to exist from BTC / USD to US stock market.

Chapter 2

In Chapter 2 we have studied three major papers. The paper of Makarov and Schoar (2020), the paper of Yu and Zhang (2020) and the paper of Gagnon and Karolyi (2004). In this section we explain the relevance of each paper to our study.

Makarov and Schoar (2020) examine the large arbitrage opportunities in bitcoin and other cryptocurrency markets. The authors show that the arbitrage opportunities are much larger between than within the same region. More specific they find that there is larger arbitrage between the US and China but smaller between the US and Europe. Also, up to January 2017, almost 95% of bitcoin trading was driven by Chinese exchanges and all the other exchanges in the rest of the world constituted only the 5%. Makarov and Schoar (2020) show that this occurred mainly due to the fact these exchanges had not transaction fees and they accepted margin trading with high leverage. However, beginning of January 2017, the People's Bank of China started applying friction on local trades to reduce speculation and price volatility. Accordingly, in January 2017 the Chinese exchanges applied fixed trading transactions of 0.2% per trade. After that, the volume in China dropped off as expected and the volume in other regions increased. Therefore, in our study we attempt to fill the gap in literature and examine the impact of this event (that the People's Bank of China imposed friction on bitcoin trades) on arbitrage opportunities. Makarov and Schoar (2020) calculate the arbitrage index at the minute level. In order to do this, they calculate the maximum price and divide it by the minimum price between all exchanges at specific minute. In the next, paragraph we show that we choose to calculate the arbitrage in the same way Yu and Zhang (2020) did.

Yu and Zhang (2020) show that during higher policy uncertainty and capital controls the arbitrage is higher as well. The observed phenomenon is essentially propelled by the absence of trust in local authorities and investors, rather than the circumvention of capital controls or the capital controls or the hedging demand against markets crashes. The main argument is that the bitcoin qualifies as another way to ease worries about local authorities during turmoil. In this paper they choose to examine three study events. The first one is the Operation Car wash in Brazil, which formally started in March 17, 2014 and is considered as the biggest scandal in Latin America. They find that the GAP ten days after the event is higher compared to the previous ten days. The second event study happened in November 2016. The Indian government reported a demonetization plan to battle the black money market, illegal activities and terrorism. The third event study occurred in December 9, 2016, the National Assembly was planned to vote on the impeachment against President Park Geun-Hey for abuse of power and coercion. By using information during these three events, they show that local currency rise post event, caused discrepancy between local and foreign bitcoin price (called the GAP). In our study we use an event study methodology -using the event of the paper Yu and Zhang (2020) when the People's Bank of China imposing friction on bitcoin trades and we also use the same calculation of GAP as Yu and Zhang (2020). In the next sections we define in more detail the way GAP works.

Additionally, Yu and Zhang (2020) use a) the Economic Policy Uncertainty index (EPU) constructed by Baker, Bloom and Davis (2016) for multiple countries and b) the Capital Controls Restrictions constructed by Fernandez et al. (2016). The Economic Policy Uncertainty index (EPU) consists of monthly data, Capital control restrictions consists of annual data. We decided not to use these variables because daily data is by nature more accurate than monthly or annual data.

It is worth to mention papers like the one of Gagnon and Karolyi (2004), that examine arbitrage in the existence of transaction costs between different markets. Particularly, Gagnon and Karolyi (2004) arbitrage opportunities are calculated by comparing daily prices of American Depositary Receipts (ADRs) and US cross-listed shares with synchronous prices from home market shares on adjusted currency basis.

Gagnon and Karolyi (2004) argue that in different markets, regarding US cross listed shares and Home market shares, the relationship of arbitrage between spreads becomes positive after the transaction costs. This is also our major argument in chapter 2. We show that arbitrage has a positive relationship with transaction costs in the form of spreads. We test the direction of the relationship using Granger causality and show that spreads in USD of BTC / USD affects the GAP before. We also show that spreads in CNY of BTC / CNY affects the GAP after the event.

Research question / Hypotheses Development

The literature review assisted us to construct our research questions and two hypotheses.

Research question: Do the two events ((a)the transactions costs increase event of January 2017 and (b) the ban of the bitcoin event of October 2017) in China affect bitcoin?

Based on existing literature, many papers examine how different markets affect each other. For example, Wanat, Papież, and Śmiech (2015) and Vazakidis and Adamopoulos (2012) had investigate the inter-relationship between stock market, foreign exchange rate market, commodity market, and cryptocurrency market. We also identify two important bitcoin events that we believe can affect the inter-relationship between bitcoin and other markets. These events are (a) People's Bank of China, on January of 2017 by introducing a fixed trading transaction of 0.2% per trade on Chinese bitcoin market, and (b) Chinese Government banning bitcoin pairs in Chinese exchanges. These events should be examined thoroughly since the Chinese market is the dominant market of bitcoin trading during this period. These events cause large changes on spreads, volumes and volatility. Having this in mind, in our study we attempt to investigate the reaction of the Bitcoin market before and after these two shocks. We also investigate the inter-relationship of the bitcoin market with other markets such as commodity market and stock market in China and US. To the best of our knowledge no other study has looked at these events and its effects on different markets.

The event study for Chapter 1 is the ban of the bitcoin in China by the Chinese government (October 2017). The main argument is coming from the paper of Makarov and Schoar (2020) and show that the ban of BTC / CNY causes a significant decrease to the previously large volume in China. Note that simultaneously we observe an increase of volume in BTC / USD in the US. Similarly, Yu and Zhang (2020) show that the 95% from the volume of Bitcoin was coming from the Chinese exchanges before the event. In their paper, they argue that the large volume in China is driven by policy uncertainties and capital controls in China which lead investors to use bitcoin as a tool to transfer the local currency yuan to foreign currency. Makarov and Schoar (2020) show that this occurred mainly due to the fact these exchanges had not transaction fees and they accepted margin trading with high leverage. Additionally, Bouoijour and Selmi (2015) show that Shanghai index affects bitcoin by examining a similar period as we do in our study. Their work further supports our results as their study also suggests a positive sign relationship. In our study, before the event, because of the volume concentration of BTC / CNY in China we do not expect the bitcoin market to lead other markets as stock market and commodity market or vice versa. However, expected to see post the event the BTC / USD and BTC / EUR affect directional US stock market due to the distributional increase of the BTC / USD volume worldwide. We argue that the increase of volume of BTC / USD in US post the event is too low comparing to the volume of BTC / CNY in China pre the event. Due to above reason, we expect directional effect from BTC / USD to stock market after the event. Therefore, according to this conclusion we build up our hypothesis for our study.

<u>Hypothesis 1:</u> There is a unidirectional relationship from Chinese stock market to BTC / CNY before the ban and after the ban there is a unidirectional effect from BTC / USD to US stock market.

Event study for Chapter 2 is the People's Bank of China in January of 2017 applying fixed trading transactions of 0.2% per trade on bitcoin in Chinese exchanges. Note, there is limitation of data regarding the BTC / CNY, so we use ten months before and ten months after the event. Based on the literature the main argument is coming from Gagnon and Karolyi (2004), who show that the increase in the transaction costs lead to an increase of the arbitrage. In particular, the authors show in a different setting, (US cross listed shares and Home market shares) that the relationship of arbitrage and spreads is positive. In our study, we calculate arbitrage based on Yu and Zhang (2020). After the event we expect an increase of the spreads because of higher transaction costs and should lead to an increase of arbitrage. In line with the above argument, we build up our hypothesis for our study and expect to derive similar results.

<u>Hypothesis 2:</u> The increase of transaction costs in China may lead to the increase in bitcoin price arbitrage.

Research design

Methodology

Below, we investigate and test at each of the two hypotheses using empirical data and the Granger methodology. Chapter 1 focuses on hypothesis 1 and Chapter 2 focuses on hypothesis 2.

To derive results, we use one main econometric model, the Vector Autoregression (VAR) Granger causality and we apply it on both event studies.

Vector Autoregression (VAR): Cristopher Sims introduced this methodology it twenty years ago as an econometric model which is used to capture the relationship across multiple quantities as they change over the long run (time-series framework). Vector Autoregression is a kind of stochastic process model and in general can be used both as a single variable model and in a multivariate setup as well. In our study we use multivariate time series. In other words, every variable will be a dependent variable and the lags of all variables are used as independent variables. Additionally, we use the statistical tool Selection-order criteria. These criteria show for each model the appropriate number of lags to use in the Vector Autoregression (VAR). In the table of Selection-order criteria you can find the Sequential modified (LL), Test statistics (LR), Final prediction error (FPE), Akaike criterion (AIC), Schwarz information criterion (SC) and Hannan-Quinn information criterion. The number of lags assigned with p-value lower than 0.05 is considered statistically significant and therefore is selected.

Empirical Models

Chapter 1

To construct the empirical model in Chapter 1 we use bitcoin in Chinese currency (BTC / CNY), gold in Chinese currency (XAU / CNY) and the Shanghai Composite index (SSE). To identify the relationships between cryptocurrency market, stock market and commodity market we use the returns of each variable and the full BTC / CNY data before the ban of Chinese government. As we previously explained, in Vector autoregression method the lags of all dependent variables are used as independent variables. Below we provide the variables definition of our model. The subscript 'j' denotes the lags of each variable whereas 't' denotes the day.

BTC / CNY = bitcoin vs Chinese currency Juan

BTC / USD = bitcoin vs US currency us dollar

XAU / CNY = gold vs Chinese currency Juan

XAU / USD = gold vs US currency us dollar

Shanghai Composite index (SSE) = the SSE is the short name of Shanghai Stock exchange index and is distributed from A – shares and B – shares. It is the biggest index in China and the 4^{th} largest stock market worldwide with capitalization at four trillion US dollars up to 2018.

Dow Jones = the common name of Dow Jones is Dow 30. This index listed the 30 largest blue-chip companies and that are trading on the New York stock exchange. It is the second oldest index and one of the largest indices in US. It can be considered as an approximation to US economy.

Nasdaq = this index consists over three thousand listed technology and biotech stocks e.g., Google, Intel, Apple and Amazon.

Standard & Poor's 500 (S&P 500) = is the capitalization of weighted average of the biggest five hundred US companies.

- $BTC / CNY_{\ t} = \alpha_{1,\ t} + \sum \beta_{1,\ j} * SSE_{\ t\text{-}j} + \sum \gamma_{1,\ j} * XAU / CNY_{\ t\text{-}j} + \sum \delta_{1,\ j} * BTC / CNY_{\ t\text{-}j}$ **(1)**
- $SSE_{\ t} = \alpha_{2,\ t} + \sum \beta_{2,\ j} * SSE_{\ t\text{-}j} + + \sum \gamma_{2,\ j} * XAU / CNY_{\ t\text{-}j} + \sum \delta_{2,\ j} * BTC / CNY_{\ t\text{-}j}$ **(2)**
- $XAUCNY_{\ t} = \alpha_{3,\ t} + \sum \beta_{3,\ j} * SSE_{\ t\text{-}j} + \sum \gamma_{3,\ j} * XAU / CNY_{\ t\text{-}j} + \sum \delta_{3,\ j} * BTC / CNY_{\ t\text{-}j}$ **(3)**

Additionally, we run the model in a similar manner regarding the US market before the ban of the BTC / CNY and after the event. The variables are bitcoin in US dollar (BTC / USD), Dow Jones (DOW), S&P 500 (S&P 500), Nasdaq (NASDAQ) and gold and US dollar XAU / USD.

- $BTC / USD_{\ t} = \alpha_{1,\ t} + \sum \beta_{1,\ j} * DOW_{\ t\text{-}j} + \sum \gamma_{1,\ j} * S\&P\ 500_{\ t\text{-}j} + \sum \delta_{1,\ j} * NASDAQ_{\ t\text{-}j} + \sum \varepsilon_{1,\ j} * XAU / USD_{\ t\text{-}j} + \sum \theta_{1,\ j} * BTC / USD_{\ t\text{-}j}$ **(1)**
- $DOW_{\ t} = \alpha_{2,\ t} + \sum \beta_{2,\ j} * DOW_{\ t\text{-}j} + \sum \gamma_{2,\ j} * S\&P\ 500_{\ t\text{-}j} + \sum \delta_{1,\ j} * NASDAQ_{\ t\text{-}j} + \sum \varepsilon_{2,\ j} * XAU / USD_{\ t\text{-}j} + \sum \theta_{1,\ j} * BTC / USD_{\ t\text{-}j}$ **(2)**

- $S\&P\ 500_{\ t} = \alpha_{3,t} + \sum \beta_{3,j} * DOW_{t\text{-}j} + \sum \gamma_{3,j} * S\&P\ 500_{\ t\text{-}j} + \sum \delta_{3,j} * NASDAQ_{t\text{-}j} + \sum \varepsilon_{3,j} * XAU/USD_{t\text{-}j} + \sum \theta_{3,j} * BTC/USD_{t\text{-}j}$ **(3)**
- $NASDAD_{\ t} = \alpha_{4,t} + \sum \beta_{4,j} * DOW_{t\text{-}j} + \sum \gamma_{4,j} * S\&P\ 500_{\ t\text{-}j} + \sum \delta_{4,j} * NASDAQ_{t\text{-}j} + \sum \varepsilon_{4,j} * XAU/USD_{t\text{-}j} + \sum \theta_{4,j} * BTC/USD_{t\text{-}j}$ **(4)**
- $XAU/USD_{\ t} = \alpha_{5,t} + \sum \beta_{5,j} * DOW_{t\text{-}j} + \sum \gamma_{5,j} * S\&P\ 500_{\ t\text{-}j} + \sum \delta_{5,j} * NASDAQ_{t\text{-}j} + \sum \varepsilon_{5,j} * XAU/USD_{t\text{-}j} + \sum \theta_{5,j} * BTC/USD_{t\text{-}j}$ **(5)**

Furthermore, we perform the same model but with each index alone. Namely, we exclude the other two indices.

Only with Dow Jones

- $BTC/USD_{\ t} = \alpha_{1,t} + \sum \beta_{1,j} * DOW_{t\text{-}j} + \sum \gamma_{1,j} * XAU/USD_{t\text{-}j} + \sum \delta_{1,j} * BTC/USD_{t\text{-}j}$ **(1)**
- $DOW_{\ t} = \alpha_{2,t} + \sum \beta_{2,j} * DOW_{t\text{-}j} + \sum \gamma_{2,j} * XAU/USD_{t\text{-}j} + \sum \delta_{2,j} * BTC/USD_{t\text{-}j}$ **(2)**
- $XAU/USD_{\ t} = \alpha_{3,t} + \sum \beta_{3,j} * DOW_{t\text{-}j} + \sum \gamma_{3,j} * XAU/USD_{t\text{-}j} + \sum \delta_{3,j} * BTC/USD_{t\text{-}j}$ **(3)**

Only with S&P 500

- $BTC / USD_{\ t} = \alpha_{\ 1,\ t} + \sum \beta_{\ 1,\ j} * S\&P\ 500_{\ t\text{-}j} + \sum \gamma_{\ 1,\ j} * XAU / USD_{\ t\text{-}j} + \sum \delta_{\ 1,\ j} * BTC / USD_{\ t\text{-}j}$ **(1)**
- $S\&P\ 500_{\ t} = \alpha_{\ 2,\ t} + \sum \beta_{\ 2,\ j} * S\&P\ 500_{\ t\text{-}j} + \sum \gamma_{\ 2,\ j} * XAU / USD_{\ t\text{-}j} + \sum \delta_{\ 2,\ j} * BTC / USD_{\ t\text{-}j}$ **(2)**
- $XAU / USD_{\ t} = \alpha_{\ 3,\ t} + \sum \beta_{\ 3,\ j} * S\&P\ 500_{\ t\text{-}j} + \sum \gamma_{\ 3,\ j} * XAU / USD_{\ t\text{-}j} + \sum \delta_{\ 3,\ j} * BTC / USD_{\ t\text{-}j}$ **(3)**

Only with NASDAQ

- $BTC / USD_{\ t} = \alpha_{\ 1,\ t} + \sum \beta_{\ 1,\ j} * NASDAQ_{\ t\text{-}j} + \sum \gamma_{\ 1,\ j} * XAU / USD_{\ t\text{-}j} + \sum \delta_{\ 1,\ j} * BTC / USD_{\ t\text{-}j}$ **(1)**
- $NASDAQ_{\ t} = \alpha_{\ 2,\ t} + \sum \beta_{\ 2,\ j} * NASDAQ_{\ t\text{-}j} + \sum \gamma_{\ 2,\ j} * XAU / USD_{\ t\text{-}j} + \sum \delta_{\ 2,\ j} * BTC / USD_{\ t\text{-}j}$ **(2)**
- $XAU / USD_{\ t} = \alpha_{\ 3,\ t} + \sum \beta_{\ 3,\ j} * NASDAQ_{\ t\text{-}j} + \sum \gamma_{\ 3,\ j} * XAU / USD_{\ t\text{-}j} + \sum \delta_{\ 3,\ j} * BTC / USD_{\ t\text{-}j}$ **(3)**

We also run the same model by replacing BTC / USD with BTC /EUR

- $BTC / EUR_{\ t} = \alpha_{\ 1,\ t} + \sum \beta_{\ 1,\ j} * DOW_{\ t\text{-}j} + \sum \gamma_{\ 1,\ j} * S\&P\ 500_{\ \ t\text{-}j} + \sum \delta_{\ 1,\ j} * NASDAQ_{\ t\text{-}j} \ \ \sum \varepsilon_{\ 1,\ j} * XAU / USD_{\ t\text{-}j} + \sum \theta_{\ 1,\ j} * BTC / EUR_{\ t\text{-}j}$ **(1)**

- $DOW_{\ t} = \alpha_{\ 2,\ t} + \sum \beta_{\ 2,\ j} * DOW_{\ t\text{-}j} + \sum \gamma_{\ 2,\ j} * S\&P\ 500_{\ \ t\text{-}j} + \sum \delta_{\ 2,\ j} * NASDAQ_{\ t\text{-}j} \ \ \sum \varepsilon_{\ 2,\ j} * XAU / USD_{\ t\text{-}j} + \sum \theta_{\ 1,\ j} * BTC / EUR_{\ t\text{-}j}$ **(2)**

- $S\&P\ 500_{\ t} = \alpha_{\ 3,\ t} + \sum \beta_{\ 3,\ j} * DOW_{\ t\text{-}j} + \sum \gamma_{\ 3,\ j} * S\&P\ 500_{\ \ t\text{-}j} + \sum \delta_{\ 3,\ j} * NASDAQ_{\ t\text{-}j} \ \ \sum \varepsilon_{\ 3,\ j} * XAU / USD_{\ t\text{-}j} + \sum \theta_{\ 3,\ j} * BTC / EUR_{\ t\text{-}j}$ **(3)**

- $NASDAD_{\ t} = \alpha_{\ 4,\ t} + \sum \beta_{\ 4,\ j} * DOW_{\ t\text{-}j} + \sum \gamma_{\ 4,\ j} * S\&P\ 500_{\ \ t\text{-}j} + \sum \delta_{\ 4,\ j} * NASDAQ_{\ t\text{-}j} \ \ \sum \varepsilon_{\ 4,\ j} * XAU / USD_{\ t\text{-}j} + \sum \theta_{\ 4,\ j} * BTC / EUR_{\ t\text{-}j}$ **(4)**

Chapter 2

In the vector autoregressive model (Granger causality methodology) we use the following five variables: 1) arbitrage in bitcoin prices between the Chinese and US markets 2) the spreads in CNY of BTC / CNY 3) the spreads in USD of BTC / USD 4) the volatility of BTC / CNY 5) the volatility of BTC / USD. As we have already mention, we use the methodology of event study. In this case, the event is when People's Bank of China applied fixed trading transactions of 0.2% per trade in the Chinese exchanges in January 2017. Regarding this period, there is a limitation on data because of the aforementioned event, the Chinese Government stopped exchanges from offering bitcoin in China. We thus use an event window of ten months before and ten months after the event. Below we provide the definition of each variable in the model.

The subscript 'j' denotes the lags of each variable and 't' denotes the day.

GAP (arbitrage): The construction is based on a triangular strategy among BTC / CNY and USD / CNY and BTC / USD. Arbitrage exist whenever there is a difference in the bitcoin prices across the countries. More specific in our study, if the GAP between China market and US market the GAP is not zero, then this implies the existence of arbitrage. GAP is calculated as the price of the bitcoin in local currency, in our case the BTC / CNY divided by the BTC / USD and multiplied by the fiat pair USD / CNY. In the other words, we measure the GAP as the difference between the actual and the synthetic price of the bitcoin:

GAP = ((BTC / CNY)/(BTC / USD * USD / CNY) – 1) * 100

The GAP can take positive or negative values meaning there is arbitrage. Below we provide two examples how GAP is works.

Case 1: The price of BTC / CNY is higher than in USD: Let the price of BTC / CNY = 7000, BTC / USD = 100 and the spot rate exchange USD/ CNY = 68. To exploit tis arbitrage opportunity, we buy BTC / USD in one exchange, then sell BTC / CNY in the other exchange, afterwards we move the BTC from the one exchange to the other exchange and finally close the position. At the end we exchange the CNY in USD. The GAP is calculated as the follows: (((BTC / CNY) / (BTC / USD) * (USD / CNY)) – 1) * 100 = (((7000) / (100) * (68)) – 1) * 100 = 2.94 %.

Case 2: The price of BTC / USD is higher than in CNY: Let the price of the BTC / CNY = 8500, the price of the BTC / USD = 100 and the spot rate exchange USD/ CNY = 87. In this case we buy BTC / USD in one exchange and then we sell BTC / CNY in the other exchange. We then move the BTC from the one exchange to the other exchange to close the position and finally we exchange the CNY in USD. The GAP is calculated as the follows: (((BTC / CNY) / (BTC / USD) * (USD / CNY)) – 1) * 100 = (((8500) / (100) * (87)) – 1) * 100 = - 2.29 %.

Spread: is the difference between ask price and bid price. Ask price is the price that the trader is willing to sell and bid price is the price that want to buy. The spread is the cost that the trader should pay to the exchange.

Volatility: reflects standard deviation of returns in a certain period. Generally, if higher volatility implies a riskier asset whereas a lower asset means the underlying asset is a safer investment.

Empirical Models

- $GAP_{t} = \alpha_{1,t} + \sum \beta_{1,j} * SPREAD\ CNY_{t-j} + \sum \gamma_{1,j} * SPREAD\ USD_{t-j} + \sum \delta_{1,j} * Volatility\ CNY_{t-j} + \sum \varepsilon_{1,j} * Volatility\ USD_{t-j} + \sum \theta_{1,j} * GAP_{t-j}$ **(1)**

- $SPREAD\ CNY_{t} = \alpha_{2,t} + \sum \beta_{2,j} * SPREAD\ CNY_{t-j} + \sum \gamma_{2,j} * SPREAD\ USD_{t-j} + \sum \delta_{2,j} * Volatility\ CNY_{t-j} + \sum \varepsilon_{2,j} * Volatility\ USD_{t-j} + \sum \theta_{2,j} * GAP_{t-j}$ **(2)**

- $SPREAD\ USD_{t} = \alpha_{3,t} + \sum \beta_{3,j} * SPREAD\ CNY_{t-j} + \sum \gamma_{3,j} * SPREAD\ USD_{t-j} + \sum \delta_{3,j} * Volatility\ CNY_{t-j} + \sum \varepsilon_{3,j} * Volatility\ USD_{t-j} + \sum \theta_{3,j} * GAP_{t-j}$ **(3)**

- $Volatility\ USD_{t} = \alpha_{4,t} + \sum \beta_{4,j} * SPREAD\ CNY_{t-j} + \sum \gamma_{4,j} * SPREAD\ USD_{t-j} + \sum \delta_{4,j} * Volatility\ CNY_{t-j} + \sum \varepsilon_{4,j} * Volatility\ USD_{t-j} + \sum \theta_{4,j} * GAP_{t-j}$ **(4)**

- $Volatility\ CNY_{t} = \alpha_{5,t} + \sum \beta_{5,j} * SPREAD\ CNY_{t-j} + \sum \gamma_{5,j} * SPREAD\ USD_{t-j} + \sum \delta_{5,j} * Volatility\ CNY_{t-j} + \sum \varepsilon_{5,j} * Volatility\ USD_{t-j} + \sum \theta_{5,j} * GAP_{t-j}$ **(5)**

Data

Chapter 1

In chapter 1 we collect all the bitcoin daily data from Bitcoinity. The website also provides bitcoin prices of all pairs fiat currency to bitcoin but for this study we focus only on the prices of BTC / CNY, BTC / USD and BTC / EUR. We take the full history of data regarding BTC / CNY from July 5th, 2011 to October 27th, 2017. Considering this period there is a limitation because of the fact on this date the Chinese Government stopped exchanges from offering bitcoin in China. In addition to that, we retrieve data regarding BTC / USD from July 5th , 2011 to August 26th , 2020 and regarding BTC / EUR from October 28th , 2017 to August 26th , 2020. The source for the indices, Shanghai Composite Index, Dow Jones, Nasdaq, S&P 500, XAU / CNY and XAU / USD data is the Thomson Reuters DataStream. The period we use for Shanghai Composite Index, XAU / CNY is from July 5th, 2011 to October 27$^{th.}$ Regarding Dow Jones, Nasdaq, S&P 500 and XAU / USD we retrieve data from October 28th, 2017 to August 26th, 2020. We use daily data to calculate returns for all variables required in chapter 1.

Chapter 2

In chapter 2 we retrieve all the bitcoin data from Bitcoinity. We focus in five variables which are the following: GAP, spread in CNY for BTC / CNY, spread in USD for BTC / USD , the volatility in CNY for BTC / CNY and volatility in USD for BTC / USD. For all variables in Chapter 2, we use data regarding ten months before and after the relevant event study. More specific the GAP measure is calculated as the price of the bitcoin in local currency, the BTC / CNY divided by the BTC / USD and multiplied the fiat pair USD / CNY as defined above.

Results

Chapter 1 Results

In this section we will provide the results for the Chapter 1 analysis. We examine whether there is a relationship and if so, whether this relationship is bidirectional or unidirectional between BTC / CNY, Shanghai Index (SSE) and XAU / CNY. In **Table I**, we observe that the BTC / CNY has the highest standard deviation. As a first step, in **Table III** the use of the criteria indicates that it is statistically meaningful to incorporate 2-lags in the Vector Autoregression model. Therefore, we run the regression with two lags and provide the relevant results. In **Table IV,** results suggest that there is Granger Causality relationship from Shanghai index to BTC / CNY and from BTC / CNY to XAU / CNY. Furthermore, numbers in **Table II** indicate a negative relationship between Shanghai index and XAU / CNY. Note that, this is consistent with the existing literature. Hood and Farooq (2013), show that gold serves as a safe heaven and as a hedging tool for Stock market. We perform the same analysis for the same period regarding the BTC / USD, XAU / USD and three majors US indices, Dow Jones, Nasdaq and S&P 500 and presents the results in **Table VIII.** We do not find any association between these variables, possibly due to the low volume during this period before the ban of BTC / CNY in China. Stavroyiannis and Babalos (2017) as well suggests that S&P500 does not affect BTC / USD for the period 2013 to 2016, similar period with our study. After the ban of the Bitcoin in China of the Chinese government, (October 2017), we perform the analysis only for the US variables. The **Table XII show** us to use two lags and the **Table XI** we illustrate the Granger Causality from BTC / USD with all three majors US indices. Furthermore, we perform the same model but with each index alone. Namely, we exclude the other two indices and we find the same results. Additionally, we run the same model, but we substitute the BTC / USD with BTC / EUR and we find the same results in **Table XIX**. Also, in **Table V** we observe that the BTC / USD has the highest standard deviation. The argument for this is the distribution of the volume after the ban of BTC / CNY in China, in other words the volume of bitcoin increases in US and hence bitcoin prices started having association with the market after the event. Our results are consistent with previous studies as the study of Bouoijour and Selmi (2015) which documents the positive association between Shanghai index and Bitcoin in a similar period. Additionally, the **Appendix Table 1 to 4** show that the results are not significant between FTSE 100 and US indices with Chinese market.

Chapter 2 Results

In this section, we present results for our hypothesis, the increase of transaction costs in China may lead to the increase in bitcoin price arbitrage. Before and after the People's Bank of China in January 2017 applied fixed trading transactions of 0.2% as a form of taxes per trade on the Chinese Bitcoin market. Due to the limitation of the data we collect data 10 months before the event and ten months after the event. The reason of this data limitation is the ban of the bitcoin and more specific of BTC / CNY in China by the Chinese government in October 2017. We construct the model in chapter 2 using the variables: Gap, Volatility in CNY, Volatility in USD, spread in USD and Spread in CNY. In **Table 3**, the selected criteria order show how many lags we shall use in the Vector Autoregression model Selection criteria model suggests the use of two lags. Results in **Table 4** indicate that before the event, there is a Granger Causality from Spreads in USD to the GAP and the sign is negative. Moreover, there is a unidirectional relationship from Volatility in USD to Volatility in CNY and the sign is positive, meaning the possible increase in Volatility in USD leads to an increase of the Volatility in CNY. In **Table 7** and **Table 8** we present the results regarding the period ten months after our event study. The **Table 7** reports 2 lags for Vector Autoregression model. In **Table 8** provide the results derived by the model. There is a Granger Causality from spreads in CNY to the GAP and the sign is positive. This is in line with the paper of Gagnon and Karolyi (2004) which they show the transactions costs, in our case the spread increases the arbitrage and in our case the GAP. The results show that before the event there is a Granger Causality from Spreads in USD to the GAP and the sign is negative. After the event there is a Granger Causality from spreads in CNY to the GAP and the sign is positive. The way that we show which relationship is more significant is to multiply the coefficients with the standard deviation. The coefficient of the spread in USD is -2.755 and standard deviation as given in **Table 1** is 0.0512798. Wee multiple the two numbers and the result is -0.141275. The coefficient of the spread in CNY is 2.350 and the standard deviation as given in **Table 5** is 0.1692384. The multiplication yields 0.397710. The conclusion is that after the event study the spread in CNY affects the GAP more than the spread in USD affects the GAP before the event. Moreover, post the event results are shown in **Table 8.** The **Graph 7** show an increase of GAP, **Graph 3** the decrease of the volume in CNY of BTC / CNY and **Graph 5** the large increase of the spreads in CNY after the event. This result show that the Chinese market absorb and adjust the taxes and we see the increase of spreads of BTC / CNY and the GAP. Additionally, we observe an increase of volume in USD in **Graph 4**, an increase of the volatility in USD in **Graph 2** and a decrease of the spreads in USD in **Graph 6** after the event. There is unidirectional relationship from Volatility in USD to Volatility in CNY, but the sign is negative for lag one with a p-value < 0.1 and for lag two the sign is positive but with p-value < 0.05. Also, **Table 2** and **Table 6** display the correlation between the Volatility in USD to Volatility in CNY is positive and additionally the coefficient for lag two is almost double than that of lag one. This is not our major result, the relationship between Volatility in USD and Volatility in CNY is a unidirectional and positive.

Conclusions

The two main arguments in Chapter 1, based on Makarov and Schoar (2020) and Bouoijour and Selmi (2015) papers. From Makarov and Schoar (2020) we find the event study when the Government in China banned the bitcoin from all exchanges and they observe an increase of the volume in US, Europe, Japan and Korea. In this study, we attempt to enrich the underlying literature by investigating this event in depth. We examine the relationship between the cryptocurrency market, stock market and commodity market in China and US before and after this event to capture the impact. Our findings meet the expectation of a Granger Causality from Chinese stock market to BTC / CNY and Granger Causality after the event study from BTC / USD to three major US indices. Moreover, we examine the BTC / EUR with the three majors US indices to confirm that BTC / EUR lead the US stock market.

In the Chapter 2, we investigate more the Gagnon and Karolyi (2004) main argument that when transactions costs increase, then arbitrage increases. One of the contributions in our study is the investigation of the event when the People's Bank of China the Chinese exchanges applied fixed trading transactions of 0.2% per trade. As per Gagnon and Karolyi (2004) we expect after the event a positive relationship between the resulting increase in the spread of BTC / CNY and bitcoin price arbitrage (price differences between US and China Bitcoin prices, i.e., the GAP). Indeed, our results agree with this argument.

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Chapter 1

Table I Descriptive Statistics

This table present the descriptive statistics the period from June of 2011 to October of 2017 in China before the ban of the BTC / CNY by the Chinese Government. The table shows the descriptive statistics for each variable we use for our model.

Variable	Obs	Mean	Std.Dev.	Min	Max
XAU / CNY	1477	.0014946	.0355306	-.0885173	.0551633
Shanghai index (SSE)	1477	-.0038312	.0122125	-.0577996	.0628299
BTC / CNY	1477	-.0000535	.0474973	-.2370957	.2785503

Table II Correlations

This table present the correlation coefficient between the variables for the period from June of 2011 to October of 2017 in China before the ban of the BTC / CNY from the Chinese Government. The table provides the correlation coefficient for each variable we use for our model.

	XAU / CNY	Shanghai index (SSE)	BTC / CNY
XAU / CNY	1		
Shanghai index (SSE)	-0.0138	1	
BTC / CNY	0.0233	0.0292	1

Table III Selection-order criteria

This criteria show us how many lags we should use in our model for the Vector Autoregression

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	105.915				3.7e-07	-.6.07922	-.5.85068	-.550615
1	1095.09	1978.4	25	0.315	1.1e-09	-6.41621	-6.27909	-6.07238*
2	1192.72	70.28*	25	0.001	8.4e-10*	-6.70311*	-6.33745	-5.78621
3	1157.58	124.97	25	0. 400	9.0e-10	-6.64202	-6.39063*	-6.01166

Table IV Vector Autoregression results for 6 years data

This table present the bidirectional or unidirectional relationship between the variables for the period from June of 2011 to October of 2017 in China before the ban of the BTC / CNY from the Chinese Government. The table provides the also the coefficient for each variable we use for our model.

	(1)	(2)	(3)
VARIABLES	XAU / CNY	SSE	BTC / CNY
L. BTC / CNY	0.0222	0.0885	0.0495
	(0.0337)	(0.162)	(0.0383)
L2. BTC / CNY	-0.0782**	0.263	-0.0220
	(0.0325)	(0.156)	(0.0370)
L. XAU / CNY	0.0707*	-0.286	-0.0451
	(0.0371)	(0.178)	(0.0422)
L2. XAU / CNY	0.0160	0.125	-0.0204
	(0.0361)	(0.173)	(0.0410)
L. Shanghai index (SSE)	-0.00675	0.301***	0.000386
	(0.00955)	(0.0458)	(0.0109)
L2. Shanghai index (SSE)	0.0153	-0.0608	0.0252**
	(0.0101)	(0.0482)	(0.0114)
Constant	-0.000491	-0.00224	-0.000100
	(0.000389)	(0.00187)	(0.000442)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table V Descriptive Statistics

This table present the descriptive statistics for period the period from June of 2011 to October of 2017 in China before the ban of the BTC / CNY from the Chinese Government. The table shows the descriptive statistics for each variable we use for our model.

Variable	Obs	Mean	Std.Dev.	Min	Max
BTC / USD	1477	-.0030352	.0342762	-.18064	.215812
GOLD / USD	1477	.0000899	.0088614	-.0334096	.0480467
DOW JONES	1477	-.0003888	.0076393	-.0380135	.0370731
NASDAQ	1477	-.0004694	.009104	-.0406702	.0429186
S&P 500	1477	-.0003152	.0077875	-.0375674	.0410308

Table VI Correlations

This table present the correlation coefficient between the variables for the period from June of 2011 to October of 2017 in China before the ban of the BTC / CNY from the Chinese Government. The table provides the correlation coefficient for each variable we use for our model.

	BTC / USD	GOLD / USD	DOW JONES	NASDAQ	S&P 500
BTC / USD	1				
GOLD / USD	-0.0014	1			
DOW JONES	0.0303	0.2016	1		
NASDAQ	0.0200	0.1840	0.8767	1	
S&P 500	0.0273	0.1801	0.9703	0.9418	1

Table VII Selection-order criteria

This criterion show us how many lags we should use in our model for the Vector Autoregression

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	5647	1.7e-22				-359.363	-357.991	-35.584
1	5672.93	37.449	25	0.110	1.8e-22	-359.023	-35.9124*	-35.8766*
2	5691.66	51.864*	25	0.040	1.7e-22*	-35.9422*	-356.398	-352.455
3	5703.07	22.83	25	0.587	1.9e-22	-358.157	-35.434	-348.605

Table VIII Vector Autoregression results for 6 years data

This table present the bidirectional or unidirectional relationship between the variables for the period from June of 2011 to October of 2017 in US before the ban of the BTC / CNY from the Chinese Government. The table provides the also the coefficient for each variable we use for our model.

VARIABLES	(1) BTC / USD	(2) GOLD / USD	(3) DOW JONES	(4) NASDAQ	(5) S&P 500
L.BTC / USD	0.206***	0.00486	0.0172	0.0304	0.0233
	(0.0537)	(0.0139)	(0.0115)	(0.0135)	(0.0116)
L2.BTC / USD	-0.104*	0.0193	0.00106	-0.00127	-0.00261
	(0.0545)	(0.0140)	(0.0117)	(0.0137)	(0.0118)
L.S&P 500	-0.174	-0.931***	-0.167	0.273	-0.0411
	(1.401)	(0.361)	(0.300)	(0.352)	(0.304)
L2.S&P 500	-1.108	-0.445	-0.303	-0.173	-0.266
	(1.362)	(0.351)	(0.292)	(0.342)	(0.295)
L.GOLD / USD	0.0996	-0.0429	-0.0418	-0.00915	-0.0317
	(0.185)	(0.0477)	(0.0396)	(0.0464)	(0.0401)
L2.GOLD / USD	-0.201	-0.0577	0.0789*	0.116**	0.0982**
	(0.199)	(0.0514)	(0.0427)	(0.0500)	(0.0432)
L.DOW JONES	-0.173	0.645**	0.0529	-0.230	-0.0665
	(0.989)	(0.255)	(0.212)	(0.248)	(0.214)
L2.DOW JONES	1.521	0.228	0.0686	-0.146	-0.0132
	(0.957)	(0.247)	(0.205)	(0.240)	(0.207)
L.NASDAQ	0.553	0.235	0.148	0.0481	0.156
	(0.580)	(0.149)	(0.124)	(0.146)	(0.126)
L2.NASDAQ	-0.218	0.223	0.192	0.294*	0.232*
	(0.601)	(0.155)	(0.129)	(0.151)	(0.130)
Constant	-0.00392**	0.000301	-0.000215	-0.000181	-5.73e-05
	(0.00164)	(0.000423)	(0.000351)	(0.000412)	(0.000355)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IX Descriptive Statistics

This table present the descriptive statistics for period the period from October of 2017 to August of 2020 in US after the ban of the BTC / CNY from the Chinese Government. The table shows the descriptive statistics for each variable we use for our model.

Variable	Obs	Mean	Std.Dev.	Min	Max
BTC / EURO	692	.0009978	.0388341	-.1622727	.2160649
BTC / USD	692	.0010048	.0388455	-.163253	.2479608
GOLD / USD	692	.0005957	.0085199	-.0570606	.0476268
DOW JONES	692	-.0000708	.0160113	-.1020521	.1484557
Nasdaq	692	-.0006294	.0161315	-.0854718	.1405283
S&P 500	692	-.000269	.0150197	-.0857792	.1361577

Table X Correlations

This table present the correlation coefficient between the variables from October of 2017 to August of 2020 in US after the ban of the BTC / CNY from the Chinese Government. The table provides the correlation coefficient for each variable we use for our model.

	BTC / EURO	BTC / USD	GOLD / USD	DOW JONES	Nasdaq	S&P 500
BTC / EURO	1					
BTC / USD	0.9945	1				
GOLD / USD	-0.1412	-0.1677	1			
DOW JONES	0.1077	0.1027	-0.0257	1		
Nasdaq	0.0961	0.0898	-0.0360	0.9193	1	
S&P 500	0.1066	0.1009	-0.0263	0.9826	0.9636	1

Table XI Vector Autoregression results for 3 years data

This table present the bidirectional or unidirectional relationship between the variables for the period from October of 2017 until August of 2020 in US after the ban of the BTC / CNY from the Chinese Government. The table provides the also the coefficient for each variable we use for our model with all US majors indices.

Table XII Selection-order criteria (with all US major indices)

This criteria show us how many lags we should use in our model for the Vector Autoregression

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	4561.05				3.2e-21	-33.0148	-32.9885	-32.9493*
1	4617.94	113.79	25	0.000	2.5e-21	-33.246	-33.0881*	-328.524
2	4644.32	52.763*	25	0.001	2.5e-21*	-33.256*	-329.665	-325.345
3	4661.21	33.779	25	0.113	2.6e-21	-331.972	-327.761	-321.478

VARIABLES	BTC / USD	GOLD / USD	DOW JONES	Nasdaq	S&P 500
L. BTC / USD	0.282***	-0.00423	-0.0105	-0.00203	-0.00897
	(0.0571)	(0.0119)	(0.0240)	(0.0239)	(0.0225)
L2. BTC / USD	0.00525	-0.0226*	0.0512**	0.0510**	0.0469**
	(0.0563)	(0.0117)	(0.0236)	(0.0236)	(0.0222)
L. GOLD / USD	-0.399*	0.0443	-0.0533	-0.0477	-0.0430
	(0.236)	(0.0491)	(0.0993)	(0.0992)	(0.0932)
L2. GOLD / USD	-0.229	0.0484	-0.190**	-0.206**	-0.188**
	(0.219)	(0.0455)	(0.0920)	(0.0919)	(0.0864)
L. DOW JONES	0.860	-0.436***	0.122	0.173	0.134
	(0.779)	(0.162)	(0.327)	(0.327)	(0.307)
L2. DOW JONES	-0.0117	-0.124	-0.0856	-0.426	-0.137

	(0.778)	(0.162)	(0.326)	(0.326)	(0.307)
L. Nasdaq	0.367	-0.0752	0.371	0.489**	0.335
	(0.573)	(0.119)	(0.241)	(0.240)	(0.226)
L2. Nasdaq	-0.192	-0.0425	-0.483**	-0.698***	-0.553**
	(0.566)	(0.118)	(0.238)	(0.238)	(0.223)
L. S&P 500	-0.876	0.496*	-0.696	-0.912*	-0.665
	(1.247)	(0.259)	(0.523)	(0.523)	(0.491)
L2. S&P 500	0.161	0.186	0.765	1.296**	0.865*
	(1.248)	(0.259)	(0.524)	(0.523)	(0.492)
Constant	0.000847	0.000768*	0.000357	-4.43e-05	0.000132
	(0.00193)	(0.000400)	(0.000809)	(0.000808)	(0.000760)

Table XIII Selection-order criteria (only with Dow Jones)

This criteria show us how many lags we should use in our model for the Vector Autoregression

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	2163.8				3.2e-11	-15.6579	-15.6422	-15.6186
1	2207.65	87.712	9	0.000	2.5e-11	-15.9105	-15.8474*	-15.7531*
2	2222.2	29.093*	9	0.001	2.4e-11*	-15.9507*	-15.8402	-15.6753
3	2225.5	6.597	9	0.679	2.5e-11	-15.9094	-15.7515	-15.5159

Table XIV Vector Autoregression results for 3 years data

This table present the bidirectional or unidirectional relationship between the variables for the period from June of 2011 until October of 2017 in US before the ban of the BTC / CNY from the Chinese Government. The table provides the also the coefficient for each variable we use for our model only with Dow Jones.

VARIABLES	(1) BTC / USD	(2) DOW JONES	(3) GOLD / USD
L. BTC / USD	0.282***	-0.0127	-0.00462
	(0.0565)	(0.0239)	(0.0118)
L2. BTC / USD	0.00552	0.0535**	-0.0222*
	(0.0562)	(0.0237)	(0.0118)
L. GOLD / USD	-0.402*	-0.0487	0.0454
	(0.234)	(0.0989)	(0.0490)
L2. GOLD / USD	-0.222	-0.191**	0.0490
	(0.217)	(0.0915)	(0.0453)
L. DOW JONES	0.399	-0.166***	-0.0509*
	(0.130)	(0.0547)	(0.0271)
L2. DOW JONES	-0.0495	0.163***	0.00709
	(0.130)	(0.0547)	(0.0271)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table XV Selection-order criteria (only with Nasdaq)

This criteria show us how many lags we should use in our model for the Vector Autoregression

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	2155.64				3.4e-11	-15.5988	-15.583	-15.5595
1	2190.79	70.302	9	0.000	2.8e-11	-15.7883	-15.7252*	-15.6309*
2	2201.76	21.948*	9	0.009	2.8e-11*	-15.8026*	-15.6921	-15.5272
3	2205.24	69.592	9	0.641	2.9e-11	-15.7626	-15.6047	-15.3691

Table XVI Vector Autoregression results for 3 years data

This table present the bidirectional or unidirectional relationship between the variables for the period from June of 2011 until October of 2017 in US before the ban of the BTC / CNY from the Chinese Government. The table provides the also the coefficient for each variable we use for our model only with Nasdaq.

VARIABLES	(1) BTC / USD	(2) Nasdaq	(3) GOLD / USD
L. BTC / USD	0.282***	-0.00389	-0.00594
	(0.0569)	(0.0243)	(0.0119)
L2. BTC / USD	0.00291	0.0597**	-0.0205*
	(0.0562)	(0.0241)	(0.0118)
L. GOLD / USD	-0.390*	-0.0472	0.0436
	(0.234)	(0.100)	(0.0491)
L2. GOLD / USD	-0.256	-0.207**	0.0535
	(0.217)	(0.0927)	(0.0454)
L. Nasdaq	0.361	-0.167***	-0.0250
	(0.131)	(0.0559)	(0.0274)
L2. Nasdaq	-0.0606	0.0720	0.0144
	(0.133)	(0.0569)	(0.0279)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table XVII Selection-order criteria (only with S&P 500)

This criteria show us how many lags we should use in our model for the Vector Autoregression

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	2180.39				2.8e-11	-15.7782	-15.624	-15.7388
1	2220.43	80.092	9	0.000	2.3e-11	-16.0031	-15.94*	-15.8457*
2	2234.4	27.921*	9	0.001	2.2e-11*	-16.0391*	-15.9286	-15.7636
3	2237.47	61.443	9	0.725	2.3e-11	-15.9961	-15.8382	-15.6026

Table XVIII Vector Autoregression results for 3 years data

This table present the bidirectional or unidirectional relationship between the variables for the period from June of 2011 until October of 2017 in US before the ban of the BTC / CNY from the Chinese Government. The table provides the also the coefficient for each variable we use for our model only with S&P 500.

	(1)	(2)	(3)
VARIABLES	BTC / USD	S&P 500	GOLD / USD
L. BTC / USD	0.283***	-0.0118	-0.00555
	(0.0565)	(0.0225)	(0.0119)
L2. BTC / USD	0.00456	0.0498**	-0.0213*
	(0.0562)	(0.0224)	(0.0118)
L. GOLD / USD	-0.394*	-0.0477	0.0443
	(0.234)	(0.0930)	(0.0490)
L2. GOLD / USD	-0.235	-0.187**	0.0521
	(0.217)	(0.0863)	(0.0455)
L. S&P 500	0.405	-0.159***	-0.0372
	(0.138)	(0.0551)	(0.0290)
L2. S&P 500	-0.0590	0.144***	0.0143
	(0.140)	(0.0557)	(0.0294)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table XIX Vector Autoregression results for 3 years data

This table present the bidirectional or unidirectional relationship between the variables for the period from June of 2011 until October of 2017 in US before the ban of the BTC / CNY from the Chinese Government. The table provides the also the coefficient for each variable we use for our model only with all major US indices and BTC / EUR.

VARIABLES	(1) BTC / EURO	(2) GOLD / USD	(3) DOW JONES	(4) Nasdaq	(5) S&P 500
L. GOLD / USD	-0.284	0.0439	-0.0519	-0.0469	-0.0414
	(0.236)	(0.0488)	(0.0987)	(0.0987)	(0.0927)
L2. GOLD / USD	-0.229	0.0510	-0.195**	-0.212**	-0.193**
	(0.218)	(0.0452)	(0.0915)	(0.0915)	(0.0859)
L. DOW JONES	0.816	-0.437***	0.124	0.175	0.136
	(0.781)	(0.162)	(0.327)	(0.327)	(0.307)
L2. DOW JONES	-0.126	-0.122	-0.0879	-0.428	-0.140
	(0.780)	(0.161)	(0.327)	(0.326)	(0.307)
L. Nasdaq	0.473	-0.0738	0.370	0.487**	0.334
	(0.574)	(0.119)	(0.241)	(0.240)	(0.226)
L2. Nasdaq	-0.226	-0.0389	-0.486**	-0.703***	-0.557**
	(0.568)	(0.118)	(0.238)	(0.238)	(0.224)
L. S&P 500	-1.015	0.496*	-0.699	-0.914*	-0.667
	(1.250)	(0.259)	(0.524)	(0.523)	(0.492)
L2. S&P 500	0.336	0.180	0.773	1.306**	0.874*
	(1.251)	(0.259)	(0.524)	(0.524)	(0.492)
L .BTC / EURO	0.286***	-0.00521	-0.0109	-0.00194	-0.00884
	(0.0565)	(0.0117)	(0.0237)	(0.0236)	(0.0222)
L2. BTC / EURO	-0.00689	-0.0221*	0.0471**	0.0479**	0.0430**
	(0.0555)	(0.0115)	(0.0232)	(0.0232)	(0.0218)
Constant	0.00106	0.000763*	0.000375	-2.65e-05	0.000148
	(0.00193)	(0.000400)	(0.000808)	(0.000808)	(0.000759)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Chapter 2

Table 1 Descriptive Statistics

This table present the descriptive statistics for period the period from February of 2016 until January of 2017 in China before the People's Bank of China and the Chinese exchanges applied fixed trading transactions of 0.2% per trade. The table shows the descriptive statistics for each variable we use for our model.

Variable	Obs	Mean	Std.Dev.	Min	Max
Gap	304	.072779	2.14011	-4.178725	9.560853
Volatility in cny	304	2.871589	2.017478	.6665004	15.67884
Volatility in usd	304	2.205241	3.445312	.2612724	24.70993
Spread in usd	304	.1436706	.0512798	.0014698	.3740229
Spread in cny	304	.0152406	.0054863	.0054983	.0332705

Table 2 Correlations

This table present the correlation coefficient between the variables from February of 2016 until January of 2017 in China before the People's Bank of China the Chinese exchanges applied fixed trading transactions of 0.2% per trade. The table provides the correlation coefficient for each variable we use for our model.

	Gap	Spread in cny	Spread in usd	Volatility in cny	Volatility in usd
Gap	1				
Spread in cny	0.2223	1			
Spread in usd	0.0468	0.2257	1		
Volatility in cny	0.0289	-0.1089	0.1471	1	
Volatility in usd	0.0567	0.1657	0.2365	0.2040	1

Table 3 Selection-order criteria

This criteria show us how many lags we should use in our model for the Vector Autoregression

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	138.084				3.1e-07	-.804136	-.781229	-.746702
1	1106.02	1935.9	25	0.000	1.0e-09	-6.50164	-63.642	-6.15704*
2	1154.78	97.515	25	0.000	8.9e-10*	-6.64519*	-6.39321*	-6.01342
3	1178	46.441*	25	0.600	9.0e-10	-6.63444	-6.26793	-57.155

Table 4 Vector Autoregression results for 10 months data

This table present the bidirectional or unidirectional relationship between the variables for the period from February of 2016 until January of 2017 in China before the People's Bank of China and the Chinese exchanges applied fixed trading transactions of 0.2% per trade. The table provides the also the coefficient for each variable we use for our model.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Spread in cny	Spread in usd	Volatility in cny	Volatility in usd	Gap
L. Gap	0.000103	0.0112***	0.145	-0.0156	1.257***
	(0.000256)	(0.00307)	(0.131)	(0.0317)	(0.0521)
L2. Gap	-8.83e-05	-0.0122***	-0.123	0.0177	-0.321***
	(0.000256)	(0.00307)	(0.131)	(0.0317)	(0.0521)
L. Spread in cny	0.690***	1.353**	-30.12	0.813	18.05
	(0.0541)	(0.649)	(27.67)	(6.692)	(11.00)
L2. Spread in cny	0.163***	-0.745	9.618	0.504	-10.19
	(0.0539)	(0.646)	(27.54)	(6.661)	(10.95)
L. Spread in usd	0.00178	0.571***	2.683	0.675	-0.579
	(0.00459)	(0.0550)	(2.345)	(0.567)	(0.932)
L2. Spread in usd	-0.00270	0.179***	-0.265	-0.0966	-2.755***
	(0.00467)	(0.0559)	(2.387)	(0.577)	(0.949)
L. Volatility in cny	-0.000127	7.15e-05	0.609***	-0.00455	-0.0102
	(0.000107)	(0.00129)	(0.0549)	(0.0133)	(0.0218)
L2. Volatility in cny	4.55e-05	0.000659	0.0638	0.0184	0.0145
	(0.000105)	(0.00126)	(0.0539)	(0.0130)	(0.0214)
L. Volatility in usd	0.000649	-0.00124	0.444**	0.687***	0.0700
	(0.000442)	(0.00530)	(0.226)	(0.0547)	(0.0899)
L2. Volatility in usd	-0.000428	0.00517	-0.183	0.0666	0.0294
	(0.000445)	(0.00533)	(0.228)	(0.0550)	(0.0905)
Constant	0.00234***	0.0207***	0.645*	0.0862	0.259**
	(0.000649)	(0.00778)	(0.332)	(0.0803)	(0.132)

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5 Descriptive Statistics

This table present the descriptive statistics for period the period from January of 2017 until October of 2017 in China after the People's Bank of China and the Chinese exchanges applied fixed trading transactions of 0.2% per trade. The table shows the descriptive statistics for each variable we use for our model.

Variable	Obs	Mean	Std.Dev.	Min	Max
Gap	304	1.102929	7.483.765	-17.40608	19.66972
Volatility in cny	304	6.233381	4.839366	8.656655	293.5838
Volatility in usd	304	8.257232	8.939448	1.090564	59.57351
Spread in usd	304	.1300716	.0405117	.0552367	.2761822
Spreadi n cny	304	.3601364	.1692384	.011915	1.016187

Table 6 Correlations

This table present the correlation coefficient between the variables from January of 2017 until October of 2017 in China before the People's Bank of China the Chinese exchanges applied fixed trading transactions of 0.2% per trade. The table provides the correlation coefficient for each variable we use for our model.

	Gap	Volatility in cny	Volatility in usd	Spread in cny	Spread in usd
Gap	1				
Volatility in cny	0.0620	1			
Volatility in usd	0.1456	0.5148	1		
Spread in cny	0.0048	0.5283	0.4825	1	
Spread in usd	0.1658	0.2931	0.4154	0.3404	1

Table 7 Selection-order criteria

This criteria show us how many lags we should use in our model for the Vector Autoregression

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-2615.3				184.985	19.4097	19.4364	19.4763
1	-1737.69	1755.2	25	0.000	.334423	13.094	13.2567	13.6954
2	-1694.92	85.531	25	0.004	.293242*	12.9624*	13.2546*	13.4938*
3	-1670.97	47.905*	25	0.400	.295665	12.9702	13.3983	14.0364

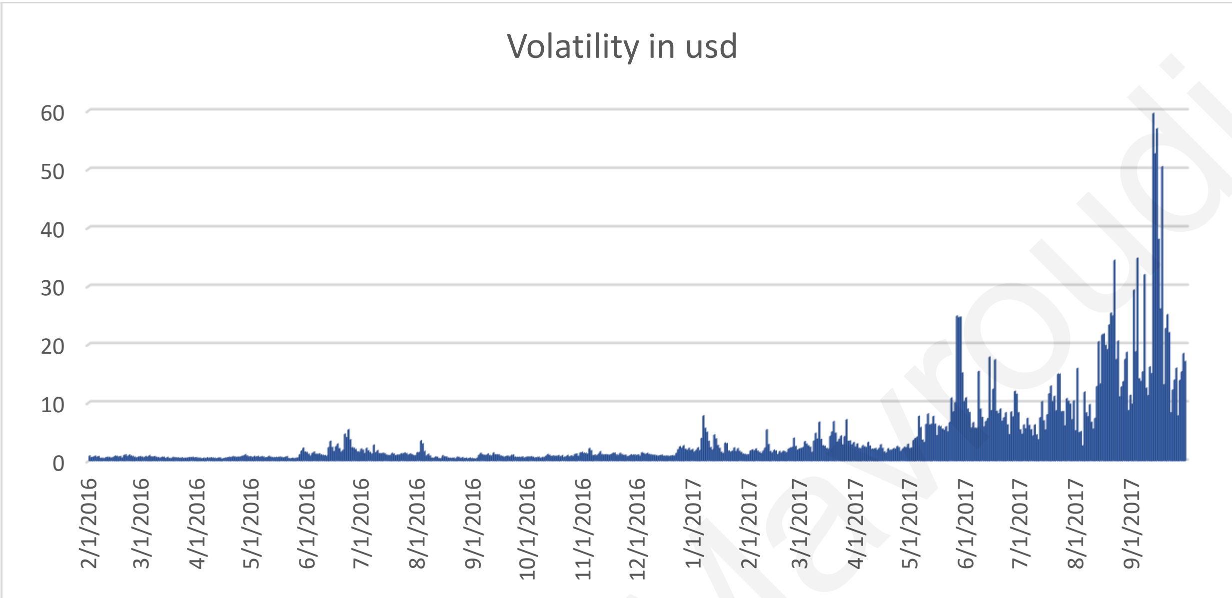
Table 8 Vector Autoregression results for 10 months data

This table present the bidirectional or unidirectional relationship between the variables for the period from January of 2017 to October of 2017 in China after the People's Bank of China and the Chinese exchanges applied fixed trading transactions of 0.2% per trade. The table provides the also the coefficient for each variable we use for our model.

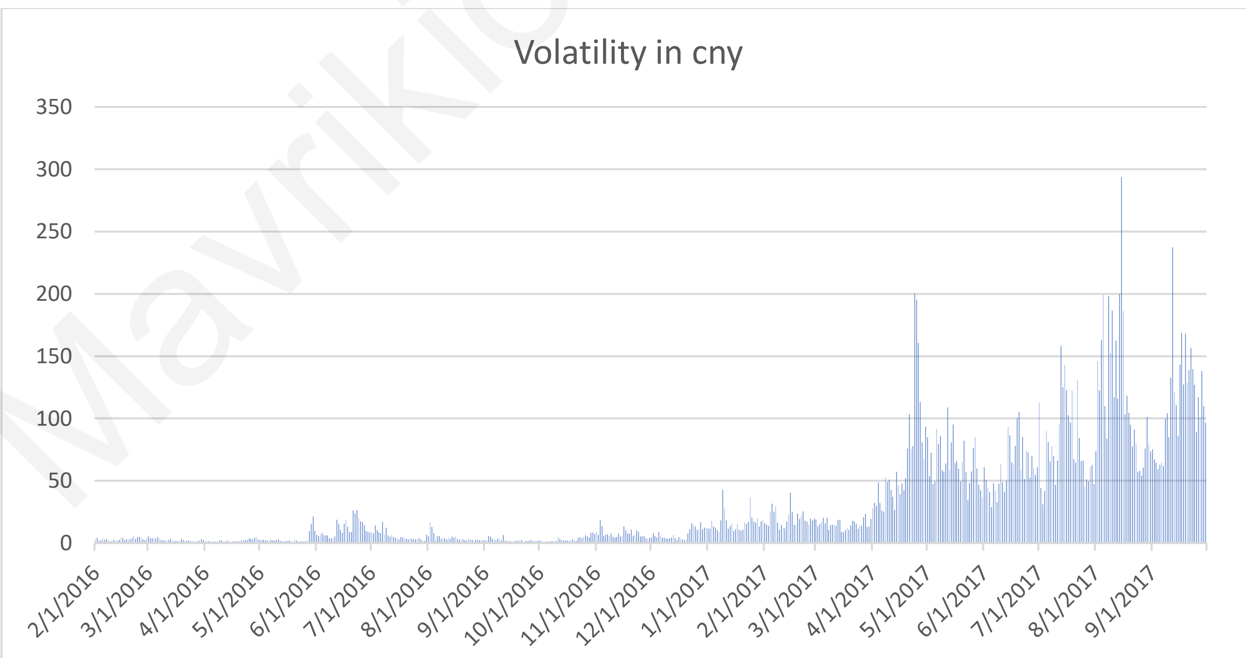
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Gap	Spread in cny	Spread in usd	Volatility in cny	Volatility in usd
L.Gap	1.154***	0.00217	0.000374	0.323	0.701
	(0.0602)	(0.00301)	(0.000920)	(0.918)	(0.179)
L2.Gap	-0.184***	-0.00218	-0.000294	-0.361	-0.692
	(0.0601)	(0.00301)	(0.000919)	(0.917)	(0.179)
L.Spread in cny	-1.443	0.596***	-0.00508	5.252	-4.514
	(1.202)	(0.0602)	(0.0184)	(18.33)	(3.571)
L2.Spread in cny	2.350**	0.192***	-0.00542	26.18	2.843
	(1.199)	(0.0600)	(0.0183)	(18.29)	(3.563)
L.Spread in usd	3.729	-0.0292	0.729***	-28.25	3.458
	(4.046)	(0.203)	(0.0618)	(61.71)	(12.02)
L2.Spread in usd	-2.856	-0.175	-0.0447	20.13	-5.061
	(4.040)	(0.202)	(0.0618)	(61.63)	(12.01)
L.Volatility in cny	0.00357	0.000167	-1.59e-05	0.703***	0.0203*
	(0.00399)	(0.000200)	(6.10e-05)	(0.0609)	(0.0119)
L2.Volatility in cny	-0.00197	6.76e-05	7.20e-05	0.0761	0.00598
	(0.00403)	(0.000202)	(6.16e-05)	(0.0614)	(0.0120)
L.Volatility in usd	-0.00847	0.00401***	0.000526*	-0.494*	0.452***
	(0.0194)	(0.000971)	(0.000296)	(0.296)	(0.0576)
L2.Volatility in usd	-0.0209	-0.00112	2.15e-05	0.706**	0.351***
	(0.0201)	(0.00101)	(0.000307)	(0.306)	(0.0596)
Constant	-0.271	0.0677***	0.0370***	2.322	0.874
	(0.406)	(0.0203)	(0.00621)	(6.197)	(1.207)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

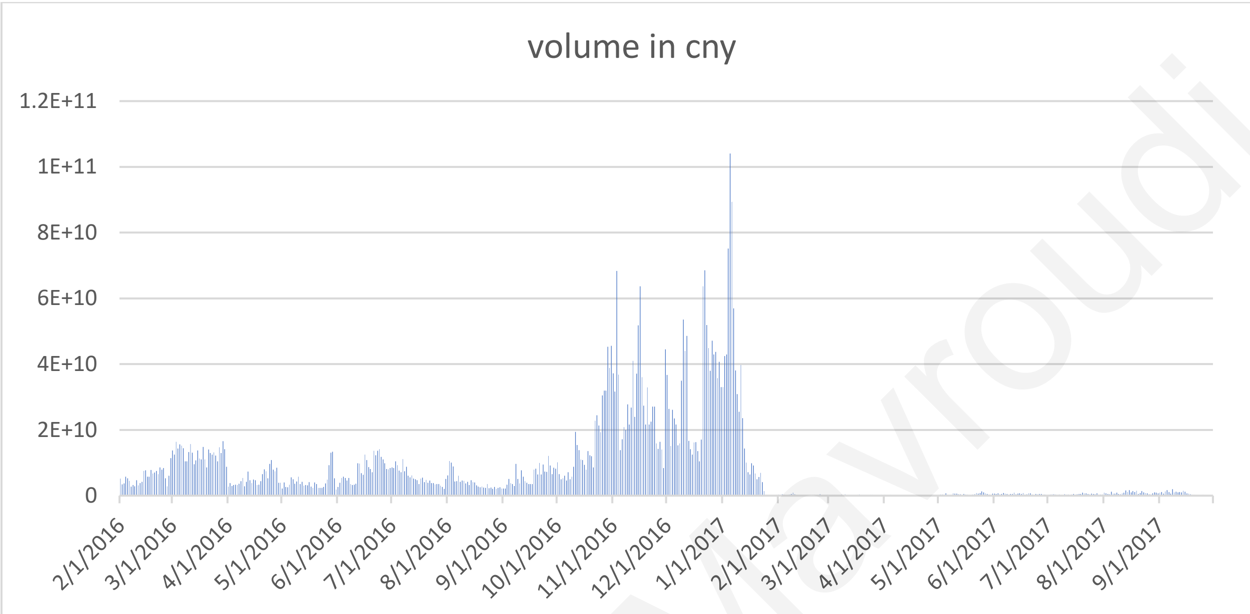
Graph 1: The graph presents the volatility in USD for the BTC / USD for all twenty months, ten before our event study and ten months after.



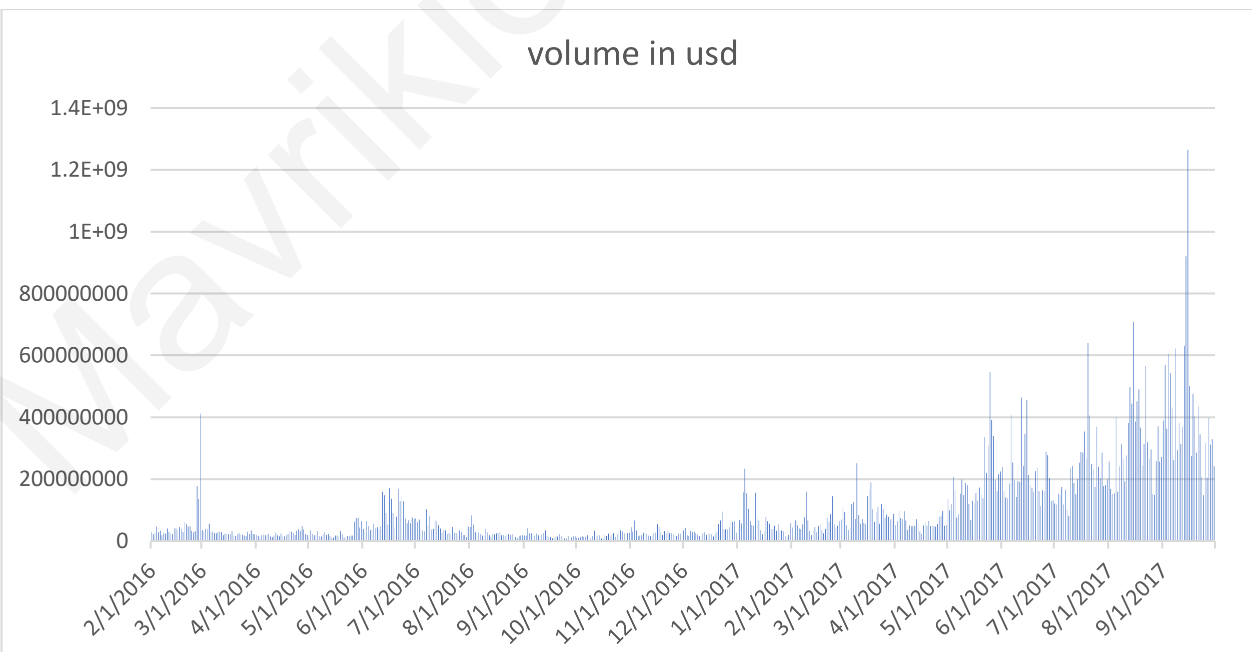
Graph 2: The graph presents the volatility in CNY for BTC / CNY for all twenty months, ten before our event study and ten months after.



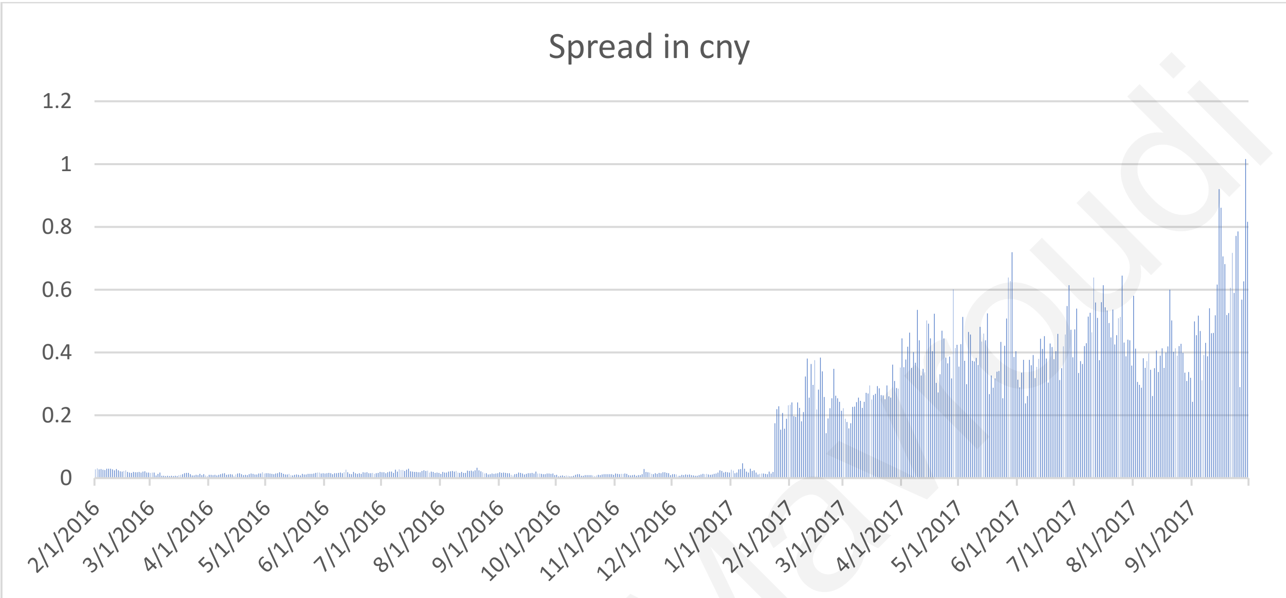
<u>Graph 3:</u> The graph presents the volume in CNY for the BTC / CNY for all twenty months, ten before our event study and ten months after.



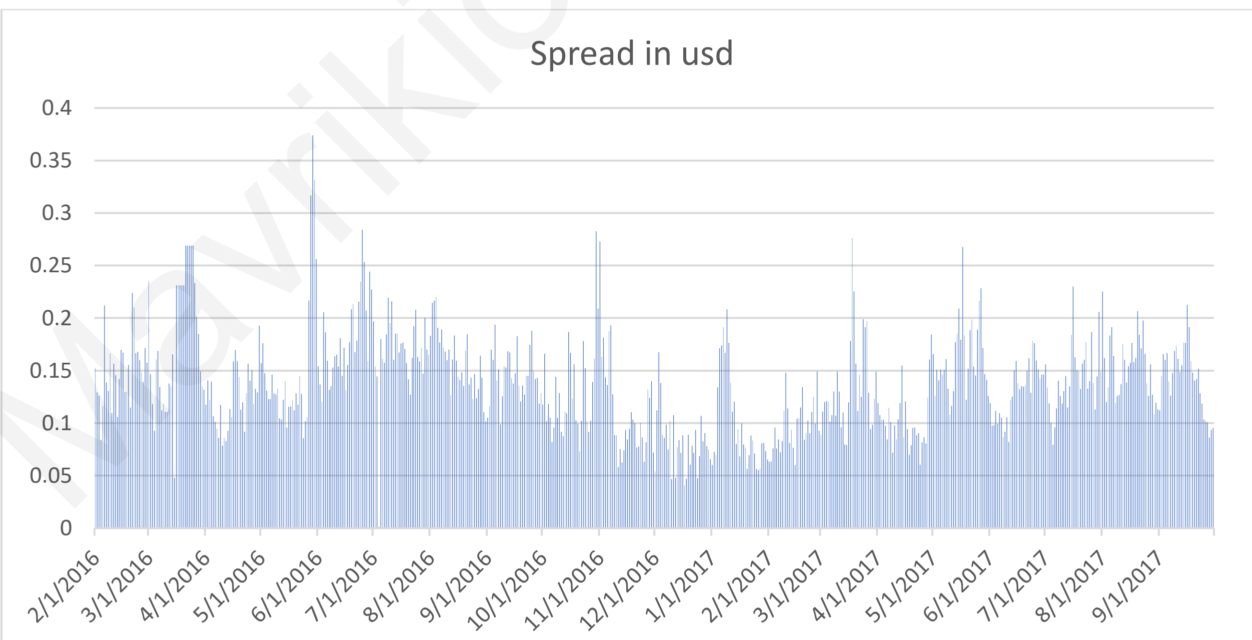
<u>Graph 4:</u> The graph presents the volume in USD for the BTC / USD for all twenty months, ten before our event study and ten months after.



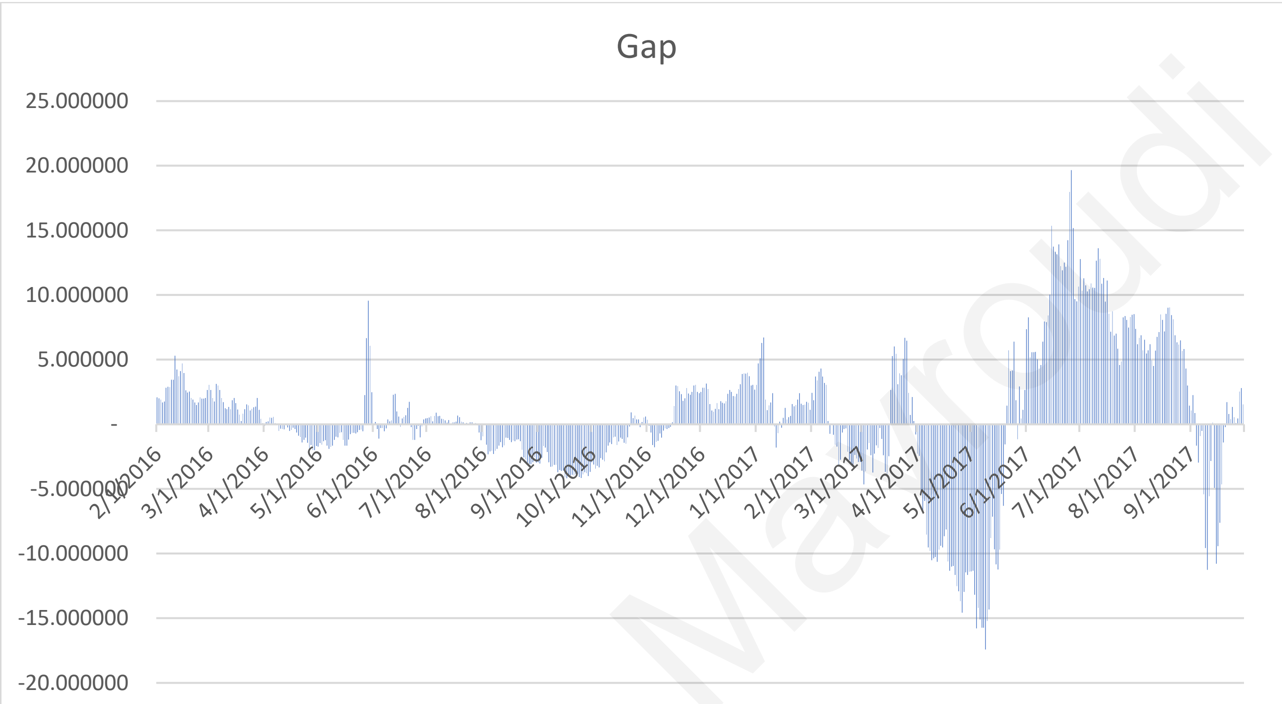
Graph 5: The graph presents the spread in CNY for the BTC / CNY for all twenty months, ten before our event study and ten months after.



Graph 6: The graph presents the spread in USD for the BTC / USD for all twenty months, ten before our event study and ten months after.



Graph 7: The graph presents the Gap for all twenty months, ten before our event study and ten months after.



Appendix

Appendix Table 1

VARIABLES	btccny	SSE	XAUCNY	FTS100
L.btccny	1.336***	0.00360	-6.40e-07	1.65e-05
	(0.0406)	(0.00542)	(1.94e-06)	(0.000148)
L2.btccny	-0.343***	-0.00260	6.63e-07	-1.76e-05
	(0.0408)	(0.00544)	(1.95e-06)	(0.000149)
L.XAUCNY	-68.23	-152.3	0.932***	-0.0520
	(735.4)	(97.99)	(0.0351)	(2.681)
L2.XAUCNY	70.73	163.3	0.0651*	-0.406
	(736.4)	(98.12)	(0.0352)	(2.684)
L.SSE	-0.121	1.095***	-8.21e-06	-0.000369
	(0.260)	(0.0347)	(1.24e-05)	(0.000949)
L2.SSE	0.148**	-0.109***	1.04e-05	0.000493
	(0.261)	(0.0347)	(1.25e-05)	(0.000950)
L.FTS100	-0.546	3.310	-5.39e-06	-0.0327
	(9.686)	(1.291)	(0.000463)	(0.0353)
L2.FTS100	7.380	3.608	0.000540	-0.0681**
	(9.298)	(1.239)	(0.000444)	(0.0339)
Constant	-66.71	27.59*	-0.00320	0.175
	(108.1)	(14.41)	(0.00517)	(0.394)

Appendix Table 2

VARIABLES	btccny	SSE	XAUCNY	DOWJONES
L.btccny	1.336***	0.00341	-6.47e-07	5.94e-07
	(0.0407)	(0.00547)	(1.94e-06)	(1.36e-06)
L2.btccny	-0.342***	-0.00235	6.77e-07	-6.44e-07
	(0.0408)	(0.00549)	(1.95e-06)	(1.37e-06)
L.XAUCNY	-15.98	-117.2	0.937***	-0.0115
	(733.7)	(98.75)	(0.0350)	(0.0246)
L2.XAUCNY	16.23	127.5	0.0597*	0.0117
	(734.4)	(98.85)	(0.0351)	(0.0246)
L.SSE	-0.109	1.095***	-7.31e-06	-4.82e-06
	(0.259)	(0.0348)	(1.24e-05)	(8.67e-06)
L2.SSE	0.135**	-0.110***	9.34e-06	4.57e-06
	(0.259)	(0.0349)	(1.24e-05)	(8.69e-06)
L.DOWJONES	318.0	-81.27	0.00955	-0.185***
	(1,055)	(142.0)	(0.0504)	(0.0354)
L2.DOWJONES	-62.29	-24.73	-0.0520	0.0860**
	(1,058)	(142.5)	(0.0506)	(0.0355)
Constant	-64.55	31.76**	-0.00282	0.000411
	(107.9)	(14.53)	(0.00516)	(0.00362)

Appendix Table 3

VARIABLES	btccny	SSE	XAUCNY	NASDAQ
L.btccny	1.336***	0.00334	-6.45e-07	1.62e-06
	(0.0406)	(0.00547)	(1.94e-06)	(1.69e-06)
L2.btccny	-0.343***	-0.00229	6.74e-07	-1.60e-06
	(0.0408)	(0.00549)	(1.95e-06)	(1.69e-06)
L.XAUCNY	-5.837	-117.5	0.937***	-0.000704
	(733.7)	(98.78)	(0.0351)	(0.0305)
L2.XAUCNY	6.766	127.5	0.0598*	-8.60e-05
	(734.5)	(98.88)	(0.0351)	(0.0305)
L.SSE	-0.113	1.095***	-7.62e-06	1.79e-08
	(0.259)	(0.0349)	(1.24e-05)	(1.08e-05)
L2.SSE	0.139**	-0.110***	9.65e-06	-2.75e-07
	(0.260)	(0.0350)	(1.24e-05)	(1.08e-05)
L.NASDAQ	310.9	-36.50	0.0116	-0.121***
	(867.8)	(116.8)	(0.0415)	(0.0360)
L2.NASDAQ	-239.0	-3.101	-0.0378	0.0942***
	(871.4)	(117.3)	(0.0416)	(0.0362)
Constant	-63.82	31.69**	-0.00280	0.00121
	(108.0)	(14.54)	(0.00516)	(0.00449)

Appendix Table 4

VARIABLES	btccny	SSE	XAUCNY	SP500
L.SP500	385.5	-83.32	0.00402	-0.178***
	(983.6)	(132.4)	(0.0470)	(0.0351)
L2.SP500	-104.4	-23.89	-0.0471	0.0974***
	(985.3)	(132.6)	(0.0471)	(0.0352)
L.btccny	1.336***	0.00341	-6.22e-07	9.42e-07
	(0.0407)	(0.00547)	(1.94e-06)	(1.45e-06)
L2.btccny	-0.342***	-0.00235	6.52e-07	-9.62e-07
	(0.0408)	(0.00549)	(1.95e-06)	(1.46e-06)
L.XAUCNY	-11.79	-117.5	0.937***	-0.00825
	(733.7)	(98.75)	(0.0351)	(0.0262)
L2.XAUCNY	11.89	127.8	0.0599*	0.00810
	(734.4)	(98.85)	(0.0351)	(0.0262)
L.SSE	-0.111	1.095***	-7.46e-06	-2.48e-06
	(0.259)	(0.0348)	(1.24e-05)	(9.24e-06)
L2.SSE	0.137**	-0.110***	9.47e-06	2.61e-06
	(0.259)	(0.0349)	(1.24e-05)	(9.26e-06)
Constant	-64.44	31.80**	-0.00278	-0.000491
	(108.0)	(14.53)	(0.00516)	(0.00386)