Norwegian School of Economics
Bergen, "[Spring, 2018]"

Bitcoin Liquidity in a Market Microstructure

by

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"Master thesis, MSc Economics & Business Administration"
"Major in Financial Economics"

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Abstract

This master thesis investigates Bitcoin liquidity in a market microstructure setting and has been divided into two parts. In the first part we examine whether there is any correlation between the results generated by three liquidity measurement techniques (The Rolls, ILLIQ and Coefficient of elasticity) and the actual market microstructure spread. We find that only ILLIQ shows a moderate, statistically significant correlation with the spread.

The second part investigates whether selected primary and secondary variables affect the spread and whether their relationship is in line with existing financial research and our intuition. This part also examines whether there is any weekly cyclicality in Bitcoin liquidity, and if occurrence of events affects Bitcoin liquidity or not. We find that the *primary* and *secondary variables* have a significant impact on the *bid ask spread*, and that the nature of the relationship is in line with empirical research and our intuition. Interestingly, we find that variables which are not directly related to the market microstructure have a relatively higher impact on the spread in comparison to variables that are directly related. We also find that Bitcoin liquidity does not have any cyclical, weekly trends and only a few of the events have any sort of significant impact on liquidity.

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1. Introduction

Cryptocurrencies are a relatively new phenomenon, which have gained a lot of attention and popularity globally. There is an increasing debate in academic circles and industry about their application and long-term viability. Bitcoin (BTC), the first cryptocurrency, was launched in 2008 as an alternate transaction system designed to be independent from any central processing or management apparatus. Since then there has been a mushroom growth in the number of cryptocurrencies and altcoins. As of today, there are approximately 1560 cryptocurrencies and altcoins available and the total market capitalization of cryptocurrencies is close to US $339 Bn[1]. There are close to 10,000 different online and offline markets today that deal in cryptocurrencies. These markets process a trading volume of more than US $12 Bn daily.

There is extensive debate whether BTC is a currency or an asset. (Nakamoto, 2008) defines BTC as a peer-to-peer electronic cash system allowing parties to send payments directly between themselves, without any intervention from financial institutions. This suggests that BTC was primarily designed to be used as a currency rather than an investment. On the other hand, (Baur, Lee, & Hong, 2015) use transaction data to show that BTC is mainly being used as an investment instead of an alternative currency. This research also finds that statistical properties of BTC show little to no correlation with traditional assets such as stocks and bonds and can offer large diversification benefits.

(Christian, 2014) provides similar strong indications and concludes that uninformed users approaching digital currencies are not interested in an alternate transaction system, but only seek to interact with BTC as an investment. The research finds that the BTC payment system, based on blockchain, is predominant in terms of absolute transaction volumes, but that most of the growth in the number of users is on trading exchanges. Blockchain is defined as an accumulation of Peer-to-Peer (P2P) nodes which are responsible for validating transactions through consensus about the transactions legitimacy. All valid transactions in the network are put in time stamped blocks and are irreversible once added to a block (Koteska, Karafiloski, & Mishev, 2017).

Among other issues like security, mass adaptability and volatility, liquidity of BTC is a growing concern. Since the price of BTC experiences considerable volatility, liquidity is an

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[1] Billion

important area for crypto investors to keep an eye on. Liquidity is defined as the ability to convert an asset into cash, on demand, without any difficulty. Although liquidity is a well-studied topic for established asset classes like stocks and bonds, there is close to no research on the topic of cryptocurrency liquidity. A comparative study between cryptocurrencies and S&P 500 stocks based on average daily trading amount, reveals that the daily trading volume of cryptocurrencies is lower than the 25 percent quantile of S&P 500 stocks (Trimborn, Li, & Härdle, 2017). (Chordia, Sarkar, & Subrahmanyam, 2005), while conducting an empirical study of stock and bond market liquidity, find that there is a positive relationship between trading volume and liquidity. Keeping these two papers in context we believe that liquidity is a highly relevant issue to research for crypto currency markets.

Liquidity is a major concern among crypto investors as it can significantly affect any trading strategy and investor profitability. Investors are reluctant to hold on to illiquid assets, because in periods of volatility disposal of such assets becomes harder. Return on illiquid assets usually also carries an illiquidity premium that increases the price of the asset, moving it away from its true fundamental value. Furthermore, liquidity is considered a major hurdle in the mass adaption of BTC as an alternate transaction system which was its primary purpose.

For this thesis, we observe BTC liquidity from two different positions. Firstly, we examine whether there is any correlation between results generated by three commonly used liquidity measurement techniques and the actual market microstructure *bid ask spread*. These liquidity measurement techniques are the Rolls measure, ILLIQ and Coefficient of elasticity (CET). Since the exchange specific spread and the results generated by the liquidity measurement techniques are both measures of liquidity, we believe that they should exhibit co-movement. We are interested in seeing if they share any co-movement and what is the strength of this relationship.

The second part of the thesis attempts to find the magnitude and direction of relationship between different variables and the *bid ask spread*. These variables are divided into *primary* and *secondary variables*. Furthermore, we also attempt to measure the impact of certain events on BTC liquidity. These events are categorized as market microstructure or BTC ecosystem specific events. Additionally, we try to observe and capture whether specific days of the week have any individual impact on BTC liquidity.

The underlying objective in this part of our thesis is to capture the magnitude of any existing relationship. We also aim to observe if the direction of the relationship between the spread and these variables is in line with existing financial theory that covers conventional assets. This task is undertaken by running a regression analysis between the spread and all the explanatory variables. Liquidity, represented by the *bid ask spread*, can have a strong effect on outcomes like arbitrage exploitation and investor profitability, therefore we found it interesting to test these relationships.

The overall aim of our thesis is to attain a thorough understanding of BTC liquidity in a market microstructure (exchange) setting. There is very little research covering the financial aspects of cryptocurrencies and, to our knowledge, there is close to no research on the topic of cryptocurrency liquidity at an exchange level. BTC was selected for this research because it is by far the most popular global cryptocurrency, and enjoys a dominating 40% share in the total crypto market cap. Furthermore, Bitfinex was chosen as the market microstructure (exchange) as it handles close to 30% of the global BTC trading volume.

1.1 Research Questions

Based on the explanation above, our *first research question* is: *"Is there a statistically significant correlation between BTC bid-ask spread and the results from different liquidity measurement techniques?"*

The objective is to observe whether the *bid ask spread*, as a measure of liquidity (Fleming, 2001), and the results generated by the three selected measures have any correlation.

The null and alternate hypothesis for this research question are as follows:

$$H_0 = Corr(\lambda, \theta) = 0$$

$$H_1 = Corr(\lambda, \theta) \neq 0$$

Where:
λ = *Bid Ask spread*
θ = Liquidity measures

The null hypothesis (H_0) of the first research question is that there is no statistically significant correlation between the *bid ask spread* and the results generated by different liquidity measurement techniques. The alternative hypothesis (H_1) is that there is statistically significant correlation between the *bid ask spread* and the results generated by the selected liquidity measurement techniques.

The results show that only one of the three liquidity measurement techniques, ILLIQ, has statistically significant correlation with the *bid ask spread* and can be considered a legitimate proxy for the actual BTC *bid ask spread*. It is further observed that the Rolls measure, which is one the simplest techniques for calculating implicit spreads, generates a significant number of "number errors". After implementing different corrective measures to overcome this problem, the measure shows statistically significant correlation with the spread only in one of these implemented solutions. This is insufficient proof to give a conclusive verdict on whether there is any correlation between the Rolls measure and the *spread*. The third liquidity measure, CET, does not show any statistically significant correlation with the spread.

Furthermore, following from the explanation in the introduction, our *second research question* is: *"Do the selected Primary, Secondary, Time and Event based variables affect the bid-ask spread (liquidity) and is the effect in line with existing financial research and conventional sense?"*

The null and alternate hypothesis for the second section are as follows:

$$H_0 = f(\lambda|\ \alpha, \gamma, T, \eta) = 0$$

$$H_1 = f(\lambda|\ \alpha, \gamma, T, \eta) \neq 0$$

Where:
λ = *Bid Ask spread*
α = Primary variables
γ = Secondary variables
T = Time based dummy variables
η = BTC & Bitfinex specific events

The null hypothesis (H_0) of the second research question is that there is no statistically significant relationship between the *bid ask spread* and the selected *primary*, *secondary*, *time and event based dummy* variables. The alternative hypothesis (H_1) states that there is a statistically significant relationship between the above discussed factors and the *bid ask spread*.

For this part of the research, we find that all *primary* and *secondary variables* have a statistically significant impact on the spread. Furthermore, the nature of the relationship between the explanatory variables and the spread is in line with existing financial research for the *primary variables*, and our intuition for the secondary variables. We also find that the BTC spread does not exhibit any variance based on the days of the week. Additionally, very few events have a statistically significant impact on the spread.

The remainder of this write-up is structured as follows. Chapter 2 starts by covering the literature review of our selected liquidity measurement techniques used in answering the first research question. This chapter also covers literature on the relationship between different variables and the *spread*, which is essential in answering our second research question.

Chapter 3 provides a detailed explanation of the data set and its characteristics. Additionally, this chapter provides the rationale behind making certain changes to the values of these variables. The chapter also describes the different variables used in answering the second research question, because some of them are unique. Furthermore, section 3.3 covers the methodology used in seeking answers to our research questions.

In Chapter 4, we interpret, analyze and discuss the results generated by the methodological approaches discussed in Chapter 3. Chapter 5 presents the conclusion and suggests possible new avenues for research in cryptocurrencies.

2. Literature Review

2.1 Literature on selected Liquidity Measurement Techniques

Liquidity is an intangible concept and there is a plethora of suggested ways to measure it. In this section we provide an overview of literature related to our selected liquidity measurement techniques, the basic assumptions behind them and their application in estimating equity and bond market liquidity. A complete theoretical overview of these selected techniques is provided in section 3.3.1.

(Roll, 1984), in his paper "A simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market", introduced a simple technique for inferring the effective *bid ask spread* directly from a time series of market prices. This method only requires price as an input and is based on the following assumptions:

1) The asset is traded in an informationally efficient market
2) The probability distribution of observed price changes is stationary at least for short intervals

Although the Rolls measure is simplistic, (Schultz, 2000) finds that the Rolls estimator can provide accurate spread estimates with intraday equity data if a researcher has trade prices but does not have the quotes. In contrast, (Harris, 1990), while examining the small-sample properties of the Rolls estimator for equity markets finds the estimator to be noisy even with large sample sizes.

(Bongaerts, Jong, & Driessen, 2011) use an extension to the Bayesian approach, proposed by (Hasbrouck, 2009) ,for estimating the Roll measure in order to compare the effects of expected liquidity and liquidity risk on expected U.S. corporate bond returns. The research concludes that both expected bond liquidity and exposure to equity market liquidity risk affect expected bond returns. Through their approach they successfully explained a substantial part of the credit spread differences among bonds.

(Amihud, 2002), in his paper "Illiquidity and Stock Returns: Cross-Section and Time Series Effects", presented ILLIQ as a measure of liquidity. ILLIQ is based on a hypothesis that expected stock return is an increasing function of illiquidity. We use ILLIQ as our second liquidity measure in order to answer the first research question.

(Eknemar & Short, 2011) in a quantitative study use ILLIQ to ascertain whether illiquidity is priced in the Copenhagen stock exchange or not. The researchers find evidence confirming that illiquidity is indeed priced into the stocks on the Copenhagen market. (Minaki, 2013) uses ILLIQ as a liquidity index to examine the relationship between liquidity, transaction costs and risk in the Japanese Government Bond (JGB) futures market of the Tokyo Stock Exchange (TSE). The research finds positive co-movement between transaction costs and ILLIQ, suggesting that liquidity decreases as ILLIQ increases. The research also finds co-movement between ILLIQ and announcements of macroeconomic indicators.

Our third liquidity measurement technique was presented by (Datar, 2000) in his paper "Stock Market Liquidity: Measurement and Implications". Coefficient of elasticity (CET) argues that the ideal measure of liquidity should combine price and volume. CET does this by considering the turnover ratio between trading volume and price as a measure of liquidity.

The research quoted above is mostly in favour of our selected liquidity measurement techniques and provides proof that liquidity measures are an effective way to measure liquidity. It will be interesting to compare the results generated by these liquidity measurement techniques and the Bitfinex *bid ask spread*, which is a measure of liquidity itself.

2.2 Relationship between the variables and *bid ask spread*

In this section, we will be reviewing literature pertaining to the effects of different *primary variables*, like *price* and *trading volume*, on the *bid ask spread*. It is important to understand what existing financial research tells us about the relationship between our selected variables and the *spread*, because this serves as a benchmark against which we will be comparing the results of the second research question. We have done the following division of literature review, with one segment for each *primary variable*, to ensure clarity for the reader. This separation was not necessary for time-based and event-based variables.

2.2.1 Bid ask spread as a measure of liquidity

Illiquidity is considered the cost of buyer's regret, as it is the cost of reversing an asset trade almost instantaneously after a trade has been made. In almost all markets the market maker or the dealer sets the *bid ask spread* (Damodaran, 2005). The value of the *bid ask spread* is designed to cover:

1) Risk cost of holding inventory

2) Cost of processing orders
3) Cost and risk of trading with better informed investors

The *bid ask spread* is determined keeping in mind these costs and an intent that a trade can yield the market maker reasonable profits. A change in any of the above-mentioned factors reflects as movement in the spread. Any increase in the *spread* signals an increase in illiquidity and vice versa. Relationships between different factors and the *spread* are empirically proven, and the literature pertaining to the factors used in this research follows.

2.2.2 Price and bid ask spread

(Stoll, 1978) finds a negative relationship between price and the *bid-ask spread,* when investigating the pricing of security dealer services. This relationship is hypothesized to be a proxy for the risk of the stock. Higher price implies less risk, which together with a minimum trading-cost element for lower priced stocks outweighs higher holding costs associated with higher priced stocks. This leads to a situation where an increase in price decreases the bid-ask spread.

Furthermore, (Jegadeesh & Subrahmanyam, 1993) find a similar negative relationship between price and the spread, when investigating the impact on liquidity caused by the introduction of S&P 500 Index futures contract. The impact is higher for S&P 500 stocks than other stocks but is significant for both groups. Based on the results from these papers, price is included in our model.

2.2.3 Volatility and bid ask spread

(Jegadeesh & Subrahmanyam, 1993) find a positive relationship between average monthly return volatility and the *bid-ask spread*. Since price-movement directly affects volatility of returns, we find it to be a relevant source for explaining this relationship.

(Wyart, Bouchaud, Kockelkoren, Potters, & Vettorazzo, 2008) discover a similar relationship when investigating how *volatility* affects the *spread* in order driven markets. The paper finds a correlation of 0.9 when looking at the relationship between *volatility* per trade and the *spread*. This relation implies that most of the volatility comes from trading itself, it also suggests that adverse selection dominates the *spread.* The paper assumes that volatility per trade is a measure of the amount of information included in prices. This relation holds across different stocks and for a specific stock over time, both in electronic markets and for NYSE. These results suggest that volatility should be included in our model.

2.2.4 Trading Volume and bid ask spread

(Tinic & West, 1972) find a negative relationship between trading volume and the spread, when investigating competition and the pricing of dealer services in the Over-the-Counter stock market. They find similar results for both the selected years of 1962 and 1971, but only the results for the latter year are statistically significant. The similar results for the two years show that, despite SEC reforms in 1964-1965 and the advent of the electronic exchange NASDAQ, the general relationship between trading volume and the spread did not change.

In accordance with this, Stoll (1978) finds a strongly negative relationship between trading volume and the spread. This paper also states that the negative relationship between *trading volume* and the *spread* is the generally found result from similar kinds of studies.

2.2.5 Interest Rates and bid ask spread

(Chordia, Roll, & Subrahmanyam, 2001) finds that long and short-term interest rates influence liquidity. They find a positive relationship between interest rates and the spread, both for long term treasury bond yields and for short term rates.

Contrary to these results (Van Ness, Van Ness, & Warr, 2005), in their paper on "Nasdaq Trading and Trading Costs", do not find an overall significant relationship between interest rates and the bid-ask spread. However, they do find a significant but negative relationship between interest rate changes and the spread after March 2000. This is because market makers widen the spread in the anticipation of interest rate increases, before narrowing it following the announcement.

Considering the ambivalence in the empirical research about the relationship between interest rates and the *bid ask spread*, it will be interesting to see the relationship between our selected Libor rates and Bitfinex *spread* once we conduct the regression analysis.

2.2.6 Market Capitalization and bid ask spread

(Chordia, Shivakumar, & Subrahmanyam, 2004) use market capitalization to establish firm size. They conclude that firms with greater *market capitalization* show smaller *spreads* and hence higher liquidity in comparison to firms with lower *market capitalization*. They also find that bigger firms are less prone to liquidity fluctuations when market dynamics change. Considering this we find it important to add *market capitalization* to our model.

2.2.7 Effect of events on liquidity

(Fama, 1991) presents the standard financial theory of efficient markets. It states that the price of an asset reflects all the available information in the market, and that any change in the information should reflect in the asset dynamics.

(Demsetz, 1968; Ho & Stoll, 1981; Stoll, 1978) all suggest that liquidity depends on the cost of financing dealer inventories, on factors that influence the risk of holding inventory and on extreme events that can provoke order imbalances and cause inventory overloads. Furthermore, (Admati & Pfleiderer, 1988; Kyle, 1985) both suggest that market wide changes in liquidity and informational events closely follow each other. Considering this, dummy variables depicting important events in the BTC and Bitfinex time line are incorporated into the dataset.

2.2.8 Time based variance in liquidity

(Chordia et al., 2005) find evidence of time-based variance when conducting an empirical analysis of market liquidity in stock and bond markets. The study is based on data spanning from 1991-1998, all stocks included come from NYSE. Weekly patterns are similar for both stocks and bonds. Fridays show a pattern of lower trading activity and lower liquidity, whereas Tuesdays show a pattern of higher trading activity and higher liquidity.

(Van Ness, Van Ness, & Warr, 2005) find a similar relationship with lower liquidity on Fridays, and increased liquidity on Tuesdays. Their data spans from 1993-2002 and considers NASDAQ stocks covering almost the same time-period as the NYSE stocks in the Chordia paper. As is evident from this, time-based variables can have a substantial effect on the spread.

2.2.9 Lack of literature on secondary variables

The secondary variables *sum hash rate*, *mining difficulty*, *transaction cost*, *transaction confirmation time* and *number of transactions* are BTC specific variables. As per our knowledge, the relationship between these variables and the *spread* has not been researched before. Despite this, we hold a specific intuition about what the relationship should be between secondary variables and the spread. Section 3.2.2 describes these variables and provides a discussion based on our intuition of what the relationship might be.

3. Dataset review & Methodology

Chapter 3 is divided into three subsections, where section 3.1 describes the different sources of the collected data. Furthermore, this section explains the process of data cleanup, how and why certain data points were altered and the inclusion and structuring of the dummy variables.

Section 3.2 provides a detailed explanation of the different variables. Some of the secondary variables have a complicated structure, therefore their calculation and functioning is explained thoroughly along with the formulas in the section. Section 3.2 also sheds light on the difference between the types of events included in the regression analysis.

3.1 Dataset review

The primary data source for most of the utilized *primary* and *secondary variables* was data.bitcoinity.org, which is a privately-run data aggregator. Bitcoinity.org aggregates BTC related information from all global cryptocurrency exchanges. Data from three main different market types (exchange, derivatives and over the counter (OTC)) for BTC is available on this aggregator. The aggregator also collects BTC denominations in all major currencies, like USD, EUR, JPY and GBP. Along with market microstructure specific data, the aggregator also collects blockchain specific data.

One of the secondary variables, *Transaction Cost*, was not available on bitcoinity.org. Therefore, it was downloaded from (Blockchain.info, 2018) which is a blockchain information aggregator. USD and Euro 3-month Libor were collected from the official website of Federal Reserve Bank of St. Louis (St.Louis, 2018) . The website tracks 508,000 US and international time series from 86 different sources.

The data set also includes 45 dummy variables that cover weekdays, bitcoin ecosystem specific events and market microstructure specific events. The complete list of these events is viewable in table (2)[2] & (2.1)[3]. The nature of the events is clear from the description, in addition to the positive and negative signs provided along with the description.

[2] https://99bitcoins.com/price-chart-history/
[3] https://bitcoinmagazine.com/articles/warning-signs-timeline-tether-and-bitfinex-events/

3.1.1 Data restructuring

The data set starts from 9 October,2013 and ends on 15 January,2018. This time span is the largest available on bitcoinity.org for the Bitfinex exchange and provides us with 1560 data points on a daily frequency. To make the data useable, several steps were taken to synchronize it. The first step was to align all the data points correctly based on dates for each variable. It was essential to get the synchronization correct, since multiple variables from different sources were being used.

3.1.2 Bitfinex Hack Values

Between 2 August,2016 and 8 August,2016 trading halted on Bitfinex due to a hacking. Bitcoinity.org reports these dates with a value of zero. The following alterations were made to the dataset to ameliorate the effect of this anomalous event.

The values from the last day of operations before the hack are used as plugin values to avoid introducing a bias in our results. Not implementing this change would introduce an abnormal shock in the dataset, because as soon as Bitfinex re-opened the *bid ask spread* fluctuated abnormally and its sharp movement away from the reported value of zero would have caused abnormalities.

Missing values of the explained variable, the *spread*, and the explanatory variables *price*, *trading volume* and *volatility* were changed to the values of the last working day before the hacking. This reconfiguration allows us to capture the true effect of the hack on the spread. The values of the variable *BTC spread* were updated to 4.6129e-04 for the hack dates. Whereas, variables *price*, *trading volume* and *volatility* were updated to 605.54, 19961037.40 and 1.26 respectively.

3.1.3 Dummy Variables

As discussed earlier, the dummy variables were inserted to capture the effects of any time based or event-based variance in the spread, because we postulate that BTC is influenced heavily by information-based shocks. We explain the functioning of the dummy variables with the following hypothetical example. Dummy variable for event A is activated on the date of the event (Value = 1) and is kept active for 15 consecutive days unless there is an event B. In that case event A is muted (Value=0) and event B is activated (Value = 1).

3.1.4 3 Month Libor

USD & EURO 3-month Libor were collected from the official website of Federal Reserve Bank of St. Louis. The weekend values reported as zero were replaced with the values prevalent on the preceding Friday. This was done because BTC trades continuously. Having zero as the Libor rate while having an active spread value would have introduced an abnormal shock every weekend.

3.2 Understanding the Primary & Secondary Variables

This section defines the variables used in answering the second research question. It is especially important to elaborate on the secondary variables because of the way they operate. Secondary variables are BTC Eco-System specific variables, which facilitate BTC as a currency and intuitively should have limited impact on any market microstructure related activity.

3.2.1 Explanation of Primary Variables

Bid Ask Spread

The *Bid Ask spread* used in our thesis was downloaded as the average percentage *bid ask spread*. Then the *spread* was changed to units by dividing each data point by 100. Our data source calculates the percentage *bid ask spread* as follows:

$$Bid\ Ask\ spread = \frac{Ask_{\ min} + Bid_{\ Max}}{2} \qquad \textbf{Eq (1)}$$

The *Bid-Ask spread* is our dependent variable and is related to the market microstructure.

Price

Average daily US dollar price of BTC on Bitfinex:

$$Price = \frac{Price_{\ max} + Price_{\ min}}{2} \qquad \textbf{Eq (2)}$$

Different online exchanges have different BTC prices almost all the time. *Price* is a market microstructure specific variable because the BTC trading market is divided between different exchanges and the price on these exchanges usually differs.

Market Capitalization

The formula for market capitalization of BTC USD is as follows:

$$Market\ Capitalization = Price * BTC\ in\ circulation \qquad \textbf{Eq (3)}$$

Market Capitalization is a BTC Eco-System specific variable, because this value encapsulates all the BTCs' available in circulation. The total mineable BTCs' are 21 M[4], and keeping *price* constant, BTC market capitalization can only increase as more BTCs' are mined and added to the existing pool, until the total of mineable BTC's are mined.

The value of total mineable BTC's (21 M coins) is calculated considering the following blockchain facts. Every new block in the blockchain introduces 50 new coins into the system. This quantity of (50) halves every 210,000 blocks. Hence, the 21 M coins limit is possible to estimate using a geometric series, which is as follows:

$$\sum_{n=0}^{\infty} \frac{210000 * 50}{2^n} = 210000 * 50 * \frac{1}{1 - \frac{1}{2}} = 21000000 \qquad \textbf{Eq (4)}$$

Bitcoin Trading Volume

Daily BTC trading volume on Bitfinex in US dollars. Trading volume is a market microstructure related variable.

Volatility

Volatility of price, which in this case is the standard deviation from all market trades on Bitfinex. For longer periods, it is the average of hourly deviations.

USD & EURO 3 Month Libor

Euro and USD 3-month Libor rate compiled from 9 October,2013 until 15 January,2018. The interest rates are BTC eco-system related variables. (Chordia et al., 2001) finds that interest rates have a negative relationship with liquidity. Furthermore, we believe that low interest rates could have inclined investors to borrow and invest in riskier assets like cryptocurrencies. If this is true, we should see a positive relationship between the *Libor* and the *spread* where any increase in the interest should increase the spread. One can argue that any such relationship might be unlikely, and that a regional interest rate based on the geographical location of

[4] Million

Bitfinex customers would have been more suited. Regardless of this, we use Libor rates because they serve as foundation rates for a plethora of interest bearing products around the globe and should also serve as good proxies for fluctuations in global interest rates.

3.2.2 Explanation of secondary variables

Secondary variables are mostly BTC eco-system and cryptocurrency specific variables. Hence, there is little to no empirical research available defining their relationship with the *spread*.

Sum Hash Rate

Hash rate, or hash power, is a unit of measure that indicates how much power the Bitcoin network is consuming in order to function continuously. Continuous functionality means how much hash power the network is consuming to generate or find blocks in a normal mean time of 10 minutes.

Hash rate as a unit is measured in hashes per second or [h/s] and some of its denominations are as follows:

1. 1 kHz/s = 1,000 hashes per second
2. 1 MH/s = 1,000,000 hashes per second
3. 1 GH/s = 1,000,000,000 hashes per second
4. 1 TH/s = 1,000,000,000,000 hashes per second.
5. 1 PH/s is 1,000,000,000,000,000 (one quadrillion) hashes per second.
6. 1 EH/s is 1,000,000,000,000,000,000 (one quintillion) hashes per second.

A higher hash rate is better when mining, because it increases the opportunity of finding the next block and receiving the reward. The *sum hash rat*e in our dataset signifies the total computational power available on the BTC network at the end of a particular day. Based on this description, we believe that an increase in this number should decrease the spread and positively affect liquidity.

Mining Difficulty

Mining difficulty is a unit of measurement used to show how hard it is to find a hash that is lower than a target defined by the BTC system. The movement of this number is dependent upon the ratio of the optimum time it should take to process 2016 blockchain blocks, which is 14 days, and the actual time it is taking right now to process 2016 blocks.

Mining difficulty is calculated using the following formula:

$$M_t = M_{t-1} * \frac{\prod_{14}}{\prod_t} \qquad \textbf{Eq (5)}$$

Where:

M_t = Mining difficulty at time t

$\prod_t$= Time it takes to mine 2016 blocks

$\prod_{14}$= Time it should take to mine 2016 blocks

A higher *mining difficulty* number means that it is easier to mine, whereas a reduction in this number means an increase in mining difficulty. Considering this we believe that any increase in this number should decrease the spread, signifying an increase in liquidity.

Transaction Cost

Transaction cost is calculated by dividing miner revenue with the number of transactions in a day. It represents the amount of money required to move BTC from one location to another. It does not mean the transaction cost associated with BTC trading and investing, which is captured by the *bid ask spread*.

Transaction size and the time a transacting party is willing to wait for their transaction to confirm are the two primary factors affecting transaction costs. Smaller transactions pay lesser fees than larger transactions, because miners can include more of them into a block. We believe that an increase in transaction cost should increase the spread, hence leading to lower liquidity.

Transaction Confirmation Time

Transaction confirmation time is the median time it takes to process a BTC transaction. This variable represents the time it takes to move BTC between two transacting parties. The speed of movement of an asset has an impact on its liquidity. It is also a critical factor in exploiting inter exchange arbitrage.

(Makarov, 2018) finds that there are large arbitrage opportunities in cryptocurrencies across exchanges relative to fiat currencies, and that these arbitrage opportunities can persists for several days or weeks. This paper also finds that such opportunities are larger across regions in comparison to within regions. He estimates that the estimated total size of arbitrage profits from December 2017 to February 2018 was about $1 Bn. Intuitively, any increase in transaction confirmation time adds to investor risk and should reflect as an increase in the spread, which means a decrease in liquidity.

Number of Transactions

Number of transactions defines the total number of transactions that occur on the BTC network. It is different from the number of trades on Bitfinex, BTC *trading volume* explains this. An increase in the *number of transactions* signifies more usage and adaption, therefore we believe that this should reduce the *spread* and increase liquidity.

3.2.3 Time Based Variables & Events

Time Based Variables

(Chordia et al., 2005) suggests that liquidity can have weekly trends. The paper finds that *Fridays* exhibit lower trading activity and liquidity, whereas *Tuesdays* exhibit higher trading activity and liquidity. To observe any day specific trends in the *spread,* we include dummy variables for all days of the week. These variables might reveal fluctuation in liquidity.

Events and liquidity

Efficient market theory states that the market reflects all available information and that market prices adjust to reflect new information (Admati & Pfleiderer, 1988; Demsetz, 1968; Fama, 1991; Ho & Stoll, 1981; Kyle, 1985; Stoll, 1978). Considering the nature of BTC, we add *events specific* dummy variables to see if the addition of new critical information has any significant impact on the spread. The selected events have been divided into BTC-ecosystem specific events (EE’s) and Bitfinex specific events (BRE’s). Table (2) & (2.1) exhibit the *EE's* and the *BRE's* in chronological order.

3.3 Methodology

3.3.1 Methodology of Liquidity Measures

This section explains the methodology utilized to answer both the research questions. The first research question is stated as follows:

“Is there a statistically significant correlation between BTC bid-ask spread and the results from different liquidity measurement techniques?”

Our null hypothesis states that the there is no statistically significant correlation between the spread and the values generated by the chosen liquidity measurement techniques. H_0 communicates the belief that although these techniques are simple to use, which makes them widely popular, they lack the depth required to capture the complicated dynamics driving liquidity fluctuations. Alternatively, H_1 means that the results generated by the liquidity measurement techniques and the spread are correlated.

Rolls Measure

(Roll, 1984) shows that trading costs are negatively serially correlated with subsequent price changes. As the spread appreciates, the trading cost of the asset also rises. Therefore, higher Rolls measure output signifies higher illiquidity.

The fundamental value of a security fluctuates randomly in an efficient market, but trading costs can induce negative serial dependence in sequential price changes. Considering this, the spread can be calculated as:

$$\mathrm{S_j} = \sqrt{2 * \{-\mathrm{Cov}(\Delta\, \mathrm{P_t} , \Delta\, \mathrm{P_{t-1)}}\}} \quad \textbf{Eq (6)}$$

Where:
S_j = Rolls generated implicit spread
$\Delta\ P_t$ = Change in price at time t

When the serial covariance in the sample is positive the formula above is undefined, therefore we substitute a default numerical value in that scenario. Hence, we can view the Rolls measure in the following manner:

$$Rolls = \begin{cases} \sqrt{2 * \{-Cov(\Delta\, P_t , \Delta\, P_{t-1)}\}}, & When\ Cov(\Delta P_t, \Delta P_{t-1}) < 0 \\ 0, & When\ Cov(\Delta P_t, \Delta P_{t-1}) \geq 0 \end{cases}$$

Problems faced calculating Rolls Measure

The preliminary calculation was done in Microsoft excel and is reviewable in excel file[5]. An attempt to generate daily Rolls measure based implicit spreads resulted in only 946 values out of 1560 days of available data. 611 values came out as “number errors”.

This error occurs when the trading costs fail to induce a negative serial dependence in sequential price changes. This can lead to continuous positive price change that, when multiplied with the negative sign and square-rooted, generates “number errors”.

(Corwin & Schultz, 2012) mention that to overcome this problem, one of the following steps is usually taken:

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[5] Excel file: Dataset.xls, Sheet: Rolls Raw

1) The observation is treated as missing

2) The Rolls measure estimate is set to zero

3) The covariance is multiplied by negative one, resultantly the spread is estimated, and then multiplied by negative one

Correctional technique number three generates negative implicit spreads, which may prove useful when average spread calculation is required. To see if there is any disparity in the results, we calculate both daily and monthly implicit Rolls spreads. These spreads are tested for correlation with the daily and monthly Bitfinex *spreads*. The monthly Bitfinex *spread* is the average spread value for a month. These calculations can be viewed in the excel sheet[6].

ILLIQ Measure

(Amihud, 2002) builds the case that over time the expected market illiquidity positively affects expected stock excess return, which is return exceeding the treasury bill rate. This is constant with the positive cross-sectional relationship between stock returns and illiquidity. When investors anticipate higher market illiquidity, they will price the stock in a manner that generates higher expected returns. This advocates that the stock excess return, which is traditionally interpreted as a risk premium, includes an illiquidity premium as well. Therefore, it can be reasoned that the expected return exceeding the yield on treasury securities should be considered as a compensation for illiquidity, along with being interpreted as a compensation for risk.

The ILLIQ is calculated as follows:

$$ILLIQ_{iy} = \frac{1}{D_{dyt}} \sum_{t=1}^{Diy} \frac{R_{iyd}}{VOLD_{ivyd}} \qquad \textbf{Eq (7)}$$

Where:
R = Return
i = Particular stock
y = Particular year
t = Particular day
VOLD = Daily volume in dollars

[6] Excel file: Dataset.xls, Sheet: Rolls Multiplied -1

The provided excel file[7] covers both daily and monthly ILLIQ values. The monthly ILLIQ numbers are compared against monthly Bitfinex spread numbers. The monthly Bitfinex spreads, as before, is the average spread value for a month.

Coefficient of Elasticity (CET) Measure

A simple way to measure asset liquidity is to base it on the frequency of trading. More frequent trading translates into improved liquidity, but in any such measure it is not possible to quantify the amount of liquidity among frequently traded assets. (Datar, 2000) introduced the Coefficient of Elasticity, which uses the argument that the ideal measure of liquidity should combine price and volume.

The following formula is used for calculating CET:

$$CET = \frac{\%\ \Delta\ Trading\ Volume}{\%\ \Delta\ Price} \qquad \textbf{Eq (8)}$$

Table (3) provides a better explanation of how the CET-output should be interpreted. A CET score lies between positive and negative infinity. It will be positive when the direction of change is the same for both volume and price, and negative when the direction of change in both volume and price is different. A high value of CET in either direction means that small changes in price are accompanied by large changes in volume, which is consistent with high liquidity. On the other hand, a low value of CET means that small changes in volume accompany small changes in price, which means low liquidity.

The correlation tests are run both on daily and monthly CET numbers. Monthly CET is calculated by dividing the sum of monthly percentage change in trading volume over the sum of monthly percentage change in price. These numbers can be viewed in the excel sheet[8]. Regardless of the sign, a higher percentage change in volume followed by a low percentage change in price implies high liquidity and vice versa. The discussion on all the results from these correlation tests is in Chapter 4.

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[7] Excel file: Dataset.xls, Sheet: ILLIQ and ILLIQ Monthly

[8] Excel file: Dataset.xls, Sheet: CET and CET Monthly

3.3.2 Methodology of the Regression Analysis

This section explains the methodology used for the second research question. Furthermore, the tools and techniques used to reach a correct, workable model are also discussed in this section.

The second research question is as follows:

"Do the selected Primary, Secondary, Time and Event based variables affect the bid-ask spread and is the effect in line with existing financial research and conventional sense?"

The null hypothesis for this research question states that there is no statistically significant relationship between the selected variables and the *bid ask spread*. The alternate hypothesis is that there is a statistically significant relationship between the spread and the explanatory variables.

It is also of interest to see whether that relationship is in line with existing financial research for primary, time and event-based variables, and whether secondary variables exhibit a relationship with the spread that is in line with our intuition.

Treating the dataset as Cross-Section rather than Time Series:

Although our data spans over four years, it is treated as cross-sectional rather than time series. This is because the objective of this research is not to measure how the relationship between these variables has evolved over the selected period. Neither does it aim to observe whether the lagged values of the explained or explanatory variables have any effect on the spread value today. Furthermore, treating this dataset as timeseries would have made sense if the aim was to develop a predictive model of BTC liquidity.

The objective is to understand whether BTC liquidity adheres to the empirically proven laws of finance, and whether it is in line with our intuition in the case of secondary variables. Keeping this in mind, we treat the data set as cross sectional rather than time series.

Looking at graph (1) we see that some of the variables show an apparent time trend. However, it is necessary to remember that price, volatility, mining difficulty, transaction cost, transaction confirmation time and number of transactions directly relate to BTC popularity and not necessarily time. BTC saw an increase in popularity in year 2017, which reflects as a seemingly exponential time-based increase in the above-mentioned variables. However, it is merely an increase in the popularity of BTC which caused this evident appreciation rather than time.

Raw Econometric Equation

To estimate this relationship, we start with the following econometric equation:

$$\lambda = \pm \alpha_P \pm \alpha_{TV} \pm \alpha_V \pm \alpha_{IR} \pm \gamma_{SHR} \pm \gamma_{TC} \pm \gamma_{TCT} \pm \gamma_{NT} \pm \gamma_{MD} \pm T_{WD} \pm \eta_{BTC} \pm \eta_{Bitfinex} \pm \varepsilon \qquad \textbf{Eq (9)}$$

Where:

λ = *Bid Ask spread*

α_P = Price

α_{TV} = Trading volume

α_V = Volatility

α_{IR} = USD & EUR Libor interest rates

γ_{SHR} = Sum hash rate

γ_{TC} = Transaction cost

γ_{TCT} = Transaction costnfirmation time

γ_{NT} = Number of transactions

γ_{MD} = Mining difficulty

T_{WD} = Week day dummies

$\eta_{BTC\ specific}$ = BTC network specific event dummy variables

$\eta_{Bitfinex\ specific}$ = Bitfinex specific event dummy variables

Equation (9) exhibits the relationship that we intend to test in the second research question. As discussed earlier, the idea is to observe if there is a statistically significant relationship between the *bid ask spread* and *primary* and *secondary variables*. The equation also includes time and events based dummy variables. For ease of understanding, the *event* dummy variable has been further divided into BTC *network specific events* and *Bitfinex specific events*.

Overall, there are *fifty-six* variables in the raw econometric equation Eq (9). *Eleven* of these variables are *primary* and *secondary* variables that are continuous in nature. The remaining *forty-five* variables are dummy variable, which are dichotomous in nature. These variables are divided in the following manner. *Seven* dummy variables represent the days of the week, whereas *twenty-six* of them cover BTC ecosystem related events. *Twelve dummy* variables cover Bitfinex specific events. The results from Eq (9) are discussed in chapter 4.

Multi-collinearity & omitted variable bias

To reach an accurate model that limits problems of multi-collinearity and omitted variable bias, we use the following methods and techniques:

Correlation Matrix

High correlation between variables can lead to the problem of multi-collinearity. Multi-collinearity arises when two or more independent variables have a linear relationship. Perfect collinearity is rare, but high collinearity is common and can cause problems in the regression analysis. Section 4.2.2 discusses the results from the correlation matrix and provides an overview of the variables that were dropped.

Variance Inflation Factor

Multi-collinearity results in the inflation of the standard errors and the variance of estimated coefficients. The variance inflation factor (VIF) test quantifies this inflation. This test is used as one of the criteria for the elimination of variables that have the potential of causing multi-collinearity.

Theoretical Justification

We also use theoretical reasoning and empirical evidence proving that two of the variables in our data set cannot work together, in order to justify the removal of one of them. Theoretical frameworks are developed after consistent testing under different scenarios and circumstances. Therefore, using them as one of the reasons for elimination is justified.

Process of elimination

The following criteria are used to eliminate variables from Eq (9):

a) Variables that show up as statistically insignificant and have a sign that defies existing financial research, theory and conventional sense are removed.
b) Variables that have extremely high or perfect correlation with other variables and there is theoretical proof or empirical evidence justifying that they should not be used together are removed.
c) Variables that show extremely high VIF scores and have a substitute available are removed.

Standardized Regression Coefficients:

The standardized regression coefficients estimate the standard deviation change in the dependent variable for a one standard deviation change in the independent variable, holding other variables constant. This process of standardizing is a fundamental manipulation used in the improvement of numerical computation. It is also useful in understanding and reporting statistical models, while making different coefficients comparable to each other.

The standardized coefficient β is not to be confused with the regular OLS coefficients, just because both use similar notations. The standardized coefficients provide us the relationship in the data as if it were scaled in z-score form:

$$\beta = \frac{\sigma_x}{\sigma_y} b$$

These results can be achieved in STATA using the **regress, beta** command**.** The limitation though, is that the above given classical formula works only with additive models and does not perform well for models which have interactive terms. Fortunately, the econometric models in this research Eq (9) & (10) are additive and do not contain any interaction terms.

Addressing Heteroscedasticity

An important assumption of the linear regression model is homoscedasticity, which means that the variance of the error term is constant and does not increase or decrease with the values of the independent variables. A violation of this assumption is labeled as heteroscedasticity. The resulting model will no longer have the best, linear, unbiased estimators (BLUE).

To check for heteroscedasticity, we use the **Breusch Pagan** test. This test is run in STATA using the **estat hettest** command. If there is evidence of heteroscedasticity, a standard method for controlling it is to use **regress, robust** command in STATA. This command reports the OLS coefficient estimates but adjusts the standard errors for heteroscedasticity without transforming the model.

4. Result & Discussion

In this section we discuss the results of both our research questions. To maintain clarity, we have divided the discussion into two parts, where each part discusses in detail the results for each research question. At the end of each part, based on our findings, we conclude by rejecting or failing to reject our devised hypothesis.

4.1 Results & Analysis –Research Question 1

4.1.1 Rolls Measure

The results from the different iterations of the correlation tests between the Rolls measure generated implicit spread and the Bitfinex *spread* are provided in table (7). The graphical comparisons of these results are viewable in graph (2), (3), (4) & (5). Since the Rolls measure assumes that the covariance between the change in price and the lagged change in price is negative, any violation of this assumption leaves us with "number errors" in the dataset. (Corwin & Schultz, 2012) provide some solutions to overcome this problem, which are discussed in section 3.3.1. The results clearly illustrate that even after making the adjustments these two-different measures of liquidity fail to show any correlation.

The first column of table (7) shows the iteration where the number errors are adjusted by multiplying them with negative one. The correlation coefficient of -0.0326 for daily data is statistically insignificant. The second column represents the data accumulated for the same configuration as above, but at a monthly level for both the Rolls generated implicit spread and the Bitfinex *spread*. The resulting correlation -0.122 is statistically insignificant. Graph (2) & (3) provide illustrative comparisons of the results.

The iteration in column three represents the scenario where all "number errors" are converted to zero. The correlation coefficient is -0.0517 and it is statistically significant at a 5% level. Column four shows the original results where the "number errors" have been left as missing. The correlation coefficient in this case is -0.0618 and it is statistically insignificant. Both the above discussed results are based on daily data. Graph (4) & (5) provide a comparison of the discussed outputs.

It is surprising to find a lack of statistically significant correlation between the Rolls measure generated spread and the actual Bitfinex *spread.* Furthermore, the direction of the correlation is also opposite to our expectations. Because the Rolls measure is supposed to generate an implicit spread, it was anticipated that there would be a statistically significant correlation between these two spreads and that the sign of this correlation would be positive.

One obvious reason for the lack of cohesion between the Rolls measure and the *spread* is the simplicity of this method. The Rolls measure calculates the spread using the covariance between price changes. Therefore, price is the only factor that drives the calculation of the implicit spread. This limits the effectiveness of the Rolls measure, because there might be a problem of omitted variables which are not considered in the Rolls measure. Keeping in view the empirical work quoted in the literature review, we know that a number of factors affect the spread, including price. (Ciaian, Rajcaniova, & Kancs, 2016) find that BTC price formation is affected by several factors including exchange rates, supply & demand and asset attractiveness, yet it is hard to conclude whether these factors and resultantly the price alone is significant enough to have an impact on the spread.

Furthermore, (Goyenko, Holden, & Trzcinka, 2008) dub the Rolls measure as a low frequency spread proxy which might get inhibited if the trading volumes are high. BTC trading exhibits a lot of variation and movement in trading volumes. Additionally, the Rolls measure assumes that the changes in prices have a negative covariance, an assumption that is consistently violated in BTC trading. Adding to this, (Harris, 1990) while examining the small-sample properties of the Rolls estimator for equity markets finds the estimator to be noisy even if the sample size is large.

Even though one of the four scenarios generate a statistically significant result, the null hypothesis $H_0 = Corr(\lambda, \theta) = 0$ **cannot be rejected** due to lack of sufficient proof.

4.1.2 Coefficient of Elasticity Measure (CET)

Table (9) provides the correlation results between CET and the *spreads*. The correlation coefficients for daily and monthly comparisons are -8.85e-03 and -0.106 respectively, and both these results are statistically insignificant. The CET is equivalent to measuring the price elasticity of demand for BTC and uses this relationship as a measure of liquidity. It captures any change in trading volume for every $1 change in price. This makes CET a different measure than the Bitfinex *spread*, which is a composite of several factors. We believe that this difference in how the liquidity measures are formulated is the primary reason behind the lack of correlation. Therefore, based on the consistency of the results we ***fail to reject*** the null hypothesis $H_0: Corr(\lambda, \theta) = 0$. Graph (8) & (9) demonstrate the comparison between the CET results and the Bitfinex *spread* result discussed above.

4.1.3 ILLIQ Measure

Table (8) exhibits results from the correlation test between ILLIQ and the *spread*. The ILLIQ has also been calculated for daily and monthly data. The correlation coefficient for daily data is 0.241 and is statistically significant at the 0.1% level. Similarly, the correlation coefficient for monthly data is 0.434 and is significant at a 1% level. Graph (6) & (7) provide a comparison of daily and monthly ILLIQ with the spread. The results discussed above exhibit a moderate but statistically significant correlation between ILLIQ and the Bitfinex *spread*. This is also evident from the graphs, where we observe somewhat similar co-movement. Similar to our results, (Minaki, 2013) finds a positive relationship between transaction costs and ILLIQ while studying the relationship between liquidity, transaction costs and risk in the Japanese government bonds futures market. This suggests that the *bid ask spread* and ILLIQ move in tandem, which means an increase in them leads to a decrease in liquidity and vice versa.

Eq (7) shows that ILLIQ utilizes the return of an asset and volume of trade to measure liquidity. It is hard to pin-point one reason as to why ILLIQ shows significant results while others fail to do so. Perhaps it is because ILLIQ utilizes returns, which are affected by a wider range of factors just like the actual *spread*. Due to lack of empirical evidence it might be debatable to assume that the same factors affecting the *spread* are affecting the returns as well. Yet, this can be a plausible reason why there is cohesion present between these two measures of liquidity. Based on the consistency of the results we ***can reject*** the null hypothesis $H_0: Corr(\lambda, \theta) = 0$ while ***failing to reject*** the alternate hypothesis $H_1: Corr(\lambda, \theta) \neq 0$.

It is important to mention here that the objective of this exercise is to conclude whether any of the selected liquidity measures and the Bitfinex *spread* have any correlation. It is not to conclude that a certain measure is better than the other measure. All these measures are empirically tested ways of measuring market liquidity, and their accuracy cannot be challenged. Yet, it is of interest to discuss some of the reasons that might be driving this lack of correlation, which is what we have done above.

4.2 Results & Analysis –Research Question 2

4.2.1 Summary Statistics

This section utilizes table (1) to provide a general explanation and overview of the most important variables used in answering the second research question.

The total number of observations in the dataset is 1560. This dataset comprises of observations collected at a daily interval starting from October 9, 2013 until January 15, 2018.

The average *spread* during this observed period is $1.11e-03 and has a standard deviation of 2.04e-03, with minimum and maximum values of 4.66e-05 and 0.042. Graph (1, *spread*) shows that the *spread* has reduced over time, yet it experiences intraday fluctuation constantly.

The average *price* during the observed period is $ 1,411, with a standard deviation of 2,733. The min and the max values are 125.2 and 19,271 and exhibit wide divergence. The most significant price increase was seen in 2017 graph (1, *price*).

Mean *trading volume* is approximately $ 60 M. The standard deviation has a value of $19 M. Graph (1, *BTC Trading Volume USD)* shows that 2017 saw a significant increase in the trading volume, which is in line with the price increase.

Volatility is defined as the standard deviation of price from all market trades on Bitfinex, mean *volatility* is 6.034. The minimum and maximum values are 0.094 and 246.2 and exhibit a high degree of divergence. *Volatility* also saw a considerable increase in year 2017, which is in tandem with the increase in price.

Mean *USD 3-month Libor* is 6.29e-03, graph (1, USD_3M_Libor) clearly shows a rise in the interest rate. This increase is mainly due to the low interest rates that have prevailed in the recent past and signifies recovery in the global interest rates as they move towards post reduction levels. Conversely, mean *EUR 3-month Libor* is -0.011 with a SD of 2.3e-3 and a maximum value 3.2e-3 and minimum value of -3.9e-3.

The mean *market cap* is approximately $ 2.3 Bn, with a high standard deviation of $ 4.6 Bn. Year 2017 saw a significant increase in the *market cap* of BTC. This change is understandable as it is in line with the BTC *price* increase.

The *Sum hash rate,* which is the accumulated computational power available on BTC network to process transactions, has a mean value of 2 quintillion. The SD is approximately 3 quintillion. *Sum hash rate* saw a sharp increase in year 2015 and beyond as increasing BTC demand and popularity motivated a greater number of people to invest in setting up BTC mining apparatus.

The average *transaction cost* of $21.71 is considerably high. It is important to emphasize here that the *transaction cost* is the cost of processing transactions on the blockchain. This is different from the trading cost on Bitfinex, which is represented by the *spread* and is our explained variable in this scenario. In graph (1, *Transaction Cost*) we see that starting in 2013 transaction costs increased but gradually tapered off close to 2015. It started appreciating again in 2017 and reached an all-time high of $161.7 close to 2018.

Average *transaction confirmation time* is approximately nine minutes, whereas the maximum time ever experienced to process a transaction on the BTC network was approximately thirty minutes. *Transaction confirmation time* sees a significant variation throughout the entire time line, but there is greater variation in year 2016 and onwards. This is perhaps due to a greater transaction load on the block chain network, which was caused by increased demand and popularity. The standard deviation is also large, at approximately twenty-three minutes.

Mean *number of transactions* is 171,604, with a standard deviation of 93,682 transactions. The max number of transactions during the selected period was 490,644. It is important to highlight that the *number of transactions* represents transactions on the blockchain network; it does not refer to the number of trades on Bitfinex. Although there is an almost linear increase in this variable, we also see a lot of fluctuation in this upward trend.

4.2.2 Raw Econometric Equation

The results from regression Eq (9) & (10) are exhibited in table (5), but this section only discusses the results of Eq (9) viewable in table (5, column 1). As is visible from the results, the coefficients are relatively small which is understandable considering that the dependent variable is small.

Price is statistically insignificant, and the sign of the coefficient is incorrect relative to what existing financial research suggests. *Trading volume* is also statistically insignificant and has a sign that is in accord with existing financial research. Furthermore, *volatility*, *Euro & USD 3-month Libor* are statistically significant and have the correct signs.

Market capitalization, *sum hash rate* and *mining difficulty* are statistically insignificant but hold a sign that is either in line with existing financial research or conventional sense.

Transaction cost is significant at a 10% level, but the sign is opposite to expectation because an increase in *transaction cost* should increase the *bid ask spread*. *Transaction confirmation time* is statistically insignificant and has an incorrect sign, whereas *number of transactions* is statistically insignificant but has the correct sign.

The regression omits the dummy variable for *Sunday*. Furthermore, all dummy variables for the days of the week are statistically insignificant. *Tuesday* and *Friday* are not only statistically insignificant but have a sign contrary to existing research (Chordia et al., 2005; Van Ness et al., 2005).

A majority of the BTC related events (EE's) are statistically insignificant. Only five of the *EE's* are significant at the 1% & 5% level. *EE1* and *EE2* are statistically significant, but have an incorrect sign keeping in view the nature of the events. The events were positive in nature and should have reduced the *spread*, but on the contrary, they increase it. Furthermore, *EE3* and *EE4* are statistically significant at the 1% level and bear the correct sign. These two events were negative in nature and should have increased the *spread*, which is visible in the regression results.

EE8 is statistically significant at the 5% level but it is unclear whether this specific event should have had a positive or negative impact on the spread. The event covers the implementation of financial regulation on businesses that interact with bitcoin and other crypto currencies. The financial services department in New York implemented the regulation. Therefore, it is hard to conclude whether this should have had any impact on Bitfinex *spread*, and if it does, what should be the direction of that effect.

Only two Bitfinex related events *BRE3* and *BRE4* are statistically significant and have the correct sign. The coefficients of these events are 3.45e-03 and 3.20e-03 respectively. These coefficients are large relative to other coefficients, which is perhaps due to the extremity of these events. *BRE3* reflects the hacking of Bitfinex that resulted in the theft of 120,000 bitcoin units valued at approximately $72 M. BRE4 reflects the decision by Bitfinex to "socialize" the hack losses, which resulted in a generalized loss of 36.067% across all the BTC holders on Bitfinex at the time of the hack. Furthermore, the R-squared for the regression is 0.4529 whereas the adjusted R-squared is 0.4329

4.2.3 Minimizing multi-collinearity

Correlation Matrix – for Eq(9)

To reduce multi-collinearity, we use the correlation matrix to test the strength of correlation between the independent variables. Table (4) exhibits the correlation matrix and includes all the *primary* and *secondary* variables while excluding the *dummy* variables.

BTC Trading Volume

Volatility and *BTC trading volume* exhibit high correlation of 0.949, which is significant at a 0.1% level. *BTC trading volume* also exhibits a correlation value of 0.887 at a 0.1% significance level with *market cap*. Strong correlation between *trading volume* and *volatility* is also empirically proven (Downing & Zhang, 2004).

Market Capitalization

Apart from showing high correlation with *BTC trading volume*, *market capitalization* also exhibits high correlation of 0.912 and 0.907 at the 0.1% significance level with *sum hash rate* & *mining difficulty* respectively. This variable also exhibits perfect collinearity of 0.999 at a 0.1% significance level with *Price*. Since BTC supply is predictable, any movement in *market capitalization* is driven by change in *price*. Any positive movement in *price* increases the *market capitalization* and vice versa, hence this perfect correlation is understandable.

Sum Hash Rate

Sum hash rate and *price* show high correlation of 0.911 at a 0.1% level. Furthermore, *sum hash rate* and *mining difficulty* also show a high correlation of 0.989 at a 0.01% significance level. *Sum hash rate*, which is the number representing computational power on the BTC network, and *mining difficulty*, which represents the ease or difficulty of mining, are both related to the processing power of BTC network and are therefore very similar in nature.

Euro 3 Month Libor rate

Euro 3-month Libor and *USD 3-month Libor* show a high negative correlation of 0.879 at a significance level of 0.01%. These two variables are similar proxies for any possible effect of interest rate changes on the Bitfinex *spread*. *Euro 3-month Libor* also has high negative correlation of 0.919 at a 0.01% significance level with the variable *number of transactions*.

Results from (VIF) test – For Eq (9)

Table (6) exhibits the variance inflation factor (VIF) test results for Eq (9) & (10). The mean VIF for Eq (9) is 34.18, which is as an under-representation of the magnitude of multi-collinearity that is present. The low average VIF is because of the high number of dummy variables, which push the mean VIF downwards.

An individual examination of the VIF score reveals extremely high numbers of 797 and 714 for *market Cap* and *price* respectively. Furthermore, *mining difficulty* and *sum hash rate* also show high VIF scores of 94.69 and 60.19 respectively. *Euro* and *USD 3-month Libor* also exhibit a high VIF score of 47.06 and 24.79 each. These scores are an indication that variables in Eq (9) are suffering from multi-collinearity. In order to generate unbiased results, we have to remove variables that have high individual VIF scores.

Elimination of variables

Considering the points above and the criteria of elimination mentioned in subsection 3.3.2, the following variables were dropped when creating the parsimonious Eq (10):

a) BTC Trading Volume USD
b) EUR_3M_LIBOR
c) Sum Hash Rate
d) Market Cap USD
e) Dummy variables for weekdays
f) Dummy variables for BTC related events ***except*** for EE3 & EE4
g) Dummy variables for Bitfinex related events ***except*** for BRE3 & BRE4

4.2.4 Parsimonious equation

The process of elimination discussed in section 4.2.5 leaves us with the following model:

$$\lambda = \pm \alpha_P \pm \alpha_V \pm \alpha_{IR} \pm \gamma_{TC} \pm \gamma_{TCT} \pm \gamma_{NT} \pm \gamma_{MD} \pm \eta_{BTC} \pm \eta_{Bitfinex} \pm \varepsilon \qquad \textbf{Eq (10)}$$

Where:

λ = *Bid Ask spread*

α_P = Average Price

α_V = Volatility

α_{IR} = USD 3-month LIBOR interest rates

γ_{TC} = Transaction cost

γ_{TCT} = Transaction costnfirmation time

γ_{NT} = Number of transactions

γ_{MD} = Mining difficulty

$\eta_{BTC\ specific}$ = BTC network specific event dummy variables

$\eta_{Bitfinex\ specific}$ = Bitfinex specific event dummy variables

Column labeled Eq (10) in table (5) exhibits the results from the refined equation. In Eq (10) *price* becomes statistically significant at a 1% level and has a negative sign. The coefficient of *price* sees a correction from positive 3.32e-07 in Eq (9) to a negative 2.147e-07 in Eq (10). The sign of the *price* coefficient in Eq (10) is in line with the results found by (Jegadeesh & Subrahmanyam, 1993; Stoll, 1978).

Volatility remains statistically significant at the 5% level and still has a sign that is in line with existing financial research. The coefficient for *volatility* in Eq (10) is 1.10e-05, which is smaller than the coefficient value of 3.58e-05 in Eq (9). These results exhibit a similar relationship between *volatility* and *bid ask spread* as found by (Jegadeesh & Subrahmanyam, 1993; Wyart et al., 2008)

Instead of using both *Euro* and *USD 3-month Libor* rate, only the latter is used as the variable covering interest rates. There is a decrease in the size of the coefficient where the new value is 1.05e-01 in comparison to 4.22e-01 in Eq (9). Furthermore, the level of statistical significance also reduces from the 1% to the 5% level. It is important to mention that the relationship between the interest rate and the spread is in line with the positive relationship found by (Chordia, Roll, & Subrahmanyam, 2001).

Mining difficulty becomes statistically significant at a 1% level and the size of the new coefficient marginally increases from -1.14e-15 to -1.84e-15. This is perhaps due to the exclusion of the *sum hash rate*, which is similar to *mining difficulty*. The sign of mining difficulty is exactly what we anticipated. Furthermore, *transaction cost* becomes statistically significant at the 1% level. The sign of the coefficient also changes to reflect our intuition that an increase in the cost of transacting, on the BTC network, should have a negative impact on liquidity.

BTC related events *EE3* and *EE4* remain statistically significant at a 1% level. The coefficient size of *EE3* reduces from 3.51e-03 to 2.98e-03. On the contrary, the coefficient of *EE4* increases from a value of 2.763-03 to 3.02e-03.

The magnitude of *BRE3* and *BRE4* along with their statistical significance do not change much in the results of Eq (10). The coefficients for these two variables slightly decrease from 3.45e-

03 and 3.20e-03 to 3.31e-03 and 2.92e-03 respectively. A noticeable difference is the drop in R-squared, which reduces from 0.453 in Eq (9) to 0.331 in Eq (10). This is due to the reduction in the number of variables, which leads to a model that is more accurate but explains less variation in the *spread*.

Although not all the EE's and BRE's come out as statistically significant, a few of them show a significant relationship with the *spread*. This is in accordance with existing research by (Demsetz, 1968; Ho & Stoll, 1981; Stoll, 1978) which suggest that events have an impact on liquidity. Furthermore, we also observe that these events have a relationship with the *spread* which is in line with the nature of the event. This implies that a negative event increases illiquidity whereas a positive event decreases illiquidity.

Results from (VIF) test – for Eq (10)

Table (6) exhibits the VIF score from Eq (10) as well. The VIF score drops significantly from 34.18 to an average of 10.67 after the removal of the above discussed variables. Considering the high number of dummy variables utilized in Eq (9) which are not present in Eq (10), this decrease is quite significant and a step in the right direction. Furthermore, variables like *price* and *mining difficulty* that had extremely high VIF's of 713.88 and 96.69 see a significant drop to 27.54 and 35.11 respectively in Eq (10).

Controlling for Heteroscedasticity - for Eq (10)

The Breusch Pagan test provides evidence of heteroscedasticity in Eq (10)[9] and the null hypothesis of homoscedasticity is rejected. Table (5, column 5) presents the results for Eq (10) after controlling for heteroscedasticity using the **reg, robust** command. While the coefficient values stay the same, the standard errors of all the variables change. This is understandable since the equation has been controlled for heteroscedasticity.

Furthermore, the statistical significance of three variables *volatility*, *EE4*, *BRE3* and *BRE4* changes. *Volatility* becomes statistically significant at 10% level whereas the event variables become statistically insignificant.

If the dummy variables have few observations, which is the case in this research, then standard errors are not meaningful using the robust option. In such a scenario their usage only inflates

[9] The results from the Breusch-Pagan test lead us to reject the null hypothesis of homoscedasticity. The code for this test is provided in the STATA file and based on these results we decided to use the "robust" command on eq (10).

the t-statistic (Fomby & Murfin, 2005; Ford, Jackson, & Skinner, 2010). Furthermore, we also need to consider the nature of volatility and event-based shocks, as they represent movements away from the mean value. Controlling for heteroscedasticity forces the standard errors to lose abnormal values in order to eliminate any trends in the error terms. Therefore we see these variables, which in themselves represent abnormality, turning insignificant after this procedure.

Standardized Regression Coefficients - Eq (10)

Table (5, column 3 & 4) exhibit the standardized regression coefficients and the 1 SD value for all the independent variables in Eq (10). We observe that a one standard deviation (SD) increase in *price* brings a 0.288 SD decrease in the *spread*, a one SD in *price* is equivalent to $ 2,733. Similarly, a one SD change in *volatility*, which is equal to 18.23, brings an increase of 0.099 SD in the *spread*.

An increase in *USD_3M_Libor* by one SD brings a 0.223 SD increase in the *spread*. A one SD increase in *USD 3-month Libor* translates into a 0.433% increase in the *spread*. One SD increase in *mining difficulty* is equal to 4.160e+11 and brings a 0.377 SD decrease in the *spread*.

Transaction cost and *transaction confirmation* time both increase the spread, which signifies reduction in liquidity. One SD of *transaction cost* is equal to $ 23.17, whereas one SD of *transaction confirmation* time is 3.133 minutes. A one SD increase in these variables brings about a 0.448 and a 0.078 SD increase in the *spread* respectively. An increase in the *number of transactions* is an indicator of increased BTC use and adaptability. Hence, a one SD increase in the *number of transactions* brings a 0.235 SD decrease in the *spread*.

In accordance with the nature of the event dummy variables, *EE3* and *EE4* increase the *bid ask spread* signalling reduction in liquidity. *EE3* and *EE4* cause an increase of 0.143 and 0.145 SD in the *spread* respectively. Furthermore, Bitfinex related events *BRE3* and *BRE4* cause a 0.130 and 0.115 SD increase in the *spread*.

This standardization allows us to compare the magnitude of impact that different variables have on the spread. Secondary variables, which do not seem to be directly related to the Bitfinex market microstructure, have a much bigger impact in comparison to *primary variables* like *price* and *volatility*.

As is visible from the results above, *Transaction cost* has the largest impact on the *spread*. This variable can directly affect the implementation and profitability of arbitrage strategies. (Makarov, 2018) finds that the estimated total size of arbitrage profits from December 2017 to February 2018 in cryptocurrency markets amounts to approximately $1 Bn. Similarly, *mining difficulty* also has a relatively large impact on the *spread*. As explained earlier, *mining difficulty* is a representative number and its increase means that mining BTC is becoming easier and vice versa. Its increase signifies that ample resources to process BTC transactions are present on the network, which reflects as reduction of the *spread*.

Price has the third largest impact, as every 1 SD change in price reduces the *spread* by 0.288. This is in line with existing financial research, which hypothesizes *price* to be a proxy for asset risk. This means that higher prices mean lesser risk and an increase in price can lead to a reduction in the *spread*, which we observe in this case. *Number of transactions* and *USD_3M_Libor* are variables with the third and the fourth largest impact on the *spread* respectively.

Although some prominent events show up as significant, their impact when compared through standardized results is smaller than other variables. This is contrary to our premise that since BTC is primarily sentiment-driven, events should have a much larger impact. Perhaps this is because some of the discussed variables, like *price* and *number of transactions*, are directly affected by events and end up consuming some of the effect of these events. Based on both the standard regression and standardized regression results we ***can reject*** the null hypothesis $H_0: f(\lambda|\ \alpha, \gamma, T, \eta) = 0$ while ***failing to reject*** the alternate hypothesis $H_1: f(\lambda|\ \alpha, \gamma, T, \eta) \neq 0$

5. Conclusion

The objective of our thesis was to attain an understanding of BTC liquidity in a market microstructure (exchange) setting. To do so, the first part of our thesis investigated whether there was any significant correlation between the Bitfinex *spread* and results generated by three different liquidity measurement techniques. These techniques were the Rolls measure (Roll, 1984), the ILLIQ measure (Amihud, 2002) and the Coefficient of Elasticity (CET) (Datar, 2000).

Table (7) presents the results of the correlation test between the Rolls measure and the *spread*. It is clear from this table that only the iteration where the "number errors" were replaced with zeros produced statistically significant correlation results at 5%-level, the rest of the iterations were statistically insignificant. Therefore, due to lack of sufficient proof, we conclude that there is no significant correlation between these two measures.

Table (8) exhibits correlation results between ILLIQ and the *spread*. The daily and monthly comparisons both show that there is a moderate, statistically significant correlation between ILLIQ and the *spread*. Furthermore, table (9) exhibits the results from the correlation test between the CET measure and the *spread*, both for daily and monthly data. The results show that the correlations are insignificant for both the scenarios.

One of the reasons for this lack of correlation between most of the measures and the *spread* is that they are simple and only consider few factors like *price* and *trading volume* to calculate liquidity. In contrast, several different factors combine to cause the formation and movement of the market microstructure specific *spread*. Most likely, these techniques suffer from a problem of omitted variables, as they do not incorporate important factors while calculating liquidity.

The ILLIQ, on the other hand, includes the return of the asset. The return captures the effect of several factors, such as *price*, *volatility*, *volume* and *market sentiment*. Therefore, we see that ILLIQ produces a moderate but statistically significant correlation with the actual *spread*.

In the second part of our thesis, we observed different factors that might affect the *spread*. Additionally, we included dummy variables in our regression analysis that control for days of the week and important events for the BTC ecosystem and the Bitfinex market microstructure. The results from the raw econometric equation Eq (9) are exhibited in table (5_column 1). We attempt to determine whether changes in the selected variables cause any change in the *spread*, and whether the impact is in line with existing financial research and conventional sense.

Variables are removed from Eq (9) based on the criteria discussed in section 3.3.4. The resulting Eq (10) incorporates only those variables that do not suffer from multi-collinearity, while at the same time limiting the problem of omitted variable bias. We find that all remaining *primary variables* in Eq (10), like *price*, *volatility* and *USD 3-month Libor*, have a statistically significant relationship with the *spread* and that the relationship is in line with existing financial theory and research.

Furthermore, *secondary variables* like *mining difficulty*, *transaction cost*, *transaction confirmation time* and *number of transactions* also have a statistically significant relationship with the *spread*. This relationship is in line with our intuition and conventional sense. The secondary variables are concerned mainly with the BTC eco-system rather than the Bitfinex market microstructure. It might seem counter intuitive that these variables have any sort of impact on the *spread* but, as explained in section 3.2.2, the *secondary* variables affect several aspects of BTC's efficiency like moving BTC among e-wallets and exploiting arbitrage. This has a direct impact on exchange level liquidity, which is visible in the results generated by Eq (10).

Research provides evidence of patterns in spread movement based on days of the week and it has been found that Tuesday's exhibit higher liquidity and lower *spread*, whereas Fridays exhibit lower liquidity and higher *spread*. The result of our research does not find any such patterns: All dummy variables representing days of the week show up as statistically insignificant, hence they are removed from the model presented in Eq (9). This is perhaps because, contrary to conventional assets, BTC is traded continuously around the year. This means that such an effect is less likely to appear, which is in accordance with the generated results.

Only four events, *EE3*, *EE4*, *BRE3* and *BRE4*, come out as statistically significant. *EE3* represents a ban by the Chinese government on financial institutions prohibiting them from using Bitcoin. The relationship between this event and the *spread* is positive in our model, which is reasonable given the fact that this was negative news and should have increased the *spread*. *EE4* represents a denial-of-service attack on several major cryptocurrency exchanges, which forced suspension of trading on Mt. Gox, Bitstamp and BTC-e. This reflects as an increase in the *spread* on Bitfinex. This event highlighted the risk faced by online exchanges and traders trading on the exchanges. This perception of risk is reflected through the expansion of the spread.

BRE3 is a Bitfinex specific event and covers the hacking of the Bitfinex market microstructure. This event has a significant positive relationship with the *spread*, which is expected considering the negative nature of the event. *BRE4* is an event closely related to *BRE3 and* covers the effect of an announcement by Bitfinex stating that they would socialize losses incurred during the hack between the users of the platform. This event also increases the *spread*, which is understandable since this was negative news for the investors.

It was surprising to see only a small fraction of the events coming out as significant. Existing research and the belief that the price of BTC is mostly sentiment based would suggest a higher impact of events on the *spread*. Especially, BTC ecosystem specific events were expected to have a larger impact. The standardized regression results generated by Eq (9) negate this belief. One reason for this might be that other variables included in the model consume the effect of the included events. This results in only some of the extreme events showing up as significant. Looking at the results from Eq (10) in table (5), it is also clear that these events have a smaller impact on the *bid-ask spread* in comparison to *primary* and *secondary variables.*

Future Areas of research

It might be interesting to conduct separate event studies, which help capture the true magnitude of specific events on the *spread*. Furthermore, considering the nature of trading in BTC, it might be interesting to observe if there is any cyclicality in liquidity based on hourly and monthly data. It might also be fascinating to utilize time-series models on BTC liquidity. This could make it possible to forecast BTC liquidity.

Furthermore, it might be of interest to observe and compare similar relationships in Eq (10) across different exchanges or currencies. This would require use of panel data techniques and would create an opportunity to see how factors affecting the *spread* in specific exchanges or currencies change over time compared to other exchanges or currencies. This can offer valuable insights into the development of competition between different exchanges and currencies. (Kothare & Laux, 1995) find that those stocks where institutional activity increases see the biggest increase in the *bid ask spread*. Therefore, it might be of interest to see if any similar relationship exists in BTC trading as a greater number of institutional investors are now investing in BTC.

6. Tables

Table 1 – Summary Statistic:

This table provides a summarized overview of the *primary* and *secondary* variables and sheds lights on the statistical properties of the dataset. The data includes 1560 observations and is collected starting from 9 October 2013 to 15 January 2018 which makes the time length of the dataset approximately 4 years and 3 months.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	N	mean	max	min	sd	kurtosis	skewness
Spread0BTC	1,560	0.00111	0.0416	4.66e-05	0.00204	142.6	8.971
PriceAvg	1,560	1,411	19,271	125.2	2,733	19.65	3.954
BTCTradingVolumeUSD	1,560	5.977e+07	2.249e+09	210,406	1.900e+08	44.50	5.768
Volatility	1,560	6.034	246.2	0.0943	18.23	51.85	6.247
EUR3M_LIBOR	1,560	-0.011	0.0032	-0.0039	0.0023	1.67	0.29
USD3M_LIBOR	1,560	0.00629	0.0170	0.00223	0.00433	2.214	0.744
MarketCapUSD	1,560	2.26e+10	3.23e+11	1.58e+09	4.64e+10	19.96	3.99
SumHashrate	1,560	2.12e+18	1.85e+19	1.57e+15	3.23e+18	8.39	2.33
Miningdifficulty	1,560	2.789e+11	2.228e+12	1.893e+08	4.160e+11	7.662	2.209
TransactionCost	1,560	21.71	161.7	3.443	23.17	11.60	2.605
TransactionConfirmationTime	1,560	9.389	29.25	4.600	3.133	8.461	2.054
NumberofTransactions	1,560	171,604	490,644	35,947	93,682	2.007	0.373

Table 2 - Extreme Events:

Table 2 explains the date, nature and probable effect of the BTC-ecosystem specific events included in our model. This table includes 26 events in a chronologically ascending order. The first major event happens on 18 November 2013 and the last event covered by us occurs on 13 September 2017.

Event ID	**Date**	**Event Synopsis**	**Explanation**	**Probable Effect**
EE1	18.11.2013	US senate holds hearing on bitcoin	Results of the hearing were beyond expectation, and senators agreed that bitcoin had great potential.	+ve
EE2	20.11.2013	People`s bank of China OK`s bitcoin	The deputy governor of the people's bank of China approves of bitcoin, stating that people are free to invest in it. This had a considerable positive effect on active Chinese BTC markets.	+ve
EE3	05.12.2013	Chinese Government bans financial institutions from using bitcoin	Financial institutions are prohibited from using bitcoin for trading, insuring or offering other financial services.	-ve
EE4	07.02.2014	Major exchanges hit with DDOS attacks	Trading stopped on Mt. Gox, Bitstamp and BTC-e because of massive DDOS attacks that were aimed at exploiting transaction weaknesses in the software of these exchanges.	-ve

EE5	24.02.2014	MT. Gox closes	Mt. Gox was closed following hacking of their poorly implemented software; internal document shows that 744000 BTC were lost.	-ve
EE6	26.03.2014	IRS Declares Bitcoin to be taxed as property	The IRS declare bitcoin as property instead of currency, thereby making bitcoin subject to capital gains tax.	-ve
EE7	10.04.2014	Chinese Exchanges Bank Accounts Closed	The Peoples` Bank of China frequently updated restrictions against bitcoin pressured some banks to issue deadlines against exchanges, requiring them to close their accounts. The Uncertain regulatory environment causes increased use of loopholes that almost all Chinese exchanges adopt.	-ve
EE8	17.07.2014	New York DFS releases proposed "BitLicense"	The Superintendent of New York department of Financial service announces regulations for businesses that interact with bitcoin and other cryptocurrencies. The regulations would require companies that deal with bitcoin to run back-ground checks etc. These regulations would affect entities operating in New York and their customers.	Unsure
EE9	06.10.2014	The slaying of bearwhale	Unknown trader places almost 30000 BTC for sale on Bit-stamp, at a total price of $9 M USD. This order was dubbed the "Bearwhale" because of its enormous size.	Unsure

EE10	11.12.2014	Microsoft Accepts Bitcoin	Microsoft announced that it would accept Bitcoin from US customers for digital content offered on the Windows and XBOX online stores, through a partnership with Bit-pay for Bitcoin payment processing.	+ve
EE11	04.01.2015	Bitstamp hacked	Hackers were able to steal 18866 Bitcoins from Bit-stamps hot wallet, worth about $5.2M. Following the discovery, the exchange was closed for 8 days to audit its systems and rebuild its trading platform. This led to significant damage to Bitstamps reputation.	-ve
EE12	03.06.2015	New York State releases the Bitlicense	The Superintendent of New York Department of Financial service released the set of rules meant to regulate Bitcoin and digital currency businesses (linked to 17.07.2014).	Unsure
EE13	01.08.2015	Mark Karpales Arrested	The CEO of failed bitcoin exchange Mt. Gox was arrested on charges of fraud related to Mt. Gox. He faced allegations of manipulation of trade volume and using funds for personal gain.	Unsure
EE14	15.08.2015	Bitcoin XT fork released	A separate version of the bitcoin client software was released, Bitcoin XT. This was caused by a wish to replace bitcoins one-megabyte block size limit with a maximum size that grows at a predictable rate over time. This culminated fears that bitcoin might not reach a consensus on this issue.	+ve

EE15	18.09.2015	Bitcoin declared as a commodity by the US regulator	The CTFC announced that charges against a bitcoin exchange had been filed and settled. The charges concerned facilitation of trading of options on its platform. By doing this, bitcoin and other virtual currencies were properly defined as commodities.	+ve
EE16	22.10.2015	EU declares No VAT on Bitcoin trades	The ECJ declares that the exchange of virtual currencies is not subject to Value-added-tax in the EU. In other words, virtual currencies are declared only as currencies, not as goods or property (like they are in the US).	+ve
EE17	31.10.2015	Bitcoin featured on front page of The Economist	The Economist made an article ("The trust machine") about blockchain, the featured cover story in its weekly magazine. This article promoted the idea that banks and institutions can implement blockchain technology, thereby creating cheaper and more secure databases.	Unsure
EE18	21.02.2016	Bitcoin round table consensus	Important members of the Bitcoin community met to debate a development plan for the scaling of bitcoin. This concluded with a statement supporting the new segregated witness functionality and making a hard fork which would increase blocksize by July 2016. Important to mention: Only a handful of Bitcoin companies were involved in this, which the meeting was heavily criticized for.	+ve

EE19	09.07.2016	Second halving day, reward for mining BTC's is reduced	The reward for mining blocks was reduced for the second time in Bitcoins history. The result of this was a new reward of 12.5 bitcoins, per mined block.	Unsure
EE20	09.11.2016	Donald Trump elected president	Following Trumps victory, global financial markets experienced turmoil. Large stock exchanges, like Dow Jones, suffered considerable losses. Bitcoin, on the other hand, experienced an increase in value of 5% in 24 hours, before stabilizing at a total increase of 2.5%.	Unsure
EE21	10.03.2017	SEC denies Winkelvos ETF (Exchange traded fund)	The Winklevoss twin's application to operate an ETF (exchange traded fund), in order to make it easier to buy bitcoin, is denied by the US government.	Unsure
EE22	28.03.2017	SEC denies second Bitcoin ETF application	The SEC denied Intercontinental Exchange Inc`s NYSE Arca exchange the ability to trade the the SolidX Bitcoin trust. This is an exchange-traded-product that would trade like a stock and track the assets price.	Unsure
EE23	01.04.2017	Japan declares Bitcoin as legal tender	Bitcoin is recognized as legal tender in Japan, following months of debate.	+ve

EE24	01.08.2017	Bitcoin "splits" into Bitcoin (BTC) and Bitcoin Cash (BCH)	Following years of discussion on how Bitcoin should scale up, bitcoin code is split into two directions. One direction supports optimization of blocks through segregated witness (segwit), another direction supports larger blocks of up to 8 MB. The last group called their currency bitcoin Cash and doubled the holdings of people owning bitcoin before 1 August.	+ve
EE25	01.09.2017	China Bans Cryptocurrency trading	China Bans Cryptocurrency trading.	-ve
EE26	13.09.2017	Jamie Dimon says Bitcoin is not going to work	Jamie Dimon CEO of BITCOIN says Bitcoin is not going to work.	-ve

Table 2.1 - Bitfinex related Events

Table 2.1 explains the date, nature and probable effect of Bitfinex (exchange) specific events included in our model. This table includes 12 events in a chronologically ascending order. The first event happens on 22 May 2015 and the last event covered by us occurs on 12 January 2017.

Event ID	Date	Event Synopsis	Explanation	Probable Effect
BRE1	22.05.2015	1500 BTC lost	Bitfinex loses 1,500 bitcoins, worth $400,000, when its hot wallets connected directly to the internet are hacked.	-ve
BRE2	02.06.2015	Bitfinex fined	The U.S. Commodity Futures Trading Commission (CFTC) fines Bitfinex $75,000 for offering illegal off-exchange financed retail commodity transactions in bitcoin and other cryptocurrencies.	-ve
BRE3	02.08.2016	Bitfinex Hacking	Hacking of Bitfinex that resulted in the theft of 120,000 BTC.	-ve
BRE4	06.08.2016	Socialization of hacking losses	Bitfinex announces that the losses will be socialized among all BTC holders on Bitfinex at the time of the hack.	-ve
BRE5	17.08.2016	Hack Audit	Bitfinex announces the hiring of Ledger labs to conduct the audit of the hack.	+ve
BRE6	13.10.2016	BFX Tokens conversion	BFX Tokens can be converted at a value of $1 as a compensation for the hack.	+ve

BRE7	31.03.2017	Wells Fargo suspends services	Well Fargo cuts services to Bitfinex.	-ve
BRE8	17.04.2017	Taiwanese banks suspend services	Taiwanese banks cut services to Bitfinex	-ve
BRE9	19.11.2917	Tether hacked	Tether, a popular cryptocurrency closely associated with Bitfinex management is hacked and $ 31 M USD worth of Tether are stolen.	-ve
BRE10	02.12.2017	Elimination of US operations	Bitfinex announces elimination of US operations	-ve
BRE11	21.12.2017	Account registration suspension	Without prior notice, Bitfinex suspends new account registrations.	-ve
BRE12	12.01.2017	Reopening of registrations	Account registrations are reopened by Bitfinex	+ve

Table 3 – Interpreting the CET Score

Table 3 explains how the Coefficient of elasticity (CET) score should be interpreted. This score is based on the following formula:

$$CET = \frac{\%\,\Delta\,Trading\ Volume}{\%\,\Delta\,Price}$$

If percentage price-increase is higher than percentage increase in trading volume this signals a rising market trend, a “Bull run”. If percentage price-decrease is higher than percentage increase in trading volume this signals a declining market trend, a “Bear hug”.

Value of CET Price Change	>1	=1	<1
Prices Increase	Price increases supported by more than proportionate change in volumes.	Price increases matched by proportionate change in volumes	Bull Run
Prices Decline	Price declines matched by more than proportionate change in volumes	Price declines matched by proportionate change in volumes	Bear Hug

Table 4 – Correlation matrix

Table 4 exhibits the correlation matrix between all the *primary* and *secondary variables* in our model. All the variables in Table 1 have been used in this table

	PriceAvg	BTCTrading VolumeUSD	Volatility	EUR3M_ LIBOR	USD3M _LIBOR	Market CapUSD	Sum Hashrate	Mining difficulty	Transaction Cost	Transaction Confirmation Time	Numberof Transactions
PriceAvg	1										
BTCTradingVolumeUSD	0.884***	1									
Volatility	0.885***	0.949***	1								
EUR3M_LIBOR	-0.411***	-0.321***	-0.288***	1							
USD3M_LIBOR	0.683***	0.542***	0.527***	-0.879***	1						
MarketCapUSD	0.999***	0.887***	0.896***	-0.419***	0.686***	1					
SumHashrate	0.911***	0.765***	0.751***	-0.652***	0.880***	0.912***	1				
Miningdifficulty	0.906***	0.763***	0.747***	-0.665***	0.892***	0.907***	0.989***	1			
TransactionCost	0.770***	0.664***	0.726***	0.139***	0.255***	0.764***	0.574***	0.564***	1		
TransactionConfirmationTime	0.337***	0.253***	0.232***	-0.557***	0.634***	0.336***	0.506***	0.525***	0.0307	1	
NumberofTransactions	0.536***	0.451***	0.412***	-0.919***	0.904***	0.541***	0.728***	0.725***	0.0289	0.616***	1

Table 5 – Econometric equations

Table 5 provides the results from the raw-equation {Eq (9)} in column 1 and the parsimonious equation {Eq (10)} in column 2. The standardized regression coefficients estimate the standard deviation change in the dependent variable for a one standard deviation change in the independent variable, while holding other variables constant. The results of this standardization process for Eq (10) can be viewed in column 3, and the 1 standard deviation value of each variable in Eq (10) is available in column 4. Column 5 exhibits the regression results for Eq (10) after controlling for heteroscedasticity

	(1)	(2)	(3)	(4)	(5)
Variables	**Equation (9)** *BTC Spread*	**Equation (10)** *BTC Spread*	**Equation (10)** *Standardized Regression Results*	**Equation (10)** *1Standard Deviation Value*	**Equation (10)** *Controlled for Heteroscedasticity*
Price(Avg)	3.32e-07 (3.80e-07)	-2.14e-7*** (8.13e-08)	-0.288	$ 2,733	-2.14e-07*** (5.73e-08)
BTC Trading Volume	-1.42e-12 (8.99e-13)				
Volatility	3.58e-05*** (1.19e-05)	1.10e-05** (5.21e-06)	0.0986	18.23	1.10e-05* (6.09e-06)
EUR3M_LIBOR	8.60e-01*** (8.38e-02)				
USD3M_LIBOR	4.22e-01*** (6.15e-02)	1.05e-01** (5.00e-02)	0.223	0.00433	1.05e-01*** (2.67e-02)
MarketCap	-2.33e-14 (2.37e-14)				

	(1)	(2)	(3)	(4)	(5)
Variables	**Equation (9)** *BTC Spread*	**Equation (10)** *BTC Spread*	**Equation (10)** *Standardized Regression Results*	**Equation (10)** *1Standard Deviation Value*	**Equation (10)** *Controlled for Heteroscedasticity*
Sum Hash rate	5.65e-23 (9.33e-23)				
Miningdifficulty	-1.14e-15 (9.08e-16)	-1.84e-15*** (6.03e-16)	-0.377	4.160e+11	-1.84e-15*** (2.75e-16)
TransactionCost	-9.57e-06* (5.79e-06)	4.25e-05*** (4.43e-06)	0.484	$ 23.17	4.25e-05*** (3.92e-06)
TransactionConfirmationTime	-8.01e-06 (1.80e-05)	5.06e-05*** (1.80e-05)	0.0778	3.133	5.06e-05*** (1.20e-05)
NumberofTransactions	-6.60e-10 (1.75e-09)	-5.11e-09*** (1.47e-09)	-0.235	93,682	-5.11e-09*** (1.12e-09)
Mon	1.59e-04 (1.52e-04)				
Tue	1.45e-04 (1.57e-04)				
Wed	8.26e-05 (1.56e-04)				
Thur	-4.35e-05 (1.54e-04)				

	(1)	(2)	(3)	(4)	(5)
Variables	**Equation (9)** *BTC Spread*	**Equation (10)** *BTC Spread*	**Equation (10)** *Standardized Regression Results*	**Equation (10)** *1Standard Deviation Value*	**Equation (10)** *Controlled for Heteroscedasticity*
Fri	-4.54e-05 (1.53e-04)				
Sat	-1.23e-05 (1.47e-04)				
Sund	0.00e+00 (.)				
EE1	3.43e-03*** (6.32e-04)				
EE2	4.92e-03*** (4.20e-04)				
EE3	3.51e-03*** (4.26e-04)	2.98e-03*** (4.56e-04)	0.143		0.00298*** (0.000478)
EE4	2.76e-03*** (4.13e-04)	3.02e-03*** (4.42e-04)	0.145		0.00302 (0.00252)
EE5	1.16e-04 (4.13e-04)				
EE6	-2.30e-04 (4.18e-04)				

	(1)	(2)	(3)	(4)	(5)
Variables	**Equation (9)** *BTC Spread*	**Equation (10)** *BTC Spread*	**Equation (10)** *Standardized Regression Results*	**Equation (10)** *1Standard Deviation Value*	**Equation (10)** *Controlled for Heteroscedasticity*
EE7	-2.70e-04 (4.19e-04)				
EE8	-8.96e-04** (4.06e-04)				
EE9	3.15e-05 (4.04e-04)				
EE10	-5.22e-04 (4.03e-04)				
EE11	-7.16e-05 (4.05e-04)				
EE12	-4.83e-04 (4.04e-04)				
EE13	-4.85e-04 (4.03e-04)				
EE14	-8.91e-05 (4.03e-04)				
EE15	-2.05e-04 (4.04e-04)				

	(1)	(2)	(3)	(4)	(5)
Variables	**Equation (9)** *BTC Spread*	**Equation (10)** *BTC Spread*	**Equation (10)** *Standardized Regression Results*	**Equation (10)** *1Standard Deviation Value*	**Equation (10)** *Controlled for Heteroscedasticity*
EE16	2.27e-04 (5.19e-04)				
EE17	6.71e-04* (4.06e-04)				
EE18	1.08e-04 (4.04e-04)				
EE19	5.35e-04 (4.08e-04)				
EE20	8.28e-05 (4.06e-04)				
EE21	-2.89e-04 (4.10e-04)				
EE22	-2.72e-04 (9.83e-04)				
EE23	-2.23e-04 (7.17e-04)				
EE24	-2.54e-04 (4.18e-04)				

	(1)	(2)	(3)	(4)	(5)
Variables	**Equation (9)** *BTC Spread*	**Equation (10)** *BTC Spread*	**Equation (10)** *Standardized Regression Results*	**Equation (10)** *1Standard Deviation Value*	**Equation (10)** *Controlled for Heteroscedasticity*
EE25	-8.77e-05 (4.67e-04)				
EE26	3.91e-05 (4.32e-04)				
BRE1	-4.29e-04 (4.92e-04)				
BRE2	5.83e-04 (4.53e-04)				
BRE3	3.45e-03*** (6.10e-04)	3.31e-03*** (6.63e-04)	0.130		3.31e-03 (0.00225)
BRE4	3.20e-03*** (6.10e-04)	2.92e-03*** (6.64e-04)	0.115		2.92e-03 (0.00225)
BRE5	1.09e-04 (4.94e-04)				
BRE6	-7.49e-05 (4.94e-04)				

Variables	(1) Equation (9) *BTC Spread*	(2) Equation (10) *BTC Spread*	(3) Equation (10) *Standardized Regression Results*	(4) Equation (10) *1Standard Deviation Value*	(5) Equation (10) *Controlled for Heteroscedasticity*
BRE7	-1.28e-04				
	(8.00e-04)				
BRE8	-1.02e-04				
	(4.96e-04)				
BRE9	5.26e-04				
	(5.33e-04)				
BRE10	-3.19e-04				
	(5.98e-04)				
BRE11	-1.75e-03*				
	(9.94e-04)				
BRE12	4.93e-04				
	(8.54e-04)				
Constant	-2.99e-05	5.82e-04***	0.000582***		0.000582***
	(2.37e-04)	(2.03e-04)			(0.000169)
Observations	1560	1560	1,560		1,560
R^2	0.453	0.331	0.331		0.331

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 – Variance Inflation Factor (VIF) Test

Table 6 provides the results from Variance inflation factor (VIF) tests on eq (9) and eq (10). The VIF test is used to check whether multi-collinearity is an issue or not. Multi-collinearity results in inflation of the standard-errors and the variance of estimated coefficients. The table shows both the individual results for each variable, and the mean VIF for the whole model. A high VIF signifies an issue of multi-collinearity.

Eq(9)			Eq(10)		
Variables	**VIF**	**1/VIF**	**Variables**	**VIF**	**1/VIF**
MarketCapUSD	797.26	0.001254			
PriceAvg	713.88	0.001401	PriceAvg	27.54	0.036314
Miningdiff~y	94.69	0.010561	Miningdiff~y	35.11	0.02848
SumHashrate	60.19	0.016613			
USD3M_LIBOR	47.06	0.021249	USD3M_LIBOR	26.2	0.038172
Volatility	31.17	0.032087	Volatility	5.04	0.198553
EUR3M_LIBOR	24.79	0.040342			
BTCTrading~D	19.35	0.051677			
NumberofTr~s	17.75	0.056335	NumberofTr~s	10.56	0.094701
Transactio~t	11.95	0.083693	Transactio~t	5.87	0.170301
BRE7	3.78	0.264744			
EE23	3.25	0.307559			
Transactio~e	2.11	0.474385	Transactio~e	1.78	0.561495
Tue	1.99	0.502671			
Wed	1.97	0.506965			
Thur	1.94	0.516519			
Fri	1.9	0.525404			
Mon	1.89	0.530445			
Sat	1.77	0.566389			
BRE11	1.68	0.596724			
BRE3	1.64	0.610385	BRE3	1.56	0.640049
EE22	1.57	0.635102			
BRE4	1.57	0.636701	BRE4	1.57	0.638647
BRE10	1.51	0.662405			
BRE12	1.24	0.807963			
BRE9	1.2	0.83289			
EE26	1.18	0.849356			
EE3	1.15	0.871434	EE3	1.1	0.905583
EE2	1.11	0.897907			
EE7	1.11	0.902345			
EE25	1.11	0.904092			
EE24	1.1	0.906902			
EE6	1.1	0.907454			
EE4	1.08	0.926191	EE4	1.04	0.96305

Eq (9)			Eq (10)		
Variables	**VIF**	**1/VIF**	**Variables**	**VIF**	**1/VIF**
EE5	1.08	0.926524			
EE21	1.06	0.942332			
EE19	1.05	0.952293			
EE17	1.04	0.958285			
BRE2	1.04	0.960721			
BRE8	1.04	0.962022			
EE8	1.04	0.962343			
EE20	1.04	0.962497			
EE11	1.03	0.96677			
EE18	1.03	0.96843			
EE9	1.03	0.968847			
EE12	1.03	0.969111			
BRE5	1.03	0.970198			
BRE6	1.03	0.971313			
EE15	1.03	0.971623			
EE10	1.03	0.972353			
EE13	1.03	0.974877			
EE14	1.03	0.974938			
EE16	1.02	0.977302			
BRE1	1.02	0.977828			
EE1	1.01	0.986143			
EE16	1.02	0.97731			
BRE1	1.02	0.977827			
EE1	1.01	0.986148			
Mean VIF	**34.18**		**Mean VIF**	**10.67**	

Table 7– Correlation Matrix -Rolls Measure

Table 7 provides the results of the correlation between the BTC bid-ask spread and the Rolls measure generated implicit spreads. The Rolls measure assumes that trading costs are negatively serially correlated with subsequent price changes. Column 1 presents the results of the scenario where the "number error" values were multiplied with negative 1 and the resulting dataset was used to run the correlation test. Column 2 presents similar results but for monthly data. Column 3 presents the correlation results for the scenario where the "number error" values were changed to 0 and the resulting dataset was used to run the correlation test. Column 4 presents the correlation results for the scenario where the "number error" values were left as missing and the resulting dataset was used to run the correlation test. The reasons for running these different iterations have been discussed in section 3.3.1.

	(1) Daily rolls spreads *(Errors *-1)*	(2) Monthly rolls Spreads *(Errors *-1)*	(3) Daily rolls spreads *(Errors changed to 0)*	(4) Daily rolls spreads *(Errors left as missing)*
Daily Bitfinex spreads	-0.0326		-0.0517^{*}	-0.0618
Monthly (Avg) Bitfinex Spreads		-0.122		

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8 – Correlation Matrix -ILLIQ Measure

Table 8 shows the results of the correlation test between the ILLIQ measure and the BTC bid-ask spread. ILLIQ is based on the hypothesis that expected stock-return is a function of illiquidity. Column (1) shows the correlation between daily BTC bid-ask spread and daily ILLIQ spread, whereas, column (2) shows the correlation between monthly BTC bid-ask spread and ILLIQ spread.

	(1) Daily ILLIQ spreads	(2) Monthly ILLIQ spreads
Daily Bitfinex spreads	0.241^{***}	
Monthly (Avg) Bitfinex Spreads		0.434^{**}

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9– Correlation Matrix –Coefficient of Elasticity Measure

Table 9 shows the correlation between the BTC bid-ask spread and the Coefficient of Elasticity (CET) measure. CET is based on an argument that the ideal measure of liquidity should include price and volume. Column (1) shows the correlation between daily BTC bid-ask spread and daily CET spread, whereas, column (2) shows the correlation between monthly BTC bid-ask spreads and monthly CET spreads.

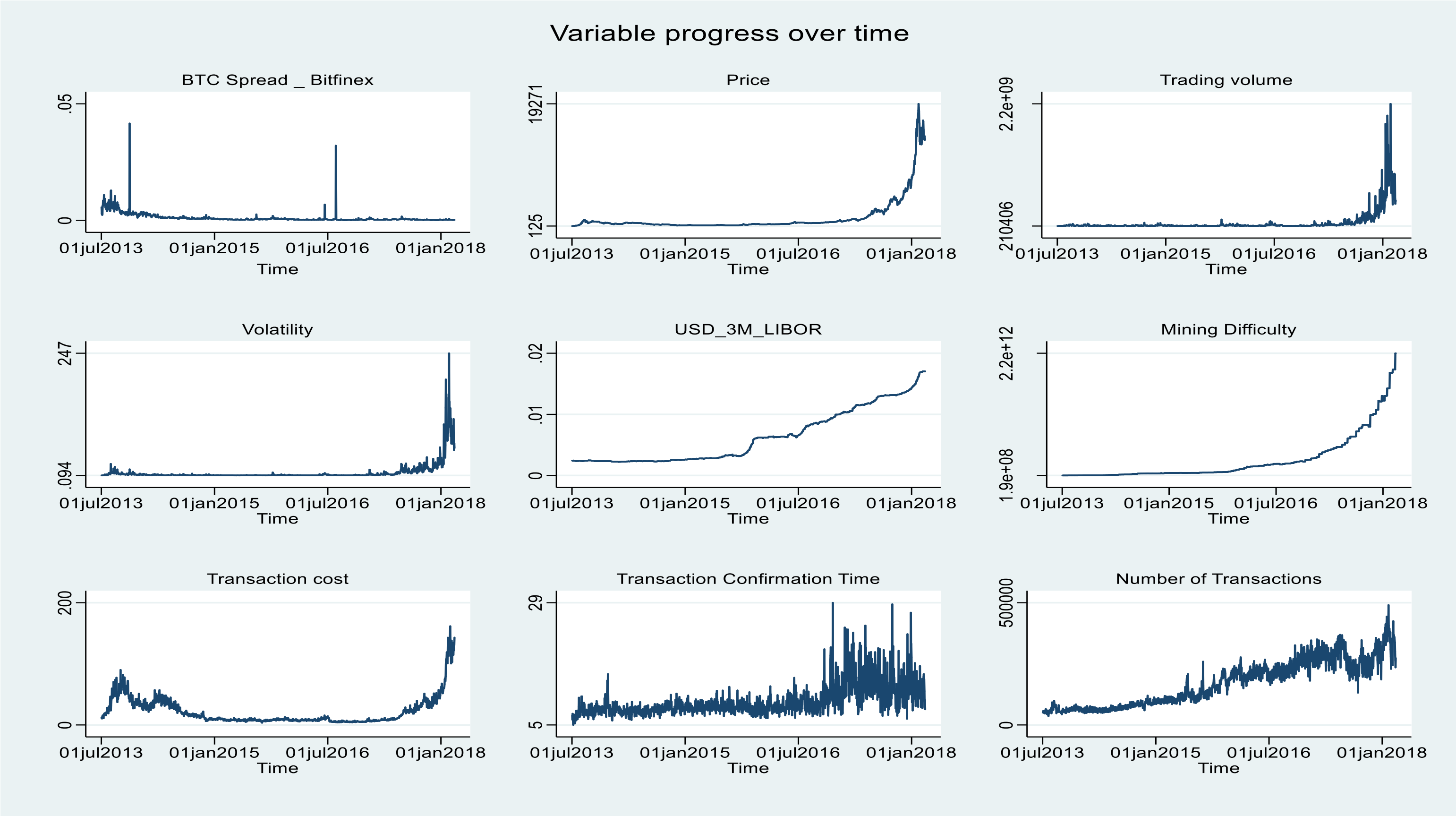
	(1) Daily CET spreads	(2) Monthly CET spreads
Daily Bitfinex spreads	-0.00885	
Monthly (Avg) Bitfinex Spreads		-0.106

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

7. Graphs

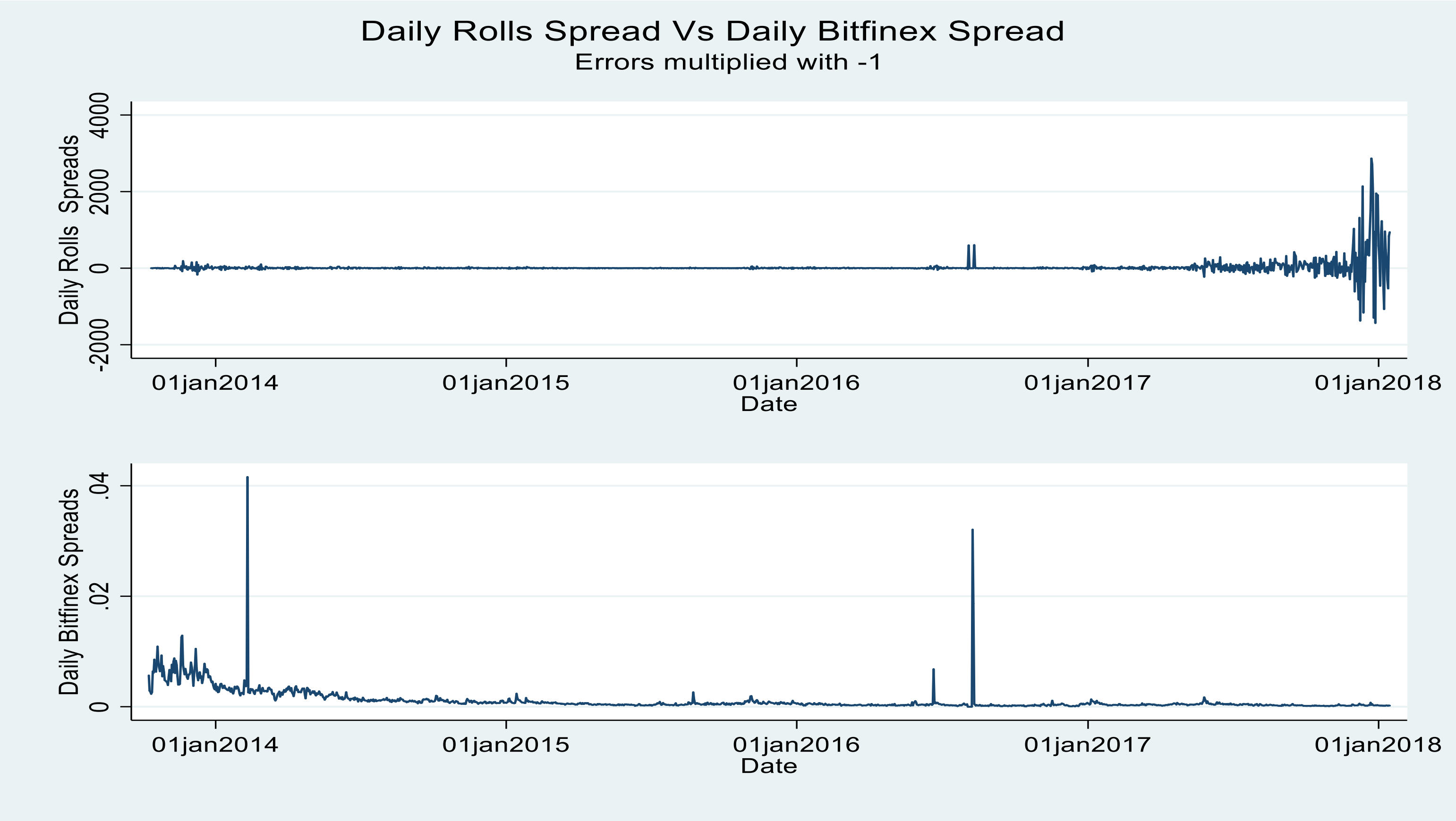
Graph 1 – Time Development of Variables

Graph 1 provides an overview of the daily development in the values of the *primary* and *secondary variables* from equation 10. This data spans between 1 July 2013 to 15 January 2018.



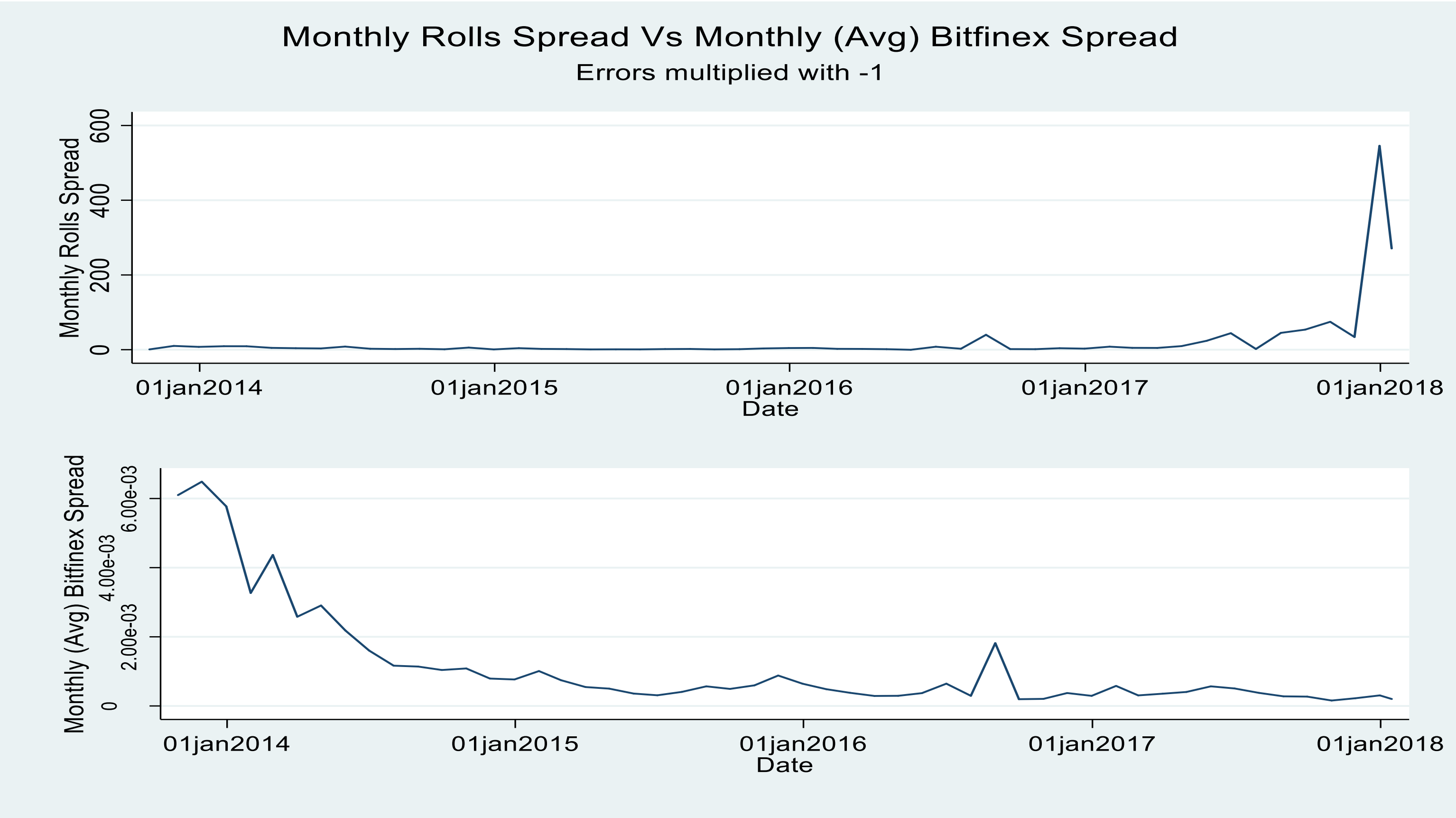
Graph 2 – Daily Rolls Spreads

Graph 2 shows a comparison between the development of daily Rolls spreads when "number errors" are multiplied with negative 1, and daily BTC bid-ask spread. The data covers 1560 days, starting from 9 October 2013 to 15 January 2018.



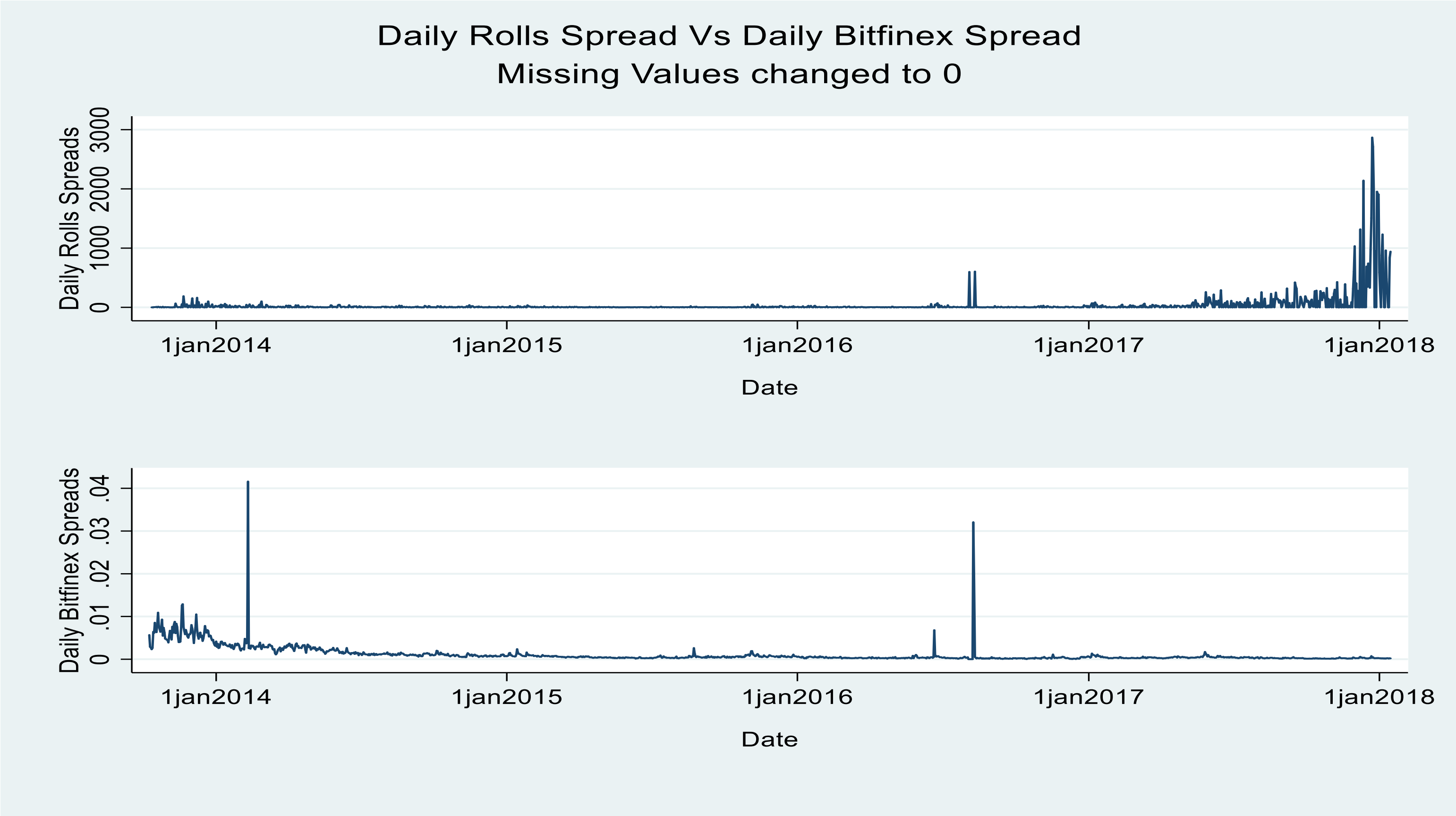
Graph 3 – Monthly Rolls Spreads

Graph 3 shows a comparison between the development of monthly Rolls spreads when "numbers errors" are multiplied with negative 1, and monthly average BTC bid-ask spread.



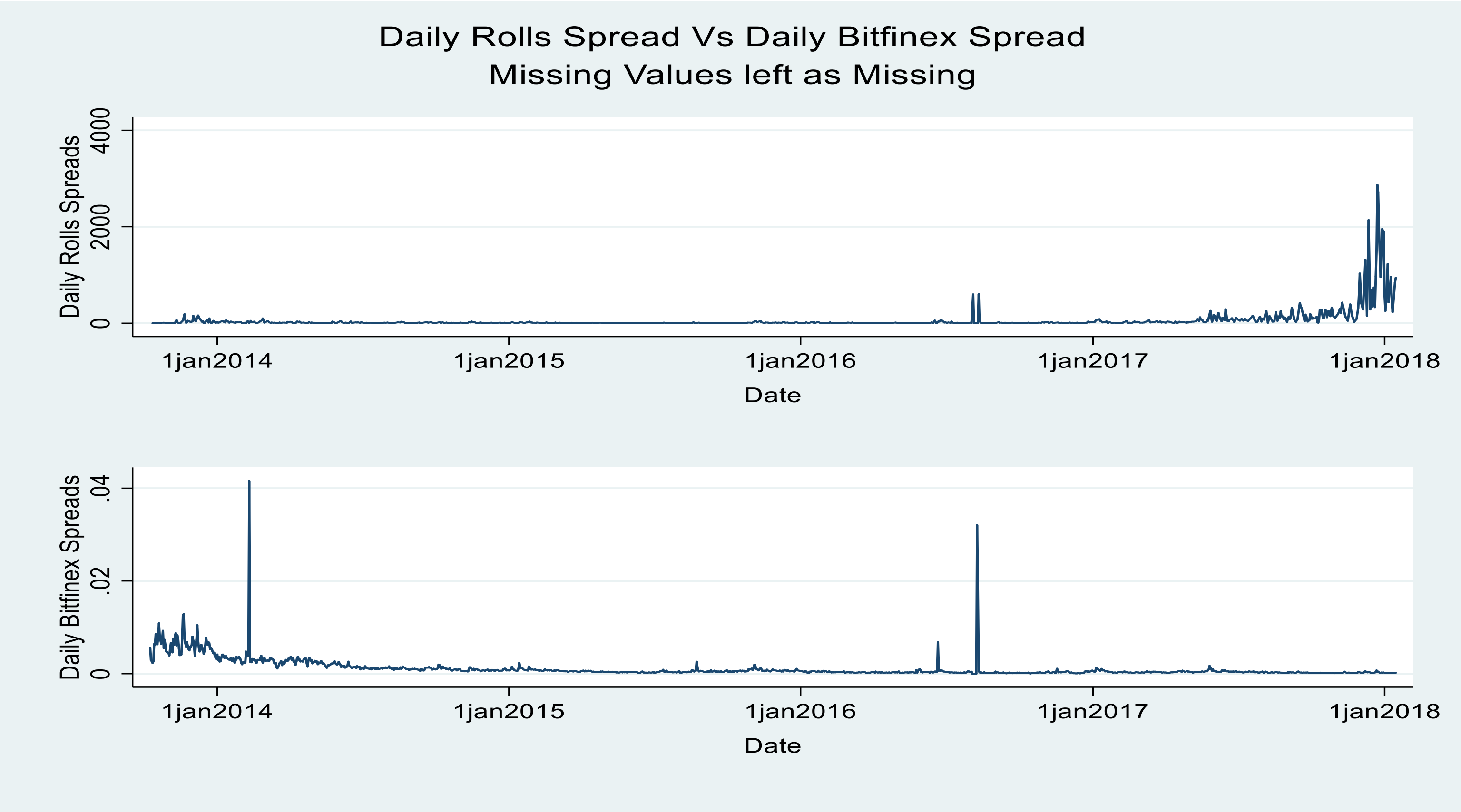
Graph 4– Daily Rolls Spreads – Number Errors Changed to 0

Graph 4 shows a comparison between the development of daily Rolls spread when “number errors” are changed to 0, and daily BTC bid-ask spread.



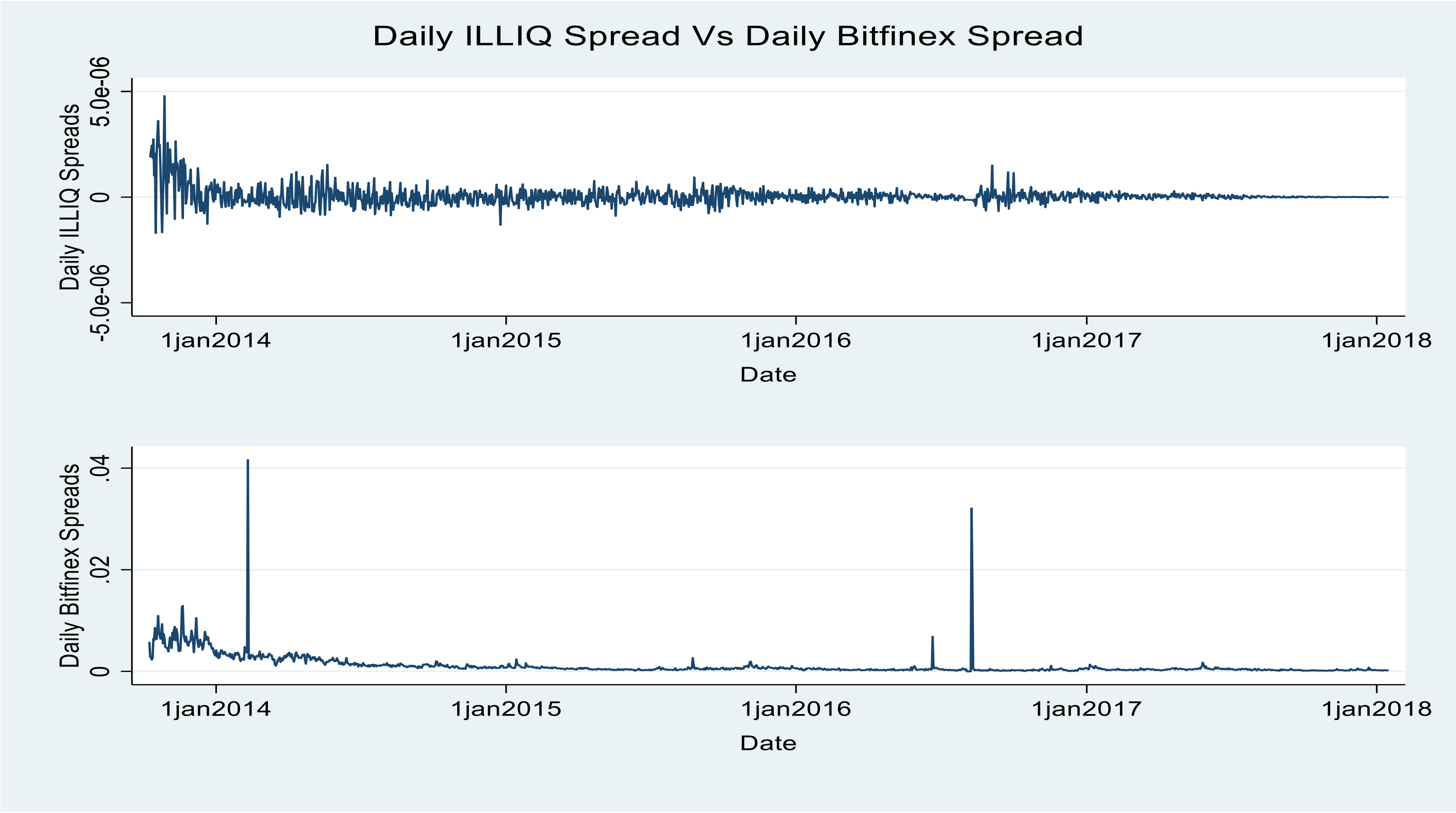
Graph 5 – Daily Rolls Spreads – Number Errors left Missing

Graph 5 shows a comparison between the development of daily Rolls spread when the "number errors" are left as missing, and daily BTC bid-ask spread.



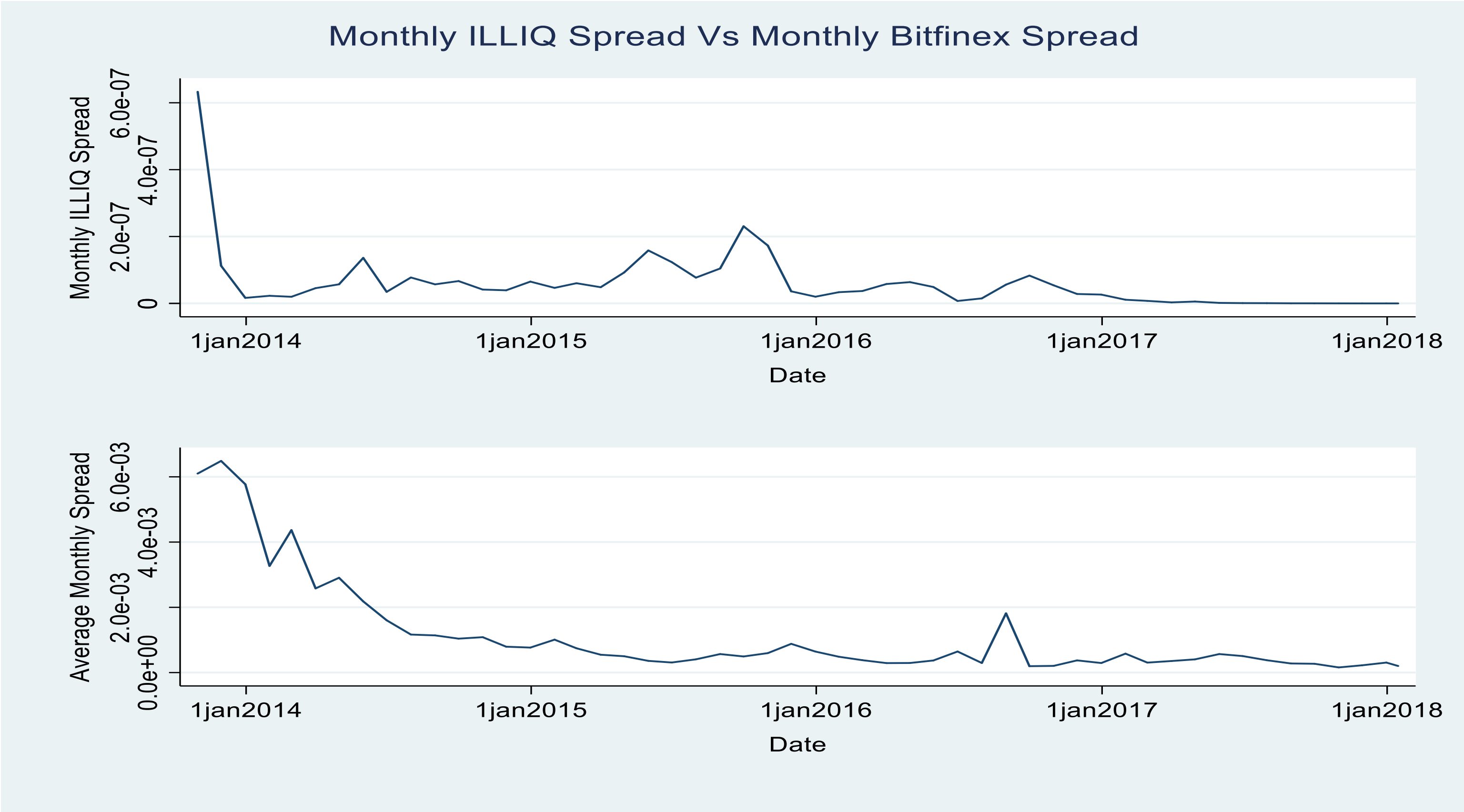
Graph 6 – Daily ILLIQ Spreads

Graph 6 provides a comparison between the development of daily ILLIQ spread and daily BTC bid-ask spread. The data covers 1560 days, starting from 9 October 2013 to 15 January 2018. The ILLIQ spread is measured as the average daily ratio of absolute stock return to dollar volume, the BTC bid-ask spread is measured in units.



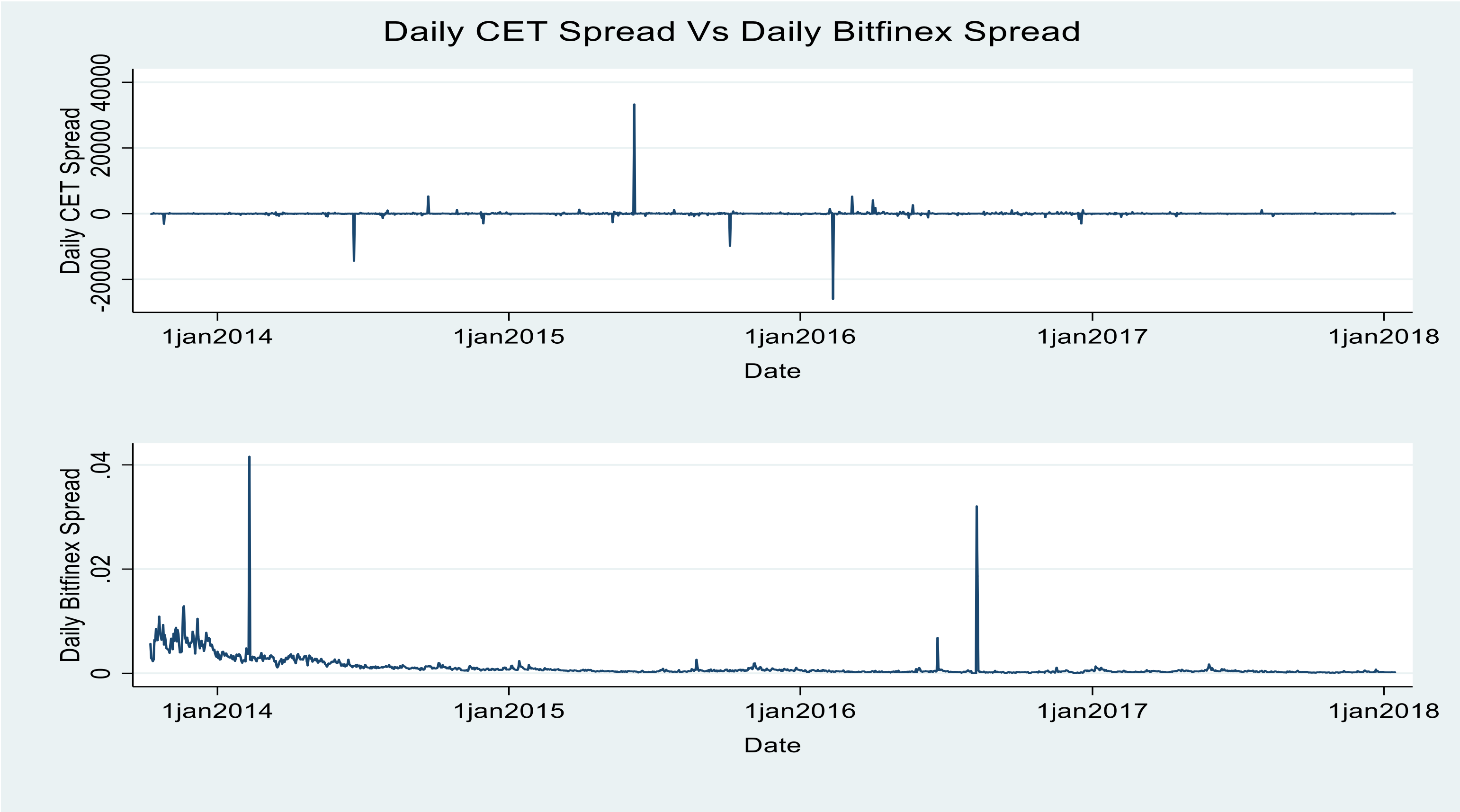
Graph 7 – Monthly ILLIQ Spreads

Graph 7 provides a comparison between the development of monthly ILLIQ spread and monthly BTC bid-ask spread.



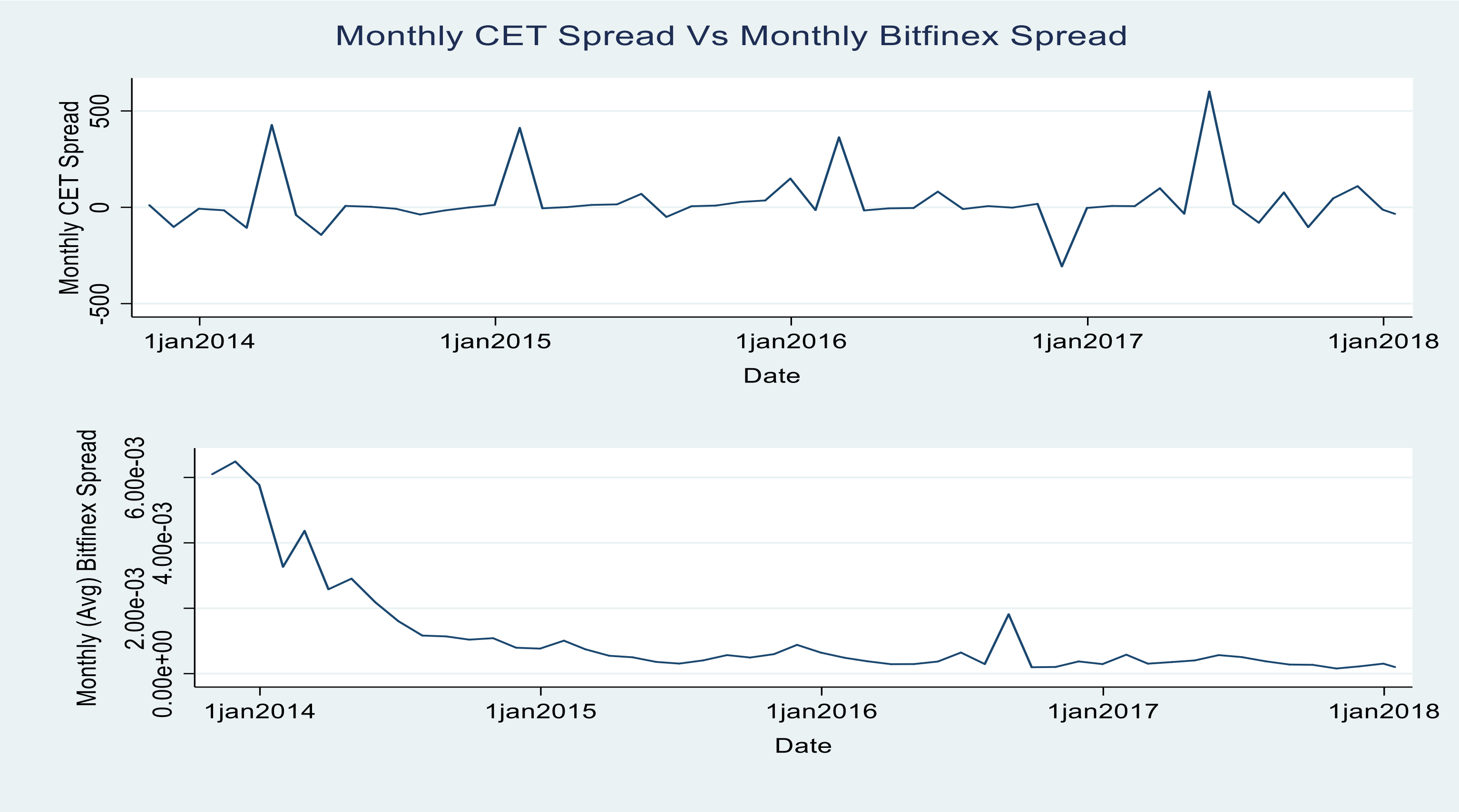
Graph 8 – Daily Coefficient Of Elasticity (CET)

Graph 8 shows a comparison between the daily Coefficient of Elasticity (CET) result and daily BTC bid-ask spread. The data covers 1560 days, a time-period starting from 9 October 2013 to 15 January 2018. The CET is measured as turnover of percentage change in trading volume and percentage change in price.



Graph 9 – Monthly Coefficient Of Elasticity (CET)

Graph 9 shows a comparison between the monthly Coefficient of Elasticity (CET) results and monthly BTC bid-ask spread.



8. Bibliogrpahy

Admati, A. R., & Pfleiderer, P. (1988). A Theory of Intraday Patterns: Volume and Price Variability. *Review of Financial Studies*, *1*(1), 3–40. http://doi.org/10.1093/rfs/1.1.3

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31–56. http://doi.org/10.1016/S1386-4181(01)00024-6

Baur, D. G., Lee, A. D., & Hong, K. (2015). Bitcoin: Currency or Investment? *SSRN Electronic Journal*, (December), 1–38. http://doi.org/10.2139/ssrn.2561183

Blockchain.info. (2018). No Title.

Bongaerts, D., Jong, F. De, & Driessen, J. (2011). An asset pricing approach to liquidity effects in corporate bond markets, (September), 1–63. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2065893%5Cnhttps://www.dropbox.com/s/09236w51qkw8oyq/2011 Bongaerts.pd

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market Liquidity and Trading Activity. *Journal of Finance*, *56*(2), 501–530. http://doi.org/10.1111/0022-1082.00335

Chordia, T., Sarkar, A., & Subrahmanyam, A. (2005). An Empirical Analysis of Stock and Bond Market Liquidity. *The Review of Financial Studies*, *18*(1), 85–129. http://doi.org/10.1093/rfs/hhi010

Chordia, T., Shivakumar, L., & Subrahmanyam, A. (2004). Recent work. *Economic Notes*, 297–309. http://doi.org/10.1093/analys/ant117

Christian, M. (2014). Bitcoin - Asset or Currency? Revealing Users' Hidden Intentions. *Twenty Second European Conference on Information Systems*, 1–14. http://doi.org/10.1007/978-3-319-42448-4_6

Ciaian, P., Rajcaniova, M., & Kancs, d'Artis. (2016). The economics of BitCoin price formation. *Applied Economics*, *48*(19), 1799–1815. http://doi.org/10.1080/00036846.2015.1109038

Damodaran, A. (2005). The Cost of Illiquidity, *Available*, 1–48.

Datar, M. K. (2000). Stock market liquidity: Measurement and implications. In *Proceedings of the 4th Capital Market Conference*. Citeseer.

Demsetz, H. (1968). The Cost of Transacting Author (s): Harold Demsetz Published by : Oxford University Press Stable URL : http://www.jstor.org/stable/1882244. *The Quarterly Journal of Economics*, *82*(1), 33–53.

Downing, C., & Zhang, F. (2004). Trading Activity and Price Volatility in the Municipal Bond Market. *Journal of Finance*, *59*(2), 899–931. http://doi.org/10.1111/j.1540-6261.2004.00652.x

Eknemar, M., & Short, W. J. (2011). Like liquid off a Danes back A quantitative study of illiquidity in the Copenhagen Stock Exchange.

Fama, E. F. (1991). Efficient Capital Markets: II. *Journal of Finance*, *46*(5), 1575–1617. http://doi.org/10.1111/j.1540-6261.1991.tb04636.x

Fleming, M. (2001). Measuring treasury market liquidity. *IDEAS Working Paper Series from RePEc*.

Fomby, T. B., & Murfin, J. R. (2005). Inconsistency of HAC standard errors in event studies with i.i.d. errors. *Applied Financial Economics Letters*, *1*(4), 239–242. http://doi.org/10.1080/17446540500143418

Ford, G. S., Jackson, J. D., & Skinner, S. J. (2010). HAC standard errors and the event study methodology: a cautionary note. *Applied Economics Letters*, *17*(12), 1153–1156. http://doi.org/10.1080/17446540902817601

Goyenko, R., Holden, C. W., & Trzcinka, C. (2008). *Do Measures of Liquidity Measure Liquidity? SSRN Electronic Journal*. http://doi.org/10.2139/ssrn.1108553

Harris, L. (1990). Statistical Properties of the Roll Serial Covariance Bid/Ask Spread Estimator. *Journal of Finance*, *45*(2), 579–590. http://doi.org/10.1111/j.1540-6261.1990.tb03704.x

Hasbrouck, J. (2009). Published by : Wiley for the American Finance Association Linked references are available on JSTOR for this article : Trading Costs and Returns for U . S . Equities : Estimating Effective Costs from Daily Data, *64*(3), 1445–1477.

Ho, T., & Stoll, H. R. (1981). Optimal dealer pricing under transactions and return uncertainty. *Journal of Financial Economics*, *9*(1), 47–73. http://doi.org/10.1016/0304-405X(81)90020-9

Jegadeesh, N., & Subrahmanyam, A. (1993). Liquidity Effects of the Introduction of the S& P 500 Index Futures Contract on the Underlying Stocks. *The Journal of Business*, *66*(2), 171–187. http://doi.org/10.1086/296600

Koteska, B., Karafiloski, E., & Mishev, A. (2017). Blockchain Implementation Quality Challenges: A Literature Review.

Kothare, M., & Laux, P. A. (1995). Trading costs and the trading systems for Nasdaq stocks. *Financial Analysts Journal*, *51*(2), 42–53.

Kyle, A. S. (1985). Continuous Auctions and Insider Trading. *Econometrica, 53*(6), 1315–1335. http://doi.org/10.3982/ECTA6822

Makarov, I. (2018). Trading and arbitrage in Cryptocurrency Markets. Retrieved from http://personal.lse.ac.uk/makarov1/research.html

Minaki, T. (2013). Liquidity in Japanese government bond futures market. *International Journal of Business*, *18*(4), 320–331.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system.

Roll, R. (1984). A Simple Implicit Measure of the Effective Bid- Ask Spread in an Efficient Market. *Journal of Finance*, *39*(4), 1127–1139. http://doi.org/10.1111/j.1540-6261.1984.tb03897.x

Schultz, P. (2000). Stock Splits, Tick Size, and Sponsorship. *The Journal of Finance*, *55*(1), 429–450. http://doi.org/10.1111/0022-1082.00211

St.Louis, F. R. B. (2018). No Title.

Stoll, H. R. (1978). THE PRICING OF SECURITY DEALER SERVICES: AN EMPIRICAL STUDY OF NASDAQ STOCKS. *Journal of Finance*, *33*(4), 1153–1172. http://doi.org/10.1111/j.1540-6261.1978.tb02054.x

Trimborn, S., Li, M., & Härdle, W. (2017). Investing with cryptocurrencies - A liquidity constrained investment approach. *IDEAS Working Paper Series from RePEc*.

Van Ness, B. F., Van Ness, R. A., & Warr, R. S. (2005). Nasdaq Trading and Trading Costs: 1993–2002. *Financial Review*, *40*(3), 281–304. http://doi.org/10.1111/j.1540-6288.2005.00103.x

Wyart, M., Bouchaud, J.-P., Kockelkoren, J., Potters, M., & Vettorazzo, M. (2008). Relation between bid– ask spread, impact and volatility in order- driven markets. *Quantitative Finance*, *8*(1), 41–57. http://doi.org/10.1080/14697680701344515