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The impact of bitcoin futures on liquidity and intraday volatility

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Abstract

This paper examines the impact of bitcoin futures on spot volatility using three GARCH type models and intraday returns, while also measuring impact on liquidity with a liquidity-adjusted CAPM. Liquidity is defined by three proxies and its relation with bitcoin return is determined by the illiquidity premium theory. The GARCH analyses reveal that volatility decreases after futures trading where the news coefficient decreases, persistence of past volatility increases and a leverage effect develops. The volatility decrease is therefore not because of an improved information flow which futures markets are expected to provide. Furthermore, a lower liquidity shows a negative impact on return in the pre-futures sample which is the opposite of the illiquidity premium theory. The post-futures sample does not give significant results which is why no clear evidence is obtained about the effect of futures on liquidity. The stabilization hypothesis is still preferred because of speculators leaving the spot market for the futures market, where the former becomes less volatile.

Keywords: Bitcoin, Volatility, GARCH, Liquidity, CAPM, Futures

Contents

1. Introduction

Over the past year bitcoin has become a hot debated item among traders, regulators and academics. While traders are eager to make a profit in these volatile markets and regulators standing on the sidelines, this new asset gives academics the opportunity to research its financial characteristics. One interesting topic is the introduction of bitcoin futures and its effect on the bitcoin spot market. The first bitcoin futures contract was introduced mid-December 2017 by Cboe Futures Exchange. In the same month, the CME Group also launched bitcoin futures. Now Nasdaq also expressed interest to launch such futures which will finalize this year probably. The possible effect of these futures on the spot market remains on the table. This paper will try to fill this gap by addressing the impact of these futures on the spot market.

The main objective is to find out how futures trading affect liquidity and volatility in the spot market. In equity research, the answer to this question is mixed. Some papers claim that a futures market has a stabilizing effect by increasing liquidity of the spot market and therefore reducing its volatility. Others show empirical evidence that futures trading has led to increased volatility. However, given the unusual type of market bitcoin belongs to, these results in equity markets certainly cannot be extrapolated to the bitcoin market. As a result, new research is required. This paper will use three GARCH type models to estimate bitcoin volatility before and after the introduction of futures. The impact of futures trading on spot market liquidity is measured by tracking the illiquidity premium on bitcoin returns. The illiquidity premium is estimated by a liquidity-adjusted capital asset pricing model. This paper defines liquidity by three proxies.

Empirical studies regarding bitcoin futures have been conducted to a lesser extent. A paper by Corbet, Lucy, Peat and Vigne (2018) examines the effect of the introduction of bitcoin futures. They study whether the ability to trade bitcoin futures decrease the volatility in the spot market in order to be able to classify bitcoin as a currency. Their analysis show that spot volatility has increased following the introduction of futures contracts and that the nature of bitcoin as a speculative asset has not been altered. Another paper by Shimeng (2017) examines the impact of bitcoin futures trading on the intraday spot volatility and liquidity. His results show that volatility has been reduced and liquidity increased.

This paper contributes to the literature by adjusting for some points of concern. First of all, both mentioned papers focus on the effect of the introduction of futures rather than the futures trading itself. They use a timeframe which is too short to fully utilize the futures trading effect and not desirable anyway as these months are not representative for the later period. Moreover, the paper by Corbet et al (2018) uses a GARCH model to estimate volatility while an asymmetric GARCH type model is also preferred since bitcoin is still officially labeled as a currency. As known for financial time-series, leverage effects could be present and that must be accounted for. Another issue is the ill-defined methodology used by Shimeng (2017) regarding the impact on liquidity. This paper corrects for these shortcomings, the amount of data will be extended and a standard GARCH, EGARCH, TGARCH will be used to explain bitcoin price volatility. Furthermore, the CAPM extended by three liquidity proxies will be used to estimate the illiquidity premium. One liquidity proxy focuses on price impact and the other two on bid-ask spreads. These are respectively the Amihud illiquidity ratio, Roll's bid-ask spread proxy and Corwin/Schultz bid-ask spread proxy. The results show that the nature of bitcoin spot volatility significantly changes after the introduction of futures. The "news" coefficient decreases while the "old news" coefficient increases, persistence of past shocks increases. The leverage effect appears after the introduction of futures. On the other hand, bitcoin futures seem to distort the information flows to the market since the news coefficient decreases. These results are in contrast with the theoretical stabilization hypothesis and with empirical work by Oduncu (2011) and Antoniou and Holmes (1995). The conditional variance shows signs of decreased volatility in the post-futures sample and supports the first hypothesis in this paper. The results regarding the liquidity analysis show that the Roll's proxy does not work well, while the Corwin/Schultz proxy is an improvement. The Amihud illiquidity proxy performs the best. Significant coefficients, if any, are only present in the pre-futures sample which is why no inferences can be made about the illiquidity premium hypothesis.

The paper is structured as follow: Section 2 gives an overview of the literature regarding futures in equity markets and bitcoin markets. Section 3 discusses data and some descriptive statistics. Section 4 states the methodology. Empirical results are presented in section 5. Finally, section 6 contains concluding remarks.

2. Literature

The impact of futures trading on the underlying spot market has been a concern for some time. There are two theoretical hypotheses on the influence of a futures market on the spot price volatility, from here on called the stabilization and destabilization hypothesis. The stabilization hypothesis states that the availability of futures, riskier and able to short, offers speculative investors opportunities which they prefer to investment in the spot market. These investors will leave the spot market and turn to the futures market, leaving the spot market to the risk-averse investors, which then becomes less volatile. This effect will draw more risk-averse investors into the spot market, increasing the liquidity and therefore reducing the volatility . The lower cost of futures trading may attract informed arbitrageurs to trade in both the future and spot market, increasing the liquidity in the latter as well (Danthine, 1978). Moreover, futures trading could improve the quality and distribution of information, which is an important factor that determines the level of prices. A theoretical contribution by Cox (1976) states that futures trading alters the flow of information into the market. Since futures markets are centralized, information flows more efficiently and distributed to both futures traders and spot market participants. As a result, the decision making process could improve and prices a better representative of their fundamental economic value, eventually reducing price volatility. Another way of interpreting the stabilization hypothesis is that the futures market allows transfer of risk from hedgers to speculators. The need to incorporate risk premium in the spot market transaction to compensate the risk of price volatility is eliminated. Therefore the spot price volatility is reduced (Figlewski, 1981).

The destabilization hypothesis states that a futures market can increase spot price volatility. There is a possibility that a futures market could cause significant hedge trading without attracting enough speculation to enable an effective risk transfer. The hedging pressure in futures can then spill over into the spot market where market participants end up bearing risk transferred through both the spot and the futures market. Futures trading may also increase volatility if investors in futures do not have sufficient information as investors in the spot market. If traders in the futures market do not have accurate or sufficient information, they will drive the spot price away from their appropriate value. In case of such a situation, it will create profitable opportunities for the better informed spot market investors whose trading will serve to stabilize futures prices while allowing higher volatility in spot prices (Figlewski, 1981). Given these two hypotheses, the issue in question remains an empirical one.

In equity research, emperical evidence on the effects of futures on the underlying asset is ambigouis. A paper by Robinson (1993) presents an analysis on the impact of futures on the FTSE-All Share Index price volatility. An augmented ARCH framework was used and the effect of changes in monetary policy taken into account as considerd an important factor of stock price conditional volatility. The results show a significant decrease in FTSE-All Share Index volatility of 17% due to futures trading. Therefore he concludes that the futures market promote stability in the London Stock Exchange. Another paper by Edwards (1988) shows that the S&P500 market volatility is lower after the introduction of futures. In contrary, a paper by Harris (1989) finds that the S&P500 spot volatility has increased afther the introduction of futures. The theoretical contribution by Cox (1976) states that futures trading alters the flow of information into the market. However, even if futures may increase the flow of information, Cox does not explain how volatility is related to the flow of information. An empircal paper by Antoniou and Holmes (1995) shed light on this exact problem. They examine the impact of trading in the FTSE-100 Stock Index Futures on the volatility of the underlying spot market. A GARCH model is used to explore the relationship between volatility and information. The results show that futures trading improves the quality and speed of information flowing to the spot markets. The authors conclude that there has been an increase in spot price volatility, but this is due to increased information in the market and not speculators having destabilizing effects. However, there can be argued that the increased volatility is a result of futures trading as it expands the ways in which information is transferred to the market. A paper by Ryoo and Smith (2004) find similar results for the Korean stock market. Lee and Ohk (1992) examine the impact of index futures using a modified GARCH type model for the US, UK, Australia, Hong Kong and Japan. Their results show increased volatility after the introduction of futures for all countries except for Austrialia and Hong Kong. A similar paper conducted by Gulen and Mayhew (2000) studies the impact of index futures in twentyfive countries. In order to capture asymmetric effects, a GJR-GARCH is used. They find increased spot volatility after futures trading in the US and Japan. Either a decrease in volatility or no effect is seen in the other countries. A more recent paper studies the impact of Chinese index futures trading in mainland China, Singapore and Hong Kong Bohl, Diesteldorf and Siklos (2015). They estimate volatility based on the standard GARCH, EGARCH and GJR-GARCH. The results showed that Chinese index futures decrease spot market volatility in all three spot markets considered. The stabiliziation hypothesis is therefore preferred.

All of the above research is focused on equity futures, while bitcoin is officially a currency rather than a stock-like instrument. A paper by Jochum and Kodres (1998) studies the effect of emerging market currency futures on their underlying volatility using a modified ARCH model (SWARCH). Their results are not very confincing, for two of the three currencies the estimated coefficients are not statistically significant. This leads to the conclusion that for these currencies the effect on spot volatility is neither negative nor positive. However they still argue that the spot market has not been destabilized after futures trading. A more recent paper by Oduncu (2011) examines the impact of the introduction of currency futures in the Turkish currency market. His analysis makes use of a standard GARCH(1,1) and a GJR-GARCH(1,1) to capture asymmetric effects. His results show that futures trading decrease the volatility in the underlying currency market. Moreover, the speed of information flows that are impounded into spot market prices increases. This confirms the argument that a futures market enchance market efficiency. The leverage effect increases post futures as well.

Even if bitcoin is classified as a currency, it has different characteristics than usual currencies. One of the main differences is that the supply of bitcoin will always be fixed, there is no central authority that can produce more supply like central banks do with standard currencies. Bitcoins are received by people instead as a reward for processing transactions on the blockchain untill all bitcoins are mined. This makes bitcoin decentralized. However, supply has been artificially increased since the introduction of futures. These futures are cash setteld which means no actual bitcoins are deliverd. The availability of these paper bitcoins inflates supply which eventually drives down the price.

There has been prior research on the financial aspects of bitcoin. A recent paper by Corbet, Lucy, Peat and Vigne (2018) examines the effect of the introduction of bitcoin futures. The main research question is whether bitcoin can be seen as a currency or speculative asset after the introduction of futures. An early research by Yermack (2015) argues that bitcoin is not a currency as it does not satisfy the condition of being a unit of account and store of value. These conditions were harmed by the high volatility of bitcoin. The paper by Corbet et al (2018) then studies if the ability to trade bitcoin futures decrease the volatility in the spot market and if the futures facilitated hedging strategies to reduce the pricing risk in the spot market, making bitcoin more look like a currency rather than a speculative asset. The authors also examine the relationship between the spot and futures market regarding the flow of information. In general, price discovery takes place in the futures market and therefore it is said that futures lead their underlying asset. They find that the spot price volatility increases around the announcement of trading in bitcoin futures. On the other hand, the hedging strategies constructed with futures results also in an increase in volatility. The price discovery analysis shows that price discovery is concentrated in the spot market, therefore contradicting the general assumption. This means that the futures traders are uninformed noise traders. With these results they conclude that bitcoin futures did not affect the nature of bitcoin as a speculative asset.

There are some points to be made about the paper by Corbet et al (2018). First of all the paper is focused on the effect of the introduction of bitcoin futures rather than futures trading itself. The limited data is probably the cause as the data only covers three futures contract expirations, from January and February 2018, which is not quite sufficient. The problem lies in the fact that the effect of the futures market is not fully utilized. Secondly, the paper uses a timeframe which covers the peak of bitcoin and its massive correction respectively in December 2017 and January 2018, see appendix figure 1. During this time there was a sudden influx of traders into the cryptocurrency markets as seen in figure 2. The transaction count per day is taken as a proxy for the variation in the amount of traders. So this period is not representative for the months later on anyway. At last and probably the most important note, the paper by Corbet et al (2018) uses only a GARCH(1,1) model for their analysis on bitcoin. An additional model is preferred which captures asymmetric effects as these have been observed for financial time-series data. Since bitcoin is originally labeld as a currency, these effects should also be taken into consideration. Intuitively, negative shocks would cause more impact as bitcoin trading is a relatively new space and uncertain asset.

The paper by Shimeng (2017) examines the impact of bitcoin futures trading on the intraday volatility and liquidity. Using high-frequency data, he finds that the introduction of futures trading significantly reduces the spot price volatility. The liquidity in the spot market improves in the post-futures period. However, this paper is also fairly limited in the amount of data. They use 5-min frequency data from 03/12/2017 to 17/12/2017 while the CBOE futures first traded on 10/12/2017 and the CME futures on 18/12/2017. Like mentioned before, this timeframe is not representative for periods to come. On the other hand, the methodology used for measuring the futures impact on liquidity is not well-defined.

This paper will try to deal with the before mentioned shortcomings, the amount of data will be extended and GARCH(1,1) EGARCH(1,1) TGARCH(1,1) will be used to explain bitcoin price volatility. Furthermore, the CAPM extended by three liquidity proxies shall be used to estimate the illiquidity premium. The latter will be explained in the methodology.

3. Data

This paper consists of two analyses and therefore of different datasets. The volatility estimation part will use hourly bitcoin price data with the price averaged across three exchanges. This data is obtained from cryptodatadownload.com. Using intraday returns has its benefits compared to daily returns. A particular asset's price can move within a day but can move not at all compared to the previous day. This leads to missing price movements and therefore important information on volatility. Martens (2001) examines whether intraday returns contain valuable information for forecasting daily exchange rate volatility. Earlier studies extended the daily GARCH(1,1) with additional intraday information such as daily high and low or volume but Martens (2001) investigates if modelling intraday returns directly results in better volatility forecasts. A noisy estimator of the realized daily volatility is the daily squared return. The sum of squared intraday returns reduces this noise. He then argues that this argument should also apply to forecasting with e.g. the GARCH(1,1) model. The squared return component of this model would give misleading information when daily return is zero while intraday returns are not. His results show that the highest frequency of intraday returns leads to superior daily forecasts with the GARCH(1,1) model. The GARCH(1,1) with intraday returns gives similar or better forecasts than the daily GARCH extended with intraday information. This paper uses the highest available frequency of intraday bitcoin returns which are the hourly series.

The liquidity analysis uses daily price data obtained from coinmarketcap.com. Moreover, daily trading volume data is extracted from blockchain.com. Trading volume is denoted in USD and originates from major cryptocurrency exchanges. There are two parties that offer bitcoin futures contracts, the CBOE and CME. The former offers trading since 10 December 2017 while the latter started on 18 December 2017. As mentioned before, both contracts are cash settled. Since there is not one particular date that marks the beginning of the futures market, it is difficult to determine the pre/-post sample. Therefore the months December 2017 and January 2018 are excluded from the dataset. This step is supported by the fact that bitcoin was at its peak at these months and experienced a massive correction, both price wise and by market participants, which is not representative for the months thereafter. Including this part of data would dilute the analyses in this paper. In case of the volatility analysis, the pre-futures sample starts from 01-07-2017 till 01-12-2017 and the post futures sample starts from 01-02-2018 till 01-07-2018. Data used in the liquidity analysis is extended to collect a reasonable amount of daily data[1]. Table 1 shows the descriptive statistics for the volatility data sample sets. The excess kurtosis and skewness change across the samples. Skewness measures the degree of asymmetry of a distribution around the mean. An outcome of zero means the distribution is symmetric or normal. The skewness of all sample returns is positive, meaning that the distribution has an asymmetric tail extending towards more positive values. When this concept is applied to returns, a positive skew means frequent small losses and a few extreme gains. The skewness of the samples is close to zero in absolute terms. However the pre-futures sample skewness is twice the full sample skewness, while the post-futures sample skewness differs quite substantially in relative terms. This shows that the price data from December 2017 and January 2018 dilutes the overall dataset as these months were prone to extreme gains. The bull run endured in this period is not likely to be seen again. Kurtosis measures the degree to which a distribution is peaked, which indicates how much of the distribution is centered on the mean. An excess kurtosis of zero is associated with a normal distribution. An excess kurtosis with a large positive value has a leptokurtic distribution and this applies for all samples. The excess kurtosis increases post futures, which shows that its distribution has more fat tails and is more peaked.

Table 1: Descriptive statistics

	Full sample	Pre-futures	Post-futures
Mean	0.0001	0.0004	-0.0001
Standard Error	0.0001	0.0002	0.0002
Median	0.0003	0.0006	0.0000
Standard Deviation	0.0119	0.0101	0.0107
Sample Variance	0.0001	0.0001	0.0001
Kurtosis	8.8312	9.8171	11.2459
Skewness	0.1102	0.2262	0.5715
Range	0.2288	0.1784	0.1840
Minimum	-0.1149	-0.0646	-0.0764
Maximum	0.1138	0.1138	0.1076
Sum	0.9805	1.3958	-0.4265
Count	8809	3661	3661

4. Methodology

This paper uses three GARCH type models as these are frequently used in similar research and allows for comparability with previous literature. The first model discussed is the standard GARCH(1,1)

[1] 01-02-2017 – 01-12-2017 and 01-02-2018 – 01-12-2018

introduced by Bollerslev (1986). Let r_t be the log normal return on day *t*. Then the standard specification of a GARCH(1,1) model is given by

$$r_t = c + \theta r_{t-1} + \varepsilon_t$$
$$\varepsilon_t = \sigma_t z_t$$
$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Where ε_t is an i.i.d. sequence with zero mean and unit variance {z_t ~ i.i.d.N(0,1)} and ω, α, β are non-negative parameters with α+β < 1.

Considering the literature, a conditional variance model is needed as well which incorporates the asymmetric effect. Therefore the EGARCH(1,1) model by Nelson (1991) will be used to estimate the price volatility of bitcoin. This type of conditional heteroscedasticity model allows for negative shocks to have a different impact on volatility than positive shocks of the same magnitude. Advantageous to the normal GARCH model, the exponential form of conditional variance lets the variance to be positive for all possible choices of the parameters. So there is no need to put non-negativity restrictions on the model parameters. Then EGARCH(1,1) is defined as follow.

$$\ln(\sigma_t^2) = \omega + \beta\ln(\sigma_{t-1}^2) + \gamma\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}$$

The garch term which is composed of lagged/logged conditional variance covers the persistence of past volatility, shown by β. The arch term with coefficient α captures the impact of a magnitude of a shock. Finally, the asymmetric effect is given by the γ coefficient. If the relation between bitcoin return and volatility is negative, a leverage effect is present when gamma is both negative and significant. Another model that is able to capture asymmetric effects is the Threshold GARCH developed by Zakoian (1994). The TGARCH(1,1) is denoted as follow.

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 - \gamma\varepsilon_{t-1}^2\eta_{t-1} + \beta\sigma_{t-1}^2$$

Where η takes a value of 1 for negative values of the residuals and 0 otherwise. This specification shows that the impact of negative shocks is higher than positive shocks, respectively α+γ and α. Asymmetry is present when γ > 0 and symmetry if y = 0.

These models shall be run for the pre-/post-futures sample with the Gaussian distribution. Even though the data experiences kurtosis, a normal distribution is assumed because of the large amount of observations. Figure 3 shows a histogram plot of the residuals against a normal distribution plot. It shows that the distribution is fairly within normal except for some outliers. Since multiple GARCH type models are used in this paper, information criteria such as the AIC/BIC values will be used to find the optimal model. This paper prefers its hypotheses to the theoretical stabilization hypothesis. Therefore the first hypothesis is presented as follow.

H1: Trading of bitcoin futures decreases spot market price volatility

Next to estimating volatility, this paper will also shed a light on liquidity. The reason for this is that liquidity plays an important role to how volatility develops during the availability of futures trading. The relation lies in the hypothesis that futures bring less volatility by increasing the liquidity in the spot market, this is basically the stabilization hypothesis. However, the futures underlying bitcoin are cash settled which means that no actual bitcoins changes hands. Therefore the futures trading itself has no impact on the spot market. There are no bitcoin settled futures yet. An investor who wants to buy/hold bitcoin itself, still has to turn to the spot market. Still, the liquidity increase in the spot market can come from arbitrageurs. But this has also issues, because in case the futures price falls below the spot price, the arbitrageur would have to short bitcoin and buy the futures contract, where the former is not possible. So the selling of bitcoin must come from current bitcoin holders. In contrary, the arbitrageurs can fix the imbalance when futures price exceeds the spot price. The arbitrageur then buys bitcoin and short the future. Consequently, the spot market liquidity experiences an increase. The question is whether current bitcoin holders will sell when the futures price < spot price. If true, futures trading would indirectly cause more liquidity as well in the spot market when futures price < spot price. If false, liquidity could only be stimulated when the futures price > spot price. Because of this specific characteristic of bitcoin, it cannot be easily concluded that illiquidity would be lower due to futures trading. Hence, the second hypothesis is derived as follow.

H2: illiquidity premium decreases in the post futures period

In order to capture the liquidity aspect of bitcoin in a model, it is necessary to examine the relation between liquidity and price return. From a theoretical point, investors will incur costs and risk when buying assets with low liquidity. Therefore they would demand a premium reflecting the cost of illiquidity. Main assumption in connection between liquidity and stock return is that return increases in illiquidity Amihud (2002). In order to see how illiquidity develops, the CAPM will be used extended by the Amihud ILLIQ factor for the pre/post futures period. A higher ILLIQ ratio means higher illiquidity. A positive beta indicates that for an increase in ILLIQ (increase in illiquidity) the expected return of bitcoin increases. In equity markets it is researched that the Amihud ILLIQ factor performs well in the CAPM model as a liquidity risk factor Martinez, Nieto, Gonzalo and Tapia (2005). Two bid/ask spread measures will also be used in the regression. A higher spread means higher illiquidity. According to the second hypothesis, the betas of the liquidity measures should decrease post futures. The liquidity proxies are specified in the next section.

Since there is no bid-ask spread data available, this paper will use three alternative proxies for liquidity. First the Amihud (2002) illiquidity (ILLIQ) measure shall be used. The ILLIQ measure is the ratio of absolute percentage return to its dollar volume. The higer the ratio is, the lower the liquidity. When a particular asset has a high value of ILLQ, it indicates that the price moves a lot in response to trading volume and, therefore, the asset is considered to be illiquid. Amihud states that this ratio can be interpreted as the daily price response associated with one dollar of trading volume, therefore functioning as a rough measure of price impact. This measure only needs daily return and volume data, which is obtainable for bitcoin.

$$ILLIQ_t = \frac{1}{D}\sum_{i=1}^{D} = \frac{|\, r_t|}{VOLD_t}$$

Where *D* is the number of trading days in a week and r_t is the absolute bitcoin return for day *t*. Then $VOLD_t$ is the daily volume. The daily ILLIQ ratio is calculated as an average over a weekly rolling window. As this measure is a bit noisy, taking the average mitigates this problem. The second proxy for liquidity is the measure by Roll (1984). This estimate of the effective bid-ask spread is based on the serial covariance of the change in price. In case the covariance is positive, the formula is undefined and therefore a default number of zero is used. Using a rolling window procedure, the serial covariance is calculated based on a 21-day period. The formula is defined as follow.

$$S_t = \begin{cases} 2\sqrt{-Cov(\Delta P_{t,}\Delta P_{t-1})} & when\ Cov(\Delta P_{t,}\Delta P_{t-1}) < 0 \\ 0 & when\ Cov(\Delta P_{t,}\Delta P_{t-1}) \geq 0 \end{cases}$$

Another way to estimate the bid-ask spread is developed by Corwin and Schultz (2012).This measure uses the daily high and low prices of an asset and an easy calculation method. The authors argue that the high-low ratio reflects the variance and bid-ask spread of the asset. The Corwin-Schultz estimater is defined in the equations below where *S* is the spread and *H* and *L* are the observed daily high and low prices. The mathematical constant is given by *e*.

$$S = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}}$$

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}$$

$$\beta = \sum_{j=0}^{1} [\ln(\frac{H_{t+j}^{o}}{L_{t+j}^{o}})]^2$$

$$\gamma = [ln(\frac{H_{t-1,t}^{o}}{L_{t-1,t}^{o}})]^{2}$$

Beta shows the sum of the price ranges over two days. Gamma presents a 2-day period high and low price adjustments to the high price, in other words, the max range of the high-low price ratio over two days. Alfa represents the difference between the adjustments of a single day and a 2-day period. In order to test the impact of futures trading on spot market liquidity, a liquidity-adjusted CAPM is used which is defined as follow.

$$R_i - r_f = \alpha_0 + \beta_1(R_m - r_f) + \beta_2 ILLIQ + \beta_3 Roll + \beta_4 CS + \varepsilon$$

The ILLIQ measure together with one of the bid-ask spread measure captures liquidity in two dimensions. The riskfree rate is based on the 1-month T-bill which is converted to daily yields for each observation. The benchmark is the Crypto Curriencies Index 30 or CCI30. This index covers the 30 largest cryptocurrencies by market capitalization. Detailled descriptions can be found on their website[2]. As similar to the volatility estimation process, the above model will be performed for the pre and post sample.

5. Results

5.1 Volatility

In this section, the AIC and BIC values for the GARCH type models with Gaussian distribution are presented in table 2. The values within each sample are compared and the lowest is highlighted. In the pre-futures sample the lowest value is shown for a GARCH(1,1). In contrary, the post-futures sample favors an asymmetric GARCH model and in particular the TGARCH(1,1). The latter applies for the full sample as well. The point to be made here is that there are probably asymmetric effects after the introduction of futures. These effects seem to be best modeled by the threshold GARCH model. On the other hand the standard GARCH model seems to fit the data the best before the introduction of futures. Since the data favors different type of models, all three models will be used in the volatility estimation analysis.

[2] https://cci30.com/

Table 2: AIC and BIC values

Model	Full sample AIC	Full sample BIC	Pre-fut AIC	Pre-fut BIC	Post-fut AIC	Post-fut BIC
GARCH(1,1)	-56344	-56315	**-24460**	**24436**	-23804	-23779
EGARCH(1,1)	-56450	-56414	-24438	-24407	-23947	-23916
TGARCH(1,1)	**-56460**	**-56425**	-24431	-24400	**-23952**	**-23921**

Each model is run for the three data sample sets. The first model to be discussed is the GARCH(1,1) presented in table 3.1. The model performs well, especially in the pre-futures period. The results show that beta increases after futures trading while being highly significant in all cases. The alfa coefficient however decreases in value as well as in significance. Another important observation is the high persistence, alfa and beta sums up to 0.98.

Table 3.1: GARCH(1,1) estimates

	ω	β	α
Full sample	0.000	0.905***	0.083***
	(0.001)	(0.000)	(0.000)
Pre-futures	0.000	0.877***	0.107***
	(0.001)	(0.000)	(0.000)
Post-futures	0.000	0.924***	0.059*
	(0.152)	(0.000)	(0.071)

Note: P-values are in parentheses
* significant at 10% level
** significant at 5% level
*** significant at 1% level

Table 3.2 shows the parameter estimates for the EGARCH(1,1) model. The results are similar to the standard GARCH regarding the beta and alfa coefficient. The difference is that alfa becomes totally insignificant in the post-futures sample while being significant at the 1% level in the pre-futures sample. The added coefficient gamma is negative and significant in the full sample and post-futures sample. So the leverage effect is present after the introduction of futures, bad news has more impact on volatility than good news of the same size.

Table 3.2: EGARCH(1,1) estimates

	ω	β	α	γ
Full sample	-0.227***	0.973***	0.172***	-0.055***
	(0.000)	(0.000)	(0.000)	(0.000)
Pre-futures	-0.288***	0.967***	0.232***	-0.019
	(0.001)	(0.000)	(0.000)	(0.196)
Post-futures	-0.215	0.975***	0.120	-0.083**
	(0.168)	(0.000)	(0.124)	(0.016)

Note: P-values are in parentheses
* significant at 10% level
** significant at 5% level
*** significant at 1% level

The last model to be discussed is the TGARCH(1,1) shown in table 3.3. As the information criteria showed, this model performs better in each sample compared to the EGARCH(1,1). Similar to the other models beta increases and stays positive and significant throughout the samples. Also, alfa decreases but shows good significance in the post-futures sample. The threshold GARCH shows a leverage effect as well after futures trading but with more significance. It is therefore a confirmation that a leverage effect develops after futures trading.

Table 3.3: TGARCH(1,1) estimates

	ω	β	α	γ
Full sample	0.000	0.911***	0.120***	-0.060***
	(0.000)	(0.000)	(0.000)	(0.000)
Pre-futures	0.000	0.881***	0.134***	-0.026
	(0.000)	(0.000)	(0.000)	(0.145)
Post-futures	0.000	0.935***	0.102**	-0.085***
	(0.144)	(0.000)	(0.016)	(0.001)

Note: P-values are in parentheses
* significant at 10% level
** significant at 5% level
*** significant at 1% level

In context of this analysis, the alfa coefficient in the GARCH type models relates to the changes in the spot price on the previous day which is attributable to market-specific factors. Then these changes in price are due to new information which is specific for bitcoin. Therefore, alfa relates to the impact of yesterday's market-specific price changes on price changes today. Given that this relates to the arrival of information yesterday, alfa can be viewed as a news coefficient, where a higher value implies that recent news has more impact on price changes. Thus an increase in alfa post-futures suggests that information is being impounded in prices more quickly due to futures trading. In this paper however, alfa decreases which means that recent information has less impact on volatility after the introduction of futures.

Beta is the coefficient on the lagged variance term and as such is picking up the impact of price changes relating to days prior to the previous day and therefore to news which arrived before yesterday. Thus beta can be seen as reflecting the impact of old news or the persistence of past volatility. Beta increases after the introduction of futures. This observation indicates higher persistence of shocks to volatility. These results show that the nature of spot market volatility has changed since the introduction of future contracts. Figure 4 shows the conditional variance of the whole dataset. The remarkable volatility spike in September 2017 coincides with the announcement of China to ban cryptocurrencies[3]. China was one of the most important countries in the crypto space as many mining farms were located there. This development worried investors that it might be the end of bitcoin. Many mining farms in China halted eventually in January 2018. Bitcoin surpassed the 10.000 dollar milestone end of November 2017. This resulted in a lot of news coverage which lead to increased exposure to the public and therefore higher volatility. The last great volatility spike occurred when the head of the Bank for International Settlements cracked down on bitcoin[4]. A decrease in volatility is seen in the post-futures sample while the volatility spikes are also much smaller. Therefore the first hypothesis can be accepted, trading of bitcoin futures decreases spot market price volatility.

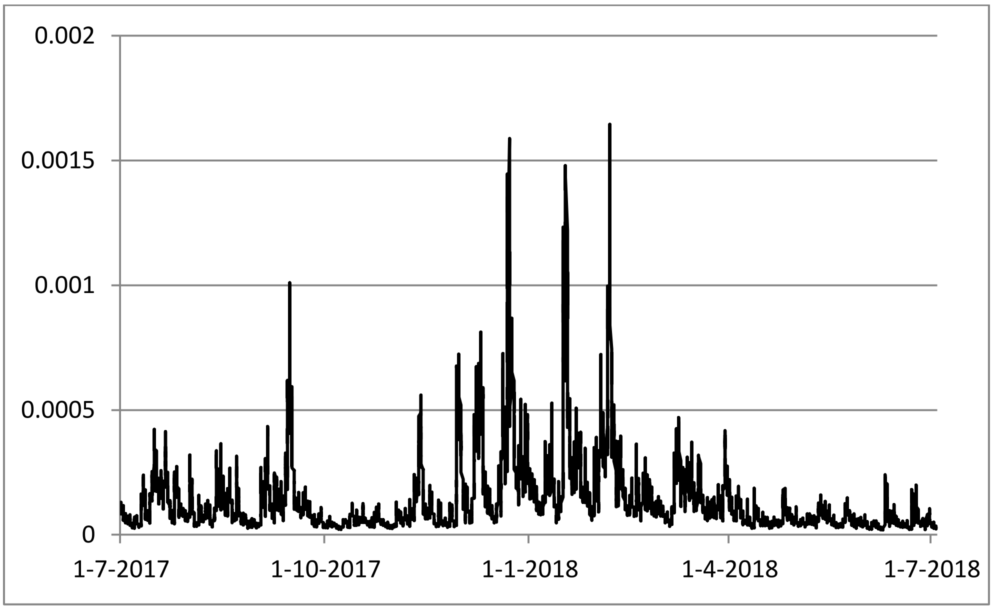
An implication about the change in the nature of bitcoin volatility is that the information flows to the spot market deteriorates since the news coefficient alfa decreases. So even though volatility decreases, it is not because of an improved information flow which futures markets usually provide. This result is in contrast of one of the theoretical arguments regarding the stabilization hypothesis but also empirical work by Oduncu (2011) and Antoniou and Holmes (1995). The former finds decreased volatility as a result of an improvement in information flows impounded into the spot market. Antoniou and Holmes (1995) find increased volatility as a result of improvement in information flows. To some extent, one might argue that the decreased bitcoin volatilty is a result of a deterioration of information flows.

Corbet et al (2018) show with their analysis that price discovery takes place in the bitcoin spot market which is the opposite of the general assumption. In other words, future traders are uninformed noise traders. My results complement these findings since the future market does not act as a place where the distribution and quality of information is improved. This might have to do with the fact that the bitcoin spot market is a 24/7 trading place, where prices are already continuously adjusted to news. Another observation is that bad news has more impact on volatility

[3] https://www.loc.gov/law/help/cryptocurrency/china.php
[4] https://www.theguardian.com/technology/2018/feb/06/bitcoin-price-crackdown-bis-cryptocurrency

than good news after bitcoin futures trading. The fact that a leverage effect comes into play shows that spot market investors became more risk-averse.

Figure 4: Bitcoin conditional variance



5.2 Liquidity

Before discussing the regression results, the relative performance of the liquidity measures are reviewed. The measures are plotted over time in figure 5 shown in the appendix. The Amihud ILLIQ ratio shows a decline over time, even before futures, but stays low after futures. This means that liquidity increased over time according to the ILLIQ measure. The plot of the Roll's measure does not give useful information because of the zero values appointed. The C/S measure in figure 5.3 shows a bid-ask spread between 0.6 and 1.2. The outlier in December 2017 shows that the market was relatively more liquid as the spread decreases but also that the huge price volatility increased the spread. The C/S spread in percentage plotted over time gives a more detailed overview as shown in figure 5.4. It is surprising that the spread percentage decreases before the introduction of futures and increases at a steady pace hereafter. This shows that liquidity decreased after the introduction of futures according to the C/S proxy and is in contrast with the ILLIQ measure performance. This discrepancy should not be an issue as these two measures capture different aspects of liquidity.

Table 4 shows the output of the liquidity-adjusted CAPM regressions. The Amihud ILLIQ ratio has been multiplied by 1 billion before regressing for statistical purposes and better understanding of the regressions. Since the ratios are very small, for example 3.9E-10, it is necessary to interpret the regression coefficient in terms of 1/1E-9 increase/decrease.

Table 4.1: liquidity-adjusted CAPM regressions

	alpha constant	Market exposure beta1	ILLIQ beta 2	Roll beta3	CS beta4
Full sample	0.000	0.719***			
	(0.604)	(0.000)			
	0.002	0.722***	-0.016*		
	(0.325)	(0.000)	(0.090)		
	0.005	0.718***	-0.022**	0.000	
	(0.014)	(0.000)	(0.024)	(0.004)	
	0.018	0.718***	-0.023**	0.000	-0.014
	(0.391)	(0.000)	(0.022)	(0.005)	(0.528)

Note: P-values are in parentheses
* significant at 10% level
** significant at 5% level
*** significant at 1% level

Table 4.2: liquidity-adjusted CAPM regressions

	alpha constant	Market exposure beta1	ILLIQ beta 2	Roll beta3	CS beta4
Pre-futures	0.000	0.716***			
	(0.787)	(0.000)			
	0.009***	0.717***	-0.039***		
	(0.001)	(0.000)	(0.001)		
	0.009***	0.718***	-0.039***	0.000	
	(0.007)	(0.000)	(0.002)	(0.861)	
	0.047**	0.705***	-0.039***	0.000	-0.039**
	(0.013)	(0.000)	(0.002)	(0.818)	(0.036)

Note: P-values are in parentheses
* significant at 10% level
** significant at 5% level
*** significant at 1% level

Table 4.1 shows the regressions for the full sample. The market exposure coefficient is always substantial and significant. This is not surprising as bitcoin dominates the crypto market about 30-50% throughout the dataset. The ILLIQ coefficient is significant and negative. On the other hand, Rolls bid-ask spread proxy does not work well since its impact is negligible. The cause of this could lie in the amount of zeros accounted for the observations with positive covariance. This dilutes the effectiveness of the measure. The Corwin/Schultz bid-ask spread proxy is insignificant as well. Table 4.2 presents the regressions for the pre-futures sample. Results are similar regarding the market exposure coefficient. The ILLIQ measure improves in significance and decreases as well. Moreover, the Corwin/Schultz proxy seems to be an improvement over the Rolls proxy before futures trading. The ILLIQ and C/S coefficient in the pre-futures sample are negative and significant at 1% level and 5% level respectively. This means that an increase in liquidity proxies, an increase in illiquidity, the expected return of bitcoin decreases. This result is the opposite of the general theory. The last pair of regressions is shown in table 4.3. The liquidity coefficients increase in the post futures sample but are all insignificant. Therefore, inferences about the second hypothesis cannot be made.

Table 4.3: liquidity-adjusted CAPM regressions

	alpha	Market exposure	ILLIQ	Roll	CS
	constant	beta1	beta 2	beta3	beta4
Post-futures	0.000	0.744***			
	(0.674)	(0.000)			
	0.000	0.744***	-0.010		
	(0.654)	(0.000)	(0.788)		
	0.000	0.746***	0.025	0.000	
	(0.779)	(0.000)	(0.535)	(0.086)	
	0.002	0.747***	0.025	0.000	0.001
	(0.879)	(0.000)	(0.538)	(0.088)	(0.912)

Note: P-values are in parentheses
* significant at 10% level
** significant at 5% level
*** significant at 1% level

6. Conclusion

The CME and CBOE launched bitcoin futures recently and other parties are also interested in creating such instruments. The impact of futures on spot market volatility remains mixed in equity markets, while bitcoin markets are barely examined. The stabilization and destabilization hypotheses contradict each other, as well as empirical evidence on whether spot volatility increases or decreases.

This paper uses three GARCH type models to explain bitcoin spot volatility before and after the introduction of futures. It adds another dimension by also measuring liquidity by means of the illiquidity premium theory. Liquidity is estimated by three proxies included in the CAPM and defined by a price impact measure and bid-ask spread proxies. The results from the GARCH analysis reveal that yesterday's market-specific news has less impact on today's volatility after the introduction of futures. The persistence of shocks increases which means that shocks decay slower over time. The conditional variance modelled shows a clear decrease of volatility after the introduction of futures. An inference hereabout is that the futures market does not improve the information flows to the market. The volatility decrease is therefore not because of an improved information flow which futures markets usually provide. The bitcoin spot market is a 24/7 trading place where prices can already continuously be adjusted to news, which makes the futures market redundant. This paper therefore supports earlier research that price discovery takes place in the bitcoin spot market. The leverage effect appears after futures trading and implies that bad news has more impact on volatility than good news of the same size. The presence of a leverage effect shows that spot market investors became more risk-averse after the introduction of futures.

The liquidity measures plotted over time show different results regarding the course of liquidity, namely the Amihud and Corwin/Schultz measure. Other concluding remarks regarding the liquidity analysis is that the C/S proxy is a better measure to capture the impact of the bid-ask spread on return. A lower liquidity has a negative impact on return in the pre-futures sample which is the opposite of the illiquidity premium theory. The liquidity-adjusted CAPM model fails to find significant relationships between return and the liquidity proxies in the post-futures sample. Therefore no clear evidence is obtained about the effect of futures on liquidity.

One of the stabilization hypothesis arguments is preferred when both results are taken into consideration, futures offers speculative investors opportunities which they prefer to investment in the spot market. These investors will leave the spot market and turn to the futures market, leaving the spot market to the risk-averse investors, which then becomes less volatile. This is confirmed by the presence of a leverage effect after the availability of futures. These speculators might not just leave for more risk/return as this is already available in the bitcoin spot market. The futures also offer a way to short bitcoin. A more important note is the accesibility that the CME and CBOE futures provide. Trading in digital currencies is still not practical which translates in being unable to swiftly adjust trades which is important for a speculator.

A limitation of this paper is still the amount of data available. A revised paper with a larger dataset is helpful to confirm the change in the nature of volatility. Another limitation is the measurement of liquidity. Further research could find other ways to examine the impact of futures on liquidity.

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Appendix

Figure 1: Bitcoin price

Figure 2: Bitcoin transaction count per day

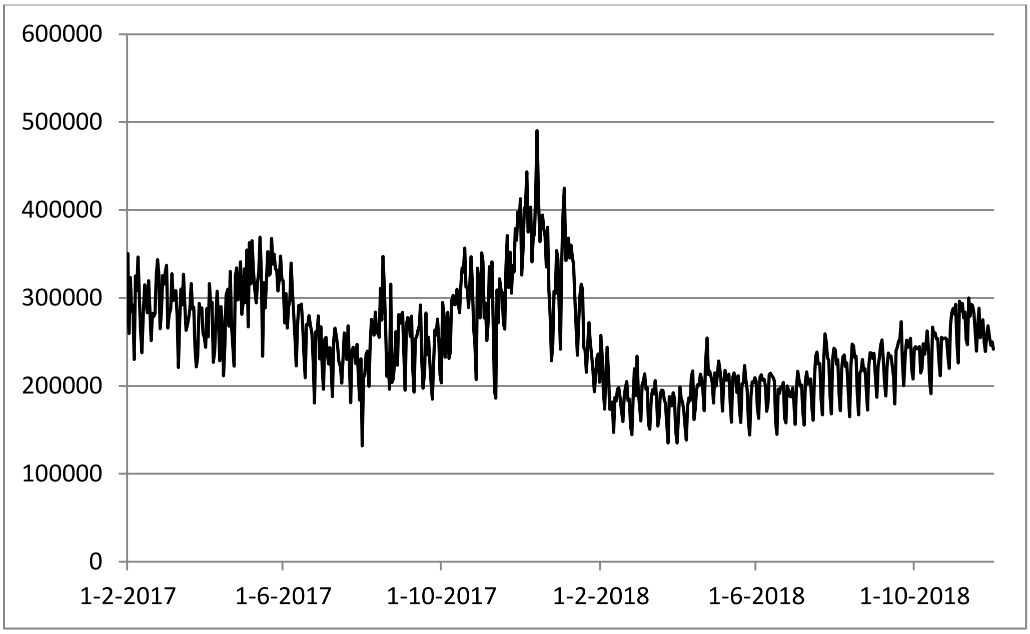

Figure 3: Distributional plot residuals, post-futures

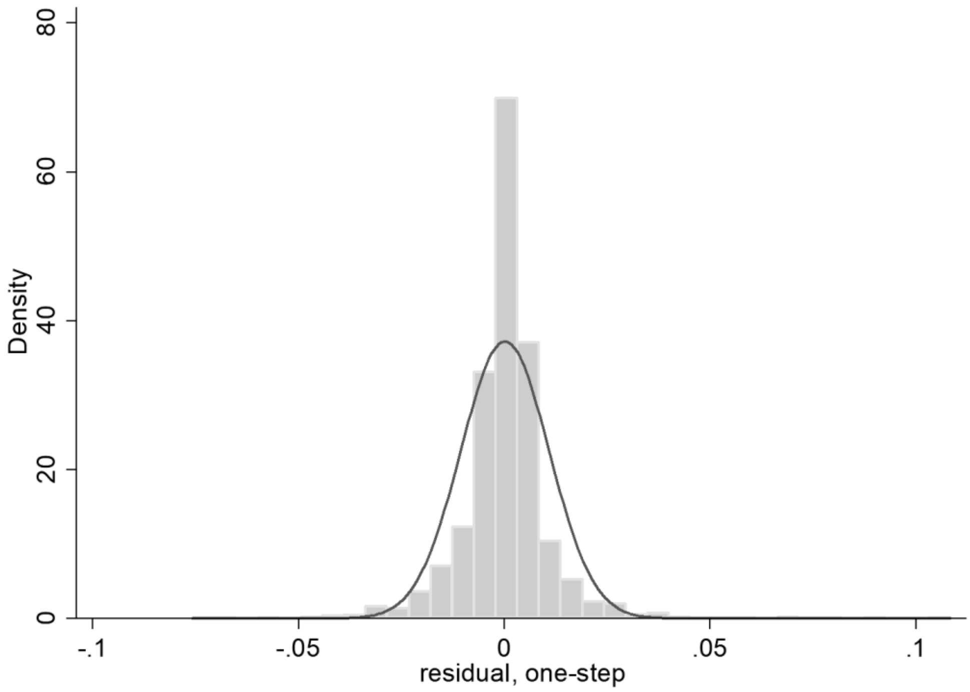

Figure 5.1: Amihud ILLIQ measure

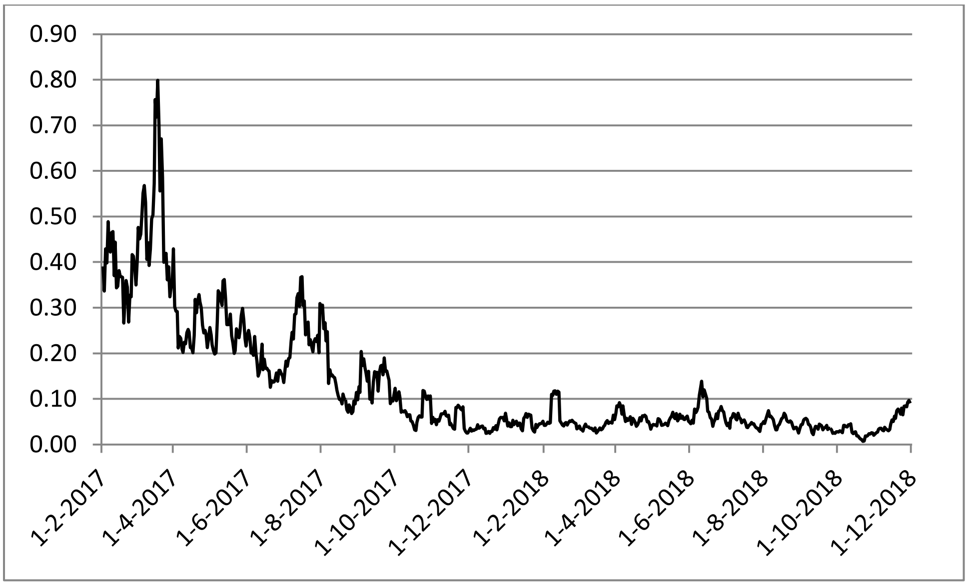

Figure 5.2: Roll's measure

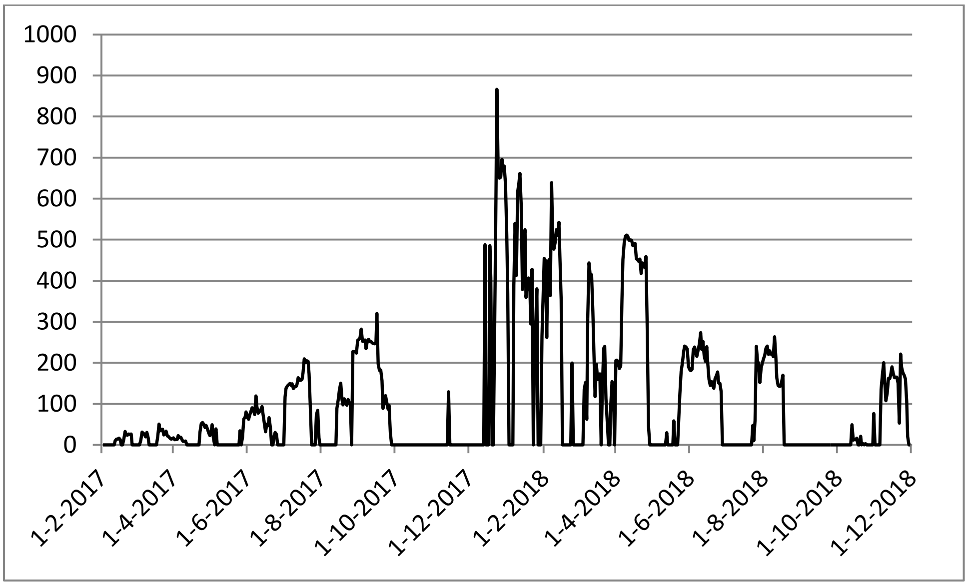

Figure 5.3: C/S measure

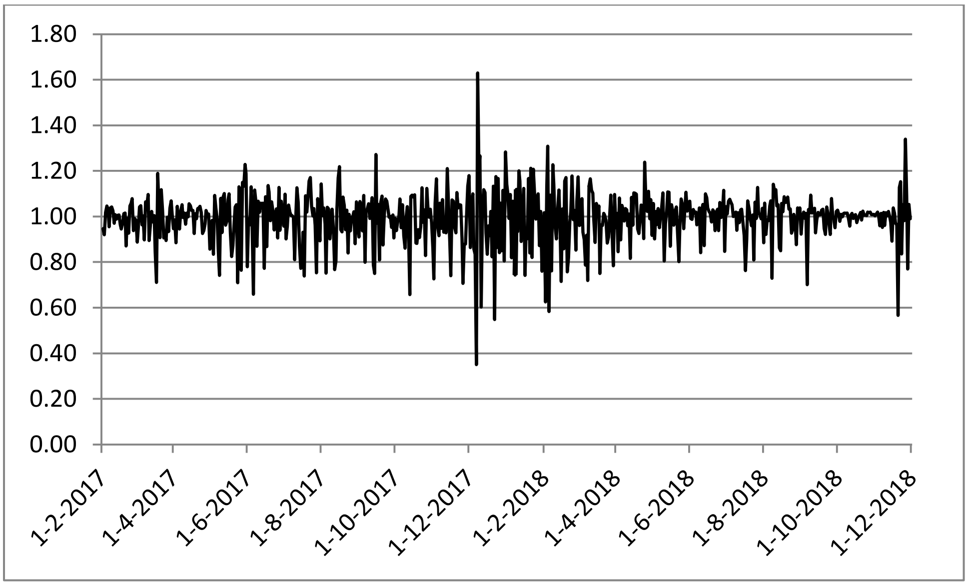

Figure 5.4: C/S spread in percentage of ask price