Bitcoin Futures: Trade It or Ban It?

Abstract

This paper examines the impact of South Korea's ban on Bitcoin futures on intraday spot volatility, liquidity, and volatility-volume relationship. The results show that while reduces the permanent component of intraday spot volatility, the imposition of a ban on Bitcoin futures trading increases the transitory component. For intraday spot liquidity, different liquidity proxies indicate heterogeneous results. Moreover, we identify a positive and unidirectional effect of intraday spot volume on volatility. This effect appears to be stronger in the post-ban period. Overall, over the past few months, South Korea's Bitcoin futures ban generally have had a significant impact on the intraday dynamics of the Bitcoin spot market.

Keywords: South Korea's Ban on Bitcoin Futures; Intraday Dynamics; Component GARCH Model

JEL Classification: G12, G13, G14

1. Introduction

From \$0.003 per unit in March 2010 to \$17,900 per unit in December 2017, Bitcoin, the most influential cryptocurrency, attracts huge attention and arouses considerable controversy. The phenomenon is argued to be a speculative bubble. Bitcoin is one of the successful applications of decentralised Blockchain technology. Its market is 24/7 trading, unregulated, opaque, and is criticised for the possibility of facilitating cybercrime and money laundering (Foley et al., 2019). Prior literature about Bitcoin discusses its nature (Yermack, 2015), return and volatility (Brandvold et al., 2015; Dyhrberg, 2016; Urquhart, 2017; Katsiampa, 2017), market efficiency (Urquhart, 2016; Tiwari et al., 2018; Bariviera, 2017; Nadarajah and Chu, 2017), liquidity (Balcilar et al., 2017; Loi, 2017), trading behaviours (Feng et al, 2017; Cheah and Fry, 2015), interactions with other cryptocurrencies/assets (Dwyer, 2015; Fry and Cheah, 2016; Ciaian, et al., 2018; Bouri et al., 2017; Corbet et al., 2018), and market regulations (Hendrickson and Luther, 2017; Pieters and Vivanco, 2017).

Orderbook is the first Bitcoin futures market, which was established in 2012 (Ozvatic, 2015). However, OrderBook is not a central counterparty for its Bitcoin futures contracts because OrderBook's contracts are more similar to forwards rather than futures. In 2014, more Bitcoin derivatives emerged, such as Bitcoin futures offered by ICTBIT.se, Bitcoin swap offered by TeraExchange, and Bitcoin option spread derivatives created by Predictious (Lo and Wang, 2014). Accompanied with the astonishing popularity of the Bitcoin spot market, the Bitcoin derivatives market expands. On 10 December 2017, the first formal U.S. Bitcoin futures offered by the Chicago Board Options Exchange (Cboe) started trading. On 18 December 2017, the trading of the CME's Bitcoin futures officially commenced. Different from OrderBook, Cboe and CME act as central counterparties for their own Bitcoin futures contracts. NASDAQ and Cantor Fitzgerald plan to design similar Bitcoin derivatives in 2018. Thomson Reuters (2017) reports the differences between the existing two U.S. Bitcoin futures in terms of contract unit, pricing and settlement, trading hours, margin rate and clearing, expirations, and price limits and trading halts. One CME's contract equals to five Bitcoins, whereas one Cboe's contract equals to one Bitcoin. Also, the price of the CME's contract is based on the Bitcoin Reference Rate (BRR), which is an index calculated by the data from four Bitcoin exchanges (i.e., Bitstamp, GDAX, itBit, and Kraken). For the Cboe's contract, the price is based on one exchange (i.e., Gemini). The more standardised Bitcoin derivative products are expected to bring cryptocurrency investments into a new era.

However, Bitcoin and the other cryptocurrencies unavoidably suffer more critiques and stricter regulations, while most of the regulations focus on spot market. There is one exception which focuses on derivative market.[1] On the 5th of December 2017, South Korea's Financial Services Commission announced a sweeping ban on Bitcoin futures offering and trading (Dinkins, 2017). One possible reason is that South Korea's authorities do not consider Bitcoin as a qualified underlying asset of derivative products (Sil, 2017). Moreover, the regulators may aim to limit institutional investors' exposure to Bitcoin and eliminate possible speculation and arbitrage opportunities (Williams-Grut, 2017). The ultimate goal is to maintain financial stability.

South Korea is one of the biggest Bitcoin markets (Williams-Grut, 2017). This strict trading ban was imposed when some major economies were planning to launch more Bitcoin derivative products, e.g., the U.S. and Japan. Hence, this ban sparks concerns over its potential influence on the Bitcoin spot market. Our study aims to shed some light on this research topic and address the following research question: How does South Korea's Bitcoin futures trading ban affect the intraday Bitcoin spot volatility, market liquidity, and volatility-volume relationship? To the best of our knowledge, we are the first to study the impact of Bitcoin derivative trading ban on its spot market. Because of the availability of high-frequency data, we can focus on the intraday dynamics of the Bitcoin spot market. Moreover, by using a component GARCH model, we are able to decompose the impact of exogenous variables on the spot price variations into transitory and permanent components.

Our findings first suggest that intraday Bitcoin spot volatility does have short- and long-term components, which is consistent with Katsiampa's (2017) study using daily data. Secondly, the Bitcoin futures trading ban imposed by South Korea significantly increases the transitory component and reduces the permanent component of intraday spot volatility. For intraday spot

[1] Based on the initiators of regulations, there are three types: 1) Governments impose bans on cryptocurrency trading and opening new trading accounts, e.g., South Korea and China; 2) Financial giants limit their clients to invest in cryptocurrencies. For instance, Merrill Lynch, JP Morgan, and Citi set certain prohibitions on their clients about Bitcoin-related investments (Cheng, 2018); 3) High-technology firms ban all cryptocurrency-related advertisements, such as search engines (Google and Bing) and social networks (Twitter and Facebook). Moreover, based on the targets of regulations, there are three types: 1) Restrictions on Initial Coin Offer (ICO); 2) Limitations on cryptocurrency trading; 3) Bans on cryptocurrency derivatives trading.

liquidity, the four liquidity proxies indicate heterogeneous results. On one hand, trading volume and Amihud's (2002) measure suggest that intraday spot liquidity significantly grows after the ban was imposed. On the other hand, for Roll's (1984) measure and Corwin and Schultz's (2012) implied bid-ask spread, the ban exerts a significant and negative impact on intraday spot liquidity. Furthermore, we find a positive causal effect of intraday spot volatility on volume: one lag of trading volume predicts current volatility, but not vice versa. During the post-ban period, the direction of the volatility-volume relationship remains unchanged, while the causal relationship seems to be stronger.

Our study makes contributions to the existing literature in several aspects. First, unlike the prior studies of Bitcoin futures, e.g., Baur and Dimpfl (2019) and Corbet et al. (2018), we make the first attempt to investigate the impact of one regulatory constraint in the futures market on the cash market. South Korea's Bitcoin futures trading ban is the first policy targeting this growing derivatives market. We find that this ban successfully tames the long-term component of spot variability. The results provide important policy implications for financial supervisors in terms of how to manage the unregulated, anonymous, and decentralised Bitcoin spot market through intervening its derivatives market. Second, employing component GARCH model and different liquidity measures, this paper improves the current understanding of the intraday dynamics of this most prevalent cryptocurrency market, which supports Katsiampa (2017) and Eross et al. (2017). Moreover, we extend the discussion of the volume-volatility relation in the Bitcoin spot market by using high-frequency data. The past volume predicts price variations, and this causal relationship becomes stronger in the post-ban period. Our paper complements the studies of Balcilar et al. (2017) and Bouri et al. (2019) who focus on only daily dynamics.

The rest of this paper proceeds as follows. Section 2 briefly reviews the related literature. Section 3 describes methodology, and Section 4 is about data and preliminary analysis. Section 5 reports the empirical findings. Section 6 concludes.

2. Related Literature

2.1 Intraday Dynamics of Financial Markets

The various possible intraday patterns of financial markets have been widely studied in prior literature. For example, some studies find that intraday return, volatility, bid-ask spread, and trading volume could exhibit a U-shaped pattern (e.g., Harris, 1986; Abhyankar et al., 1997; Cai et al., 2004). Abhyankar et al. (1997) and Baillie and Bollerslev (1991) find an M-shaped pattern of volume and volatility, respectively. Wood et al. (1985) and McInish and Wood (1992) demonstrate a reversed J-shaped pattern of volatility and bid-ask spread, respectively. Several theories are proposed to explain these intraday patterns, such as Foster and Viswanathan's (1990) information asymmetry, Brock and Kleidon's (1992) risk-sharing motivation, and Porter's (1992) day-end effects. Unlike other financial markets which have trading and non-trading hours, the Bitcoin market is 24/7 trading. Although the foreign exchange market has a 24-hour trading cycle due to the sequential trades in the distinctive time zones, it is not 24/7 trading. Eross et al. (2017) examine the stylized facts and the interactions among intraday returns, volume, bid-ask spread, and volatility of Bitcoin in the BTC-e exchange. They find that all the intraday dynamics show an N-shaped pattern and the variables have bidirectional Granger causality. The N-shaped pattern might imply that European and North American investors are the major contributors to trading volume and volatility (Eross et al., 2017).

The relation between trading volume and price volatility could shed light on the process of information dissemination and price formation (Karpoff, 1987). Daigler and Wiley (1999) use intraday data of five futures contracts (silver, the Major Market stock index, municipal bonds, Treasury notes, and Treasury bonds) and find a positive volatility-volume relationship which is driven by the traders who do not have precise information. Darrat et al. (2003) find significant lead-lag relations between intraday trading volume and volatility of the DJIA stocks, which is supported by Economics' (1976) sequential information arrival hypothesis (SIAH). Clark (1973) proposes a mixture of distribution hypothesis (MDH) which is used to explain the contemporaneous relationship between trading volume and volatility. Focusing on the Bitcoin market, with a non-parametric causality-in-quantiles test and daily data, Balcilar et al. (2017) document that volume does not predict volatility either in normal or extreme market conditions. Their findings are supported by a recent study of Bouri et al. (2019) who use daily data of seven major cryptocurrencies and a copula-quantile causality method. However, the evidence of the intraday volatility-volume relationship in the Bitcoin market is still not clear.

2.2 Impact of Futures Market on Spot Market

The debate about the impact of futures trading on its spot market is still ongoing. Theoretically, spot volatility may be reduced because trading futures facilitates risk transfer between hedgers and speculators (Figlewski, 1981). Danthine (1978) also argues that due to the lower costs of futures, more informed arbitrageurs may be attracted to do arbitrages across both futures and cash markets. A higher number of traders results in a more liquid market (Garbade and Silber, 1983). Moreover, Bae et al. (2004) show that the spot market efficiency is improved after the introduction of futures trading. However, Figlewski (1981) suggests that when futures market does not have sufficient speculators to assume unfavourable risk and/or futures market is manipulated, futures trading may exert a negative impact on the underlying market. In addition, when the futures market has a large number of uninformed speculators, the trading activities of these speculators reduce the informational efficiency of the spot asset market (Stein, 1987). Empirically, there is no agreement of whether futures trading stabilises or raises spot volatility (e.g., Antoniou and Holmes, 1995; Bessembinder and Seguin, 1992).

For the Bitcoin market, the impact of futures on the spot market has not been well investigated due to the short history of Bitcoin futures. In terms of whether Bitcoin spot market or futures market processes information more rapidly, researchers have not achieved a consensus (e.g., Baur and Dimpfl, 2019; Corbet et al., 2018; Kapar and Olmo, 2019). Based on the results of 9 tests, Köchling et al. (2018) suggest that introducing the two U.S. Bitcoin futures improves the spot market efficiency. They explain that the futures contracts facilitate institutional investors to do short selling and get easier access to the cash market. However, Corbet et al. (2018) argue that due to various restrictions in the regulated futures market, such as mandatory disclosure of traders' information, sophisticated institutional investors may not actively engage in the futures market. As a result, the Bitcoin cash market leads the futures market in price discovery. Also, they find that the distributional changes of the Bitcoin spot returns occur two days before the two exchanges officially announced to launch new Bitcoin futures products in the near future. In addition, using Cboe's futures contracts in hedging could not achieve risk reduction.[2]

[2] The major difference between Corbet et al.'s (2018) paper and our study is that we aim to examine the effect of a regulatory policy in the expanding Bitcoin futures market on its cash market rather than the impact of introducing new Bitcoin futures products.

Regarding the impact of futures trading ban, the proposition that futures trading may contribute to spot volatility provides regulators the motivation to set ban or restriction on futures trading (Clapp and Helleiner, 2012). Thus, it is expected that futures trading ban may stabilise the volatile spot market. However, setting a ban on futures trading may intensify the spot market incompleteness and make the market participants unable to achieve optimal capital allocation or effective risk management. Thus, futures trading ban may reduce the spot market efficiency (e.g., McKenzie et al., 2001). In addition, one appealing feature of futures trading is that it offers investors an option to short-sell the underlying asset. Although a short-selling ban is different from a futures trading ban, banning futures trading would mitigate, at least partially, short-selling pressure on the spot market. Therefore, the extant literature has not achieved a clear agreement about whether eliminating or reducing short-selling pressure would calm or disturb the asset markets (e.g., Jain et al., 2013).

3. Methodology

3.1 Volume-Weighted Bitcoin Close Price Index

As we aim to examine the impact of Bitcoin futures ban on the Bitcoin spot market, we construct a spot price index which is closely relevant to the existing two Bitcoin futures contracts. Based on the pricing model of the CME's Bitcoin futures contract, its price depends on Bitcoin Reference Rate (BRR). BRR is a daily reference rate of the U.S. Dollar price of one bitcoin as of 4:00 pm London time (CME, 2017). The required data to calculate BRR are from four cryptocurrency exchanges (i.e., Bitstamp, GDAX, itBit, and Kraken). Since we focus on intraday dynamics, the daily BRR calculation method is not applicable. As an alternative, we employ a volume-weighted close price index to calculate a proxy of the high-frequency BRR. The volume-weighted close price index for the m^{th} 5-minute interval on trading day t is calculated as[3]:

[3] We have at least two motivations to select 5-minute data frequency rather than other frequencies. First, 5-minute frequency data are available for the Bitcoin cash market. Second, 5-minute frequency data are commonly used in the previous high-frequency research, e.g., Darrat et al. (2003) and Bariviera et al. (2018). By using the 5-minute frequency data, we could compute 30-minute frequency liquidity measures.

$$P_{m,t} = \frac{\sum_{i=1}^{EX} TV_{m,t}^{i} P_{m,t}^{i}}{\sum_{i=1}^{EX} TV_{m,t}^{i}} \tag{1}$$

where $m = 1, \dots, 288$ and $t = 1, \dots, T$. T is the total number of days in the sample. $TV_{m,t}^{i}$ represents the trading volume of the i^{th} Bitcoin exchange for the m^{th} 5-minute interval on trading day t. $P_{m,t}^{i}$ denotes the last close price of the i^{th} Bitcoin exchange for the m^{th} 5-minute interval on trading day t. EX represents the number of Bitcoin exchanges used to construct the price index. Using the same method, the volume-weighted close price index for the n^{th} 30-minute interval on trading day t is:

$$P_{n,t} = \frac{\sum_{i=1}^{EX} TV_{n,t}^{i} P_{n,t}^{i}}{\sum_{i=1}^{EX} TV_{n,t}^{i}} \tag{2}$$

where $n = 1, \dots, 48$ and $t = 1, \dots, T$. T is the total number of days in the sample. $TV_{n,t}^{i}$ represents the trading volume of the i^{th} Bitcoin exchange for the n^{th} 30-minute interval on trading day t. EX represents the number of Bitcoin exchanges used to construct the price index. $P_{n,t}^{i}$ denotes the last close price of the i^{th} Bitcoin exchange for the n^{th} 30-minute interval on trading day t.

3.2 Impact of Futures Trading Ban on Intraday Spot Volatility

Various GARCH-type models have been used to estimate Bitcoin volatility. Katsiampa (2017) suggests that the optimal GARCH model for calculating Bitcoin returns is AR-Component GARCH (AR-CGARCH) model. Engle and Lee (1999) introduced the CGARCH model and propose that the conditional variance dynamics could be better described by including permanent and transitory components. Following the previous literature, we use AR (1)-CGARCH model. The return for the n^{th} 30-minute interval on trading day t is computed as, $r_{n,t} = ln\, P_{n,t} - ln\, P_{n-1,t}$. The specified model is:

$$r_{n,t} = \gamma_0 + \gamma_1 r_{n-1,t} + \varphi^{Return} Dummy_{n,t} + \varepsilon_{n,t} \tag{3}$$

$$h_{n,t} = \tau_{n,t} + g_{n,t} \tag{4}$$

$$\tau_{n,t} = \theta_0 + \theta_1 \tau_{n-1,t} + \theta_2 \left(\varepsilon_{n-1,t}^2 - h_{n-1,t}\right) + \varphi^{Long\_V} Dummy_{n,t}$$

$$g_{n,t} = \theta_3 \left(\varepsilon_{n-1,t}^2 - \tau_{n-1,t}\right) + \theta_4 g_{n-1,t} + \varphi^{Short\_V} Dummy_{n,t}$$

where $g_{n,t}$ is the short-run or transitory component and $\tau_{n,t}$ describes the long-run or permanent component. To examine whether the exogenous variables affect either the short-run or long-run component of the conditional variance dynamics, we include them in both permanent and transitory equations. We introduce a Futures ban dummy. Futures ban dummy takes the value of one from the date when South Korea's Financial Services Commission made the announcement of banning Bitcoin futures (05/12/2017) and zero otherwise.

3.3 Impact of Futures Trading Ban on Intraday Spot Liquidity

Although the bid-ask spread data are unavailable, this study employs four alternative liquidity proxies. Trading volume is a natural proxy of liquidity (Amihud, 2002). The log trading volume ($LTV_{n,t}$) for the n^{th} 30-minute interval on trading day t is:

$$LTV_{n,t}^i = ln(TV_{n,t}^i) \tag{5}$$

$$LTV_{n,t} = \frac{1}{EX} \sum_{i=1}^{EX} LTV_{n,t}^i$$

where $TV_{n,t}^i$ is the trading volume of the i^{th} cryptocurrency exchanges for the n^{th} 30-minute interval on trading day t. EX represents the number of Bitcoin exchanges used to construct the price index.

The second proxy is Amihud's (2002) measure, which is the ratio of the absolute return to the dollar trading volume. The 30-minute Amihud's (2002) measure ($Amihud_{n,t}$) for each Bitcoin exchange is:

$$Amihud_{n,t}^i = \frac{1}{6} \sum_{m=6(n-1)+1}^{6n} \frac{|r_{m,t}^i|}{TV_{m,t}^i P_{m,t}^i} \tag{6}$$

$$Amihud_{n,t} = \frac{1}{EX}\sum_{i=1}^{EX} Amihud_{n,t}^{i}$$

where $r_{m,t}^{i} = ln\, P_{m,t}^{i} - ln\, P_{m-1,t}^{i}$. $TV_{m,t}^{i}$ is the trading volume of the i^{th} Bitcoin exchanges for the m^{th} 5-minute interval on trading day t.

Third, Roll (1984) employs the first-order serial covariance of the changes in log-prices to approximate the effective bid-ask spread. The 30-minute Roll's measure ($Roll_{n,t}$) is:

$$Roll_{n,t}^{i} = \begin{cases} 0, & if\ cov(\Delta\, ln\, P_{n,t}^{i}\, ;\ \Delta\, ln\, P_{n-1,t}^{i}) \geq 0 \\ 2\sqrt{-cov(\Delta\, ln\, P_{n,t}^{i}\, ;\ \Delta\, ln\, P_{n-1,t}^{i})}, & otherwise \end{cases} \tag{7}$$

$$Roll_{n,t} = \frac{1}{EX}\sum_{i=1}^{EX} Roll_{n,t}^{i}$$

where $\Delta\, ln\, P_{n,t}^{i}$ represents a time series of the changes in six 5-minute log prices in the i^{th} Bitcoin exchange during the n^{th} 30-minute interval on trading day t.

Finally, Corwin and Schultz (2012) propose a simple way to calculate bid-ask spreads by relying on high and low prices. The 30-minute Corwin and Schultz's (2012) measure is denoted as $BAS_{n,t}$ and it is calculated as:

$$BAS_{n,t}^{i} = \frac{2(e^{\kappa^{i}} - 1)}{1 + e^{\kappa^{i}}} \tag{8}$$

$$BAS_{n,t} = \frac{1}{EX}\sum_{i=1}^{EX} BAS_{n,t}^{i}$$

$\kappa^{i} = \frac{\sqrt{2\kappa_{1}^{i}} - \sqrt{\kappa_{1}^{i}}}{3-2\sqrt{2}} - \frac{\kappa_{2}^{i}}{3-2\sqrt{2}}$, $\kappa_{1}^{i} = \sum_{j=0}^{1}\left[\ln\left(\frac{H_{n+j,t}^{i}}{L_{n+j,t}^{i}}\right)\right]^{2}$, and $\kappa_{2}^{i} = \left[\ln\left(\frac{\max(H_{n,t}^{i}, H_{n+1,t}^{i}}{\min(L_{n,t}^{i}, L_{n+1,t}^{i}}\right)\right]^{2}$. $H_{n+j,t}^{i}$ ($L_{n+j,t}^{i}$) denotes the volume-weighted high (low) price of the i^{th} Bitcoin exchange for the $n^{th} + j$ 30-minute interval on trading day t. The negative values of BAS are replaced by zero.

After obtaining the four liquidity proxies, we use the following linear regression to test the impact of futures trading/futures ban on spot liquidity.

$$IL_{n,t} = c^{IL} + \alpha^{IL} IL_{n-1,t} + \beta^{IL} Dummy_{n,t} + \omega_{n,t}^{IL} \tag{9}$$

where $IL_{n,t}$ is one measure of intraday spot liquidity (LTV, $Amihud$, $Roll$, or BAS) for the n^{th} 30-minute interval on trading day t. Again, we include futures trading dummy variable in the above equation.

3.4 Impact of Futures Trading Ban on Volatility-Volume Relation

To investigate the intraday spot volatility-volume relation in the Bitcoin market, we use the Geweke-Meese-Dent test proposed by Geweke et al. (1983). After the evaluations of the Granger causality test and the Sims causality test, Geweke et al. (1983) improved the Sims test by including the lags of dependent variables. Their test eliminates serially correlated residuals and does not require the variables to be filtered as in the Sims test (Cromwell, 1994). In the Geweke-Meese-Dent test, LTV is employed and volatility, h, is extracted from a simple AR (1)-CGARCH model without including any exogenous variables in the above equations (3) and (4). We regress LTV on lags, present, and leads of h and lags of LTV. If the coefficients of leads of h are zero, LTV does not cause h. The same procedure is used to test whether h does not cause LTV. In order to test whether South Korea's Bitcoin futures trading ban exerts any influence on the intraday volatility-volume relation, we conduct a sub-sample analysis and then compare the test statistics of two sub-samples.

4. Data and Preliminary Analysis

The CFE's Bitcoin futures contract is based on the Bitcoin data from Gemini exchange, and the CME's Bitcoin futures contract is based on the Bitcoin data from four Bitcoin exchanges, i.e., Bitstamp, GDAX, itBit, and Kraken. Because we could not obtain the intraday data of Gemini exchange, we download 5-minute and 30-minute frequency price and volume data of the other four exchanges from Bitcoincharts.com. Coordinated Universal Time (UTC) is employed to stamp tick data, which is interchangeable with Greenwich Mean Time (GMT). However, UTC is a time standard but not a time zone. Our sample period spans from 5th August

2017 to 5th April 2018. Table 1 shows the descriptive statistics of the 30-minute Bitcoin spot market data. The mean of spot returns is close to zero, accompanied with high Kurtosis and negative Skewness. The returns are calculated by using the volume-weighted Bitcoin close price index. Among the four liquidity indicators, trading volume has the highest standard deviation, while Amihud's (2002) measure shows the highest Kurtosis and Skewness. Dickey-Fuller and Phillips-Perron Tests are used to test the stationarity of the five time-series. Intercept and trend are included, and the optimal number of lags is selected based on Bayesian information criterion (BIC/SBC). As shown by the results in the last column of Table 1, all the time series are stationary.

(Insert Table 1 about here)

Figure 1 indicates the intraday patterns of the Bitcoin spot volatility and trading volume. The spot volatility is obtained from a simple AR (1)-CGARCH model with no dummy variables. From UTC 0:00 to UTC 9:00, trading volume gradually decreases. However, after UTC 9:00, it keeps raising and arrives at its peaks within the interval of UTC 14:00—17:00. After UTC 17:00, it starts to decline until UTC 23:00. The spot volatility exhibits a similar intraday pattern as the trading volume. Eross et al. (2017) find an N-shaped pattern for intraday trading volume and volatility, while we find a left-skewed N-shaped pattern. The reason for this difference might be our use of the data from four representative Bitcoin exchanges and our focus on the most recent period. Figure 2 indicates the cross-correlation of intraday volatility and trading volume at various lags and leads. A positive correlation is found, supporting the previous empirical findings. However, the correlation could not infer causality. Thus, the Geweke-Meese-Dent test is conducted later to confirm the causal relation.

A significant bidirectional causal relation between the price of Bitcoin and the search volume of the term "Bitcoin" on Google Trends is reported by Kristoufek (2013). Bouoiyour and Selmi (2015) claim that a lagged Google search for the term "Bitcoin" significantly explains the Bitcoin price as well. Figure 3 depicts the changes in the daily search volume of two words "Bitcoin" and "Bitcoin Futures" on Google Trends within our sample period, respectively. Two peaks exist near the dates when South Korea imposed the ban on Bitcoin futures (05/12/2017).

（Insert Figure 1 about here）

（Insert Figure 2 about here）

（**Insert Figure 3 about here**）

5. Empirical Results

5.1 Impact of Futures Trading Ban on Intraday Spot Volatility

Table 2 reports the estimation results of the AR-CGARCH model described in equations (3) and (4). The significantly positive coefficient of the variable $\varphi_{Ban}^{Short\_V}$ in the second column of Table 2 implies that the Bitcoin futures trading ban increases the short-run component of intraday spot price variations. In the same column, the negative coefficient of the variable $\varphi_{Ban}^{Long\_V}$ shows that the ban significantly calms the long-run component of intraday spot volatility. These findings suggest that South Korea's regulatory action regarding Bitcoin futures does exert a significant impact on the trading activities in at least one of the four Bitcoin exchanges. Moreover, the results show that the permanent component of intraday spot volatility declines after the Bitcoin futures trading ban was imposed, which implies that this regulatory policy may help stabilise the volatile Bitcoin spot market. This is supported by the argument that futures trading ban may reduce the spot market volatility (Clapp and Helleiner, 2012).

(Insert Table 2 about here)

Also, it is interesting to examine the effect of the introduction of the Cboe's and CME's Bitcoin futures on intraday spot volatility. We create a futures trading dummy variable which takes value of 1 from the start dates for the Cboe's futures trading (10/12/2017) and 0 otherwise. We add this dummy variable to both equations (3) and (4). The estimation results are reported in Appendix A. We find that the coefficients of $\varphi_{Futures}^{Short\_V}$ and $\varphi_{Futures}^{Long\_V}$ are both insignificant. It implies that the introduction of the new Bitcoin futures does not affect intraday Bitcoin spot volatility. One possible reason might be that the sceptical or cautious views expressed by some regulators/financial firms on Bitcoin-related investments discourage the potential investors to do cross-asset trading between futures and spot markets. Another reason may be that the potential players of futures need sufficient time to be familiar with the new products and design their futures-spot trading strategies. After we adding the futures trading dummy to the model, the signs of the coefficients of $\varphi_{Ban}^{Short\_V}$ and $\varphi_{Ban}^{Long\_V}$ remain unchanged and the ban's impact on the two components of intraday spot volatility remain significant.[4]

5.2 Impact of Futures Trading Ban on Intraday Spot Liquidity

Table 3 presents the estimation results of equation (9). Heteroscedasticity-consistent standard errors are used. Higher (lower) trading volume (Amihud's measure) suggests higher market liquidity. Thus, as shown in the second and the fourth columns of Table 3, the significantly positive coefficient of β^{IL_Ban} indicates that setting a ban on Bitcoin futures trading improves intraday liquidity in at least one of the four Bitcoin exchanges, i.e., Bitstamp, GDAX, itBit, and Kraken. The possible reason may be that this surprising regulatory action disturbs the initial plans of some potential Bitcoin futures traders and push them to adjust their investment strategies by closing or opening positions in the Bitcoin spot market. However, the results of using Roll's (1984) measure and Corwin and Schultz's (2012) BAS suggest the opposite situation. Both proxies estimate implicit bid-ask spread, and the higher values of these measures infer the lower market liquidity. As shown in the sixth and the eighth columns of Table 3, the coefficients of β^{IL_Ban} are significant and positive, implying that South Korea's ban on Bitcoin futures raises the implicit bid-ask spread in at least one of the four Bitcoin exchanges. In addition, the contradictive results above inspire us to do further research about the most appropriate liquidity proxy in the Bitcoin spot market.

(Insert Table 3 about here)

5.3 Impact of Futures Trading Ban on Intraday Spot Volatility-Volume Relation

The optimal number of leads and lags of the variables used in Geweke-Meese-Dent test is chosen based on BIC. The test statistics are reported in Table 4. In Panel A, trading volume significantly and positively causes volatility, but not vice versa. This finding, although

[4] On 01/12/2017, the Cboe and the CME announced to launch their own Bitcoin futures contracts in the near future (Corbet et al., 2018). To control for the impact of this event on the Bitcoin spot variability, we create a futures announcement dummy variable which is equal to 1 on 01/12/2017 and 0 otherwise. Both futures trading and futures announcement dummy variables are added to equations (3) and (4). Appendix B reports the estimation results. As shown, the impact of South Korea's futures trading ban on the spot variations remains the same.

inconsistent with the result of Balcilar et al. (2017), is in line with some previous studies related to high-frequency data. The reason might be that Balcilar et al. (2017) only consider the daily data from Bitstamp and their sample is from December 2011 to April 2016. Our result is related to the sequential information arrival hypothesis (SIAH) proposed by Economics (1976). SIAH assumes that market participants receive information not simultaneously, but in a sequential and random manner. The sequential response to news results in that lagged values of trading volume can explain current volatility, and vice versa. Hence, our finding is partially supported by SIAH. Using sub-sample analysis, we further test whether South Korea's Bitcoin futures ban exerts any impact on the intraday spot volatility-volume relationship. As shown in Panel B, the statistics of Geweke-Meese-Dent test increase dramatically in the post-ban period. However, the direction and significance of the causal relationship between volatility and trading volume remain the same.

(Insert Table 4 about here)

5.4 Robustness Tests

5.4.1 Equally-Weighted Bitcoin Close Price Index

To confirm the robustness of our empirical findings, we also calculate equally-weighted Bitcoin close price index and use it to calculate all the variables required in the above empirical analysis. The results are presented in Tables 5–6, respectively. As shown by the bold numbers in the tables, our previous conclusions remain unchanged.

(Insert Table 5 about here)

(Insert Table 6 about here)

5.4.2 Differences-in-Differences Method

Differences-in-Differences (DID) method is employed to check the impact of South Korea's Bitcoin futures trading ban on volatility and trading volume of the Bitcoin spot market. Based on the market capitalisation reported by coinmarketcap.com, Ripple and Ethereum are used as a control group. As intraday data of Ripple and Ethereum could not be found, their daily price and trading volume data are downloaded from coinmetrics.io. For Bitcoin, the relevant data are obtained from Bitcoincharts.com. The spot volatility of each cryptocurrency is extracted from a simple AR (1)-CGARCH model without any exogenous variables. The sample period is 05/08/2017–05/04/2018. The following DID model is estimated and heteroscedasticity-consistent standard errors are used.

$$Y_{i,t} = d_0 + d_1 Y_{i,t-1} + d_2 Treatment_{i,t} + d_3 Time_{i,t} + d_4 Time_{i,t} * Treatment_{i,t} + \varepsilon_{i,t} \quad (10)$$

where $Y_{i,t}$ denotes daily spot volatility or daily trading volume of the i^{th}cryptocurrency on trading day t. $Treatment_{i,t}$ is a treatment dummy variable of the i^{th} cryptocurrency on trading day t. It is equal to one for Bitcoin and zero otherwise. $Time_{i,t}$ is the time dummy variable of the i^{th} cryptocurrency on trading day t. It is equal to one after 05/12/2017 and zero otherwise. The coefficient for $Time_{i,t} * Treatment_{i,t}$, d_4, is the differences-in-differences estimator.

The estimation results are reported in Table 7. As seen from the second column, the DID estimator, d_4, is significantly negative. It implies that the expected mean changes in the daily Bitcoin spot volatility from before to after South Korea's Bitcoin futures ban is systematically different in the two groups. The daily Bitcoin spot volatility drops in the post-ban period, compared with the spot volatility of Ripple and Ethereum. These findings partially support our results in Section 5.1. Moreover, as shown in the fourth column, d_4 is significantly negative. This infers that the forecasted mean change in the daily Bitcoin spot trading volume from before to after the ban is systematically different in the treatment and control groups. It seems that the Bitcoin spot market becomes less liquid after the ban. This finding supports the results of using Roll's (1984) measure and Corwin and Schultz's (2012) bid-ask spread measure in Section 5.2. In sum, South Korea's Bitcoin futures trading ban exerts a significant impact on both daily and intraday dynamics of the Bitcoin spot market.

(Insert Table 7 about here)

6. Conclusion

This study contributes to the ongoing debate on the futures-spot relation by providing new evidence from the Bitcoin market. It is the first empirical analysis of the impact of South Korea's Bitcoin futures trading ban on the intraday dynamics of the cash market. This research confirms that the intraday Bitcoin spot volatility does have both transitory and permanent components. Also, the Bitcoin futures trading ban increases the short-run component, while reduces the long-run component of intraday volatility.

The four liquidity indicators show mixed results for intraday spot liquidity. According to the trading volume and Amihud's (2002) measure, the Bitcoin futures ban improves the spot liquidity. For the two proxies of bid-ask spread, i.e., Roll's (1984) measure and Corwin and Schultz's (2012) BAS, the impact of the ban on intraday spot bid-ask spread is positive and significant.

In addition, intraday spot trading volume positively influences intraday spot volatility, but the reversed causality is not supported. The imposition of the Bitcoin futures ban does not change the direction of the volatility-volume relationship. However, the causal effect becomes stronger in the post-ban period. In summary, the Bitcoin futures ban has a significant impact on the intraday dynamics of Bitcoin spot market. Nevertheless, set a ban or restrictions on financial innovations, such as Bitcoin futures, may not meet the long-term interests of financial market participants. Therefore, global regulators may make more efforts to better understand and effectively regulate cryptocurrencies.

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Table 1: Descriptive Statistics of Bitcoin Spot Market Data

	Mean	SD	Kurtosis	Skewness	Min	Max	Stationary
VW Return	0.000	0.010	9.791	-0.182	-0.117	0.100	Yes
LTV	0.715	0.079	0.235	0.281	0.430	1.033	Yes
Amihud	0.002	0.011	1770.558	32.752	0.000	0.720	Yes
BAS	0.003	0.004	30.229	3.865	0.000	0.071	Yes
Roll	0.002	0.003	24.671	3.615	0.000	0.040	Yes

Notes: Table 1 reports the descriptive statistics of the 30-minute Bitcoin spot market data (05/08/2017–05/04/2018). VW return is the 30-minute Bitcoin spot return calculated by using the volume-weighted Bitcoin close price index. LTV represents Log of trading volume. Amihud's (2002) measure is adjusted by multiplying its original values by 10^4. Roll is Roll's (1984) measure. BAS is Corwin and Schultz's (2012) measure. Dickey-Fuller and Phillips-Perron Tests are used to test stationarity.

Table 2: Impact of Futures Trading Ban on Intraday Spot Volatility

Variable	Coefficient	T-Stat
γ_0	0.026	3.765*** (0.000)
γ_1	0.002	0.196 (0.844)
φ_{Ban}^{Return}	-0.020	-1.567 (0.117)
θ_1	0.311	4.251*** (0.000)
θ_2	0.440	3.933*** (0.000)
θ_0	0.082	7.752*** (0.000)
θ_4	0.052	13.024*** (0.000)
θ_5	0.939	204.474*** (0.000)
$\boldsymbol{\varphi_{Ban}^{Short\_V}}$	**0.011**	**5.073*** (0.000)**
$\boldsymbol{\varphi_{Ban}^{Long\_V}}$	**-0.200**	**-2.761*** (0.006)**

Notes: Table 2 reports the estimation results of the AR (1)-CGARCH model described in the equations (3) and (4). *, **, and *** denote statistical significance levels at 0.10, 0.05, and 0.01, respectively. P-values are in the parentheses.

Table 3: Impact of Futures Trading Ban on Intraday Spot Liquidity

	LTV		Amihud		Roll		BAS	
Variable	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat	Coefficient	T-Stat
c^{IL}	0.201	42.709***	3.026	13.335***	0.001	35.032***	0.002	36.565***
		(0.000)		(0.000)		(0.000)		(0.000)
α^{IL}	0.711	107.734***	0.151	2.561**	0.266	15.033***	0.110	6.226***
		(0.000)		(0.010)		(0.000)		(0.000)
$\boldsymbol{\beta^{IL\_Ban}}$	**0.010**	**10.082*** **	**-2.130**	**-10.375*** **	**0.001**	**14.839*** **	**0.001**	**14.446*** **
		(0.000)		**(0.000)**		**(0.000)**		**(0.000)**
R-Bar^2	0.531		0.035		0.099		0.034	

Notes: Table 3 reports the estimation results of the equation (9). LTV represents natural logarithm of trading volume. Amihud is Amihud’s (2002) measure; Roll is Roll’s (1984) measure; and BAS represents Corwin and Schultz’s (2012) measure. Test statistics are computed using heteroscedasticity-consistent (Eicker-White) standard errors. *, **, and *** denote statistical significance levels at 0.10, 0.05, and 0.01, respectively. P-values are in the parentheses.

Table 4: Causality Test on Intraday Spot Volatility-Volume Relation

Panel A: Full Sample		
	Null Hypothesis: LogVolume does not cause AR(1)-CGARCH-based Volatility	Null Hypothesis: AR(1)-CGARCH-based Volatility does not cause LogVolume
Geweke-Meese-Dent	143.975*** (0.000)	0.364 (0.939)
Panel B: Sub-Sample		
	Pre-Ban	Post-Ban
	Null Hypothesis: LogVolume does not cause AR(1)-CGARCH-based Volatility	
Geweke-Meese-Dent	90.307*** (0.000)	219.296*** (0.000)
	Pre-Ban	Post-Ban
	Null Hypothesis: AR(1)-CGARCH-based Volatility does not cause LogVolume	
Geweke-Meese-Dent	0.204 (0.990)	0.413 (0.743)

Notes: Table 4 reports the F-test statistics of Geweke-Meese-Dent test and the p-values. *, **, and *** denote statistical significance levels at 0.10, 0.05, and 0.01, respectively.

Table 5: Impact of Futures Trading Ban on Intraday Spot Volatility—Equally-Weighted Price Index

Variable	Coefficient	T-Stat
γ_0	0.027	4.125*** (0.000)
γ_1	0.018	1.884* (0.060)
φ_{Ban}^{Return}	-0.021	-1.704* (0.088)
θ_1	0.290	4.239*** (0.000)
θ_2	0.455	4.138*** (0.000)
θ_0	0.082	7.740*** (0.000)
θ_4	0.053	12.496*** (0.000)
θ_5	0.937	190.762*** (0.000)
$\boldsymbol{\varphi_{Ban}^{Short\_V}}$	**0.011**	**5.264*** (0.000)**
$\boldsymbol{\varphi_{Ban}^{Long\_V}}$	**-0.196**	**-2.507** (0.012)**

Notes: Table 5 reports the estimation results of the AR (1)-CGARCH model described in the equations (3) and (4). *, **, and *** denote statistical significance levels at 0.10, 0.05, and 0.01, respectively. P-values are in the parentheses.

Table 6: Causality Test on Intraday Spot Volatility-Volume Relation—Equally-Weighted Close Price Index

Panel A: Full Sample		
	Null Hypothesis: LogVolume does not cause AR(1)-CGARCH-based Volatility	Null Hypothesis: AR(1)-CGARCH-based Volatility does not cause LogVolume
Geweke-Meese-Dent	180.237*** (0.000)	0.427 (0.906)
Panel B: Sub-Sample		
	Pre-Ban	Post-Ban
	Null Hypothesis: LogVolume does not cause AR(1)-CGARCH-based Volatility	
Geweke-Meese-Dent	180.237*** (0.000)	177.973*** (0.000)
	Pre-Ban	Post-Ban
	Null Hypothesis: AR(1)-CGARCH-based Volatility does not cause LogVolume	
Geweke-Meese-Dent	0.427 (0.906)	0.539 (0.747)

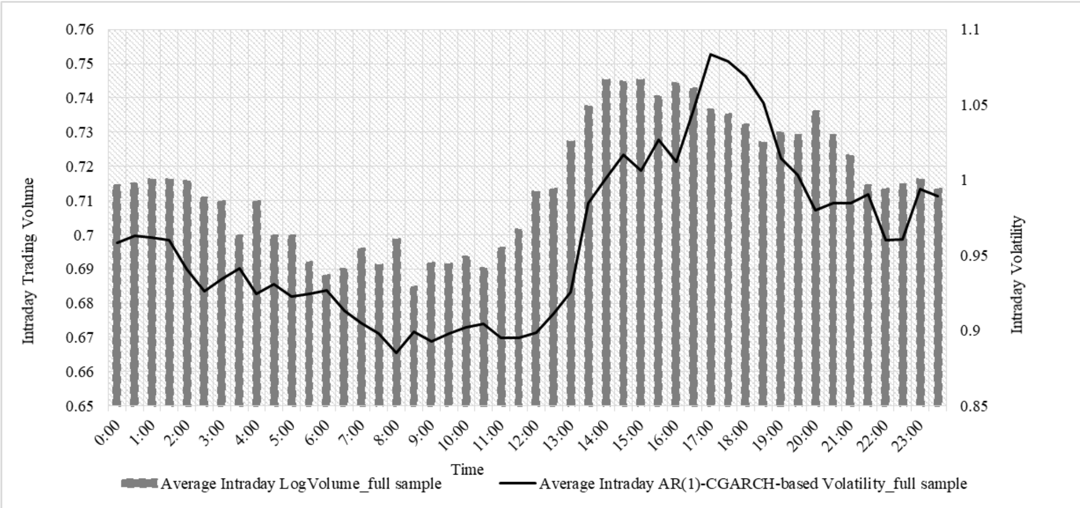
Notes: Table 6 reports the F-test statistics of Geweke-Meese-Dent test and the corresponding p-values. *, **, and *** denote statistical significance levels at 0.10, 0.05, and 0.01, respectively.

Table 7: Estimation Results of Differences-in-Differences Method

	Volatility		Volume	
Variable	Coefficient	T-Stat	Coefficient	T-Stat
d_1	0.339	2.950*** (0.003)	0.808	15.830*** (0.000)
d_2	-10.893	-3.010*** (0.003)	-0.101	-2.980*** (0.003)
d_3	46.370	3.630*** (0.000)	0.376	4.410*** (0.000)
$\boldsymbol{d_4}$	**-30.863**	**-2.310**** **(0.021)**	**-0.376**	**-4.410***** **(0.000)**
d_0	27.490	4.950*** (0.000)	0.101	2.980*** (0.003)
R-squared	0.160		0.808	

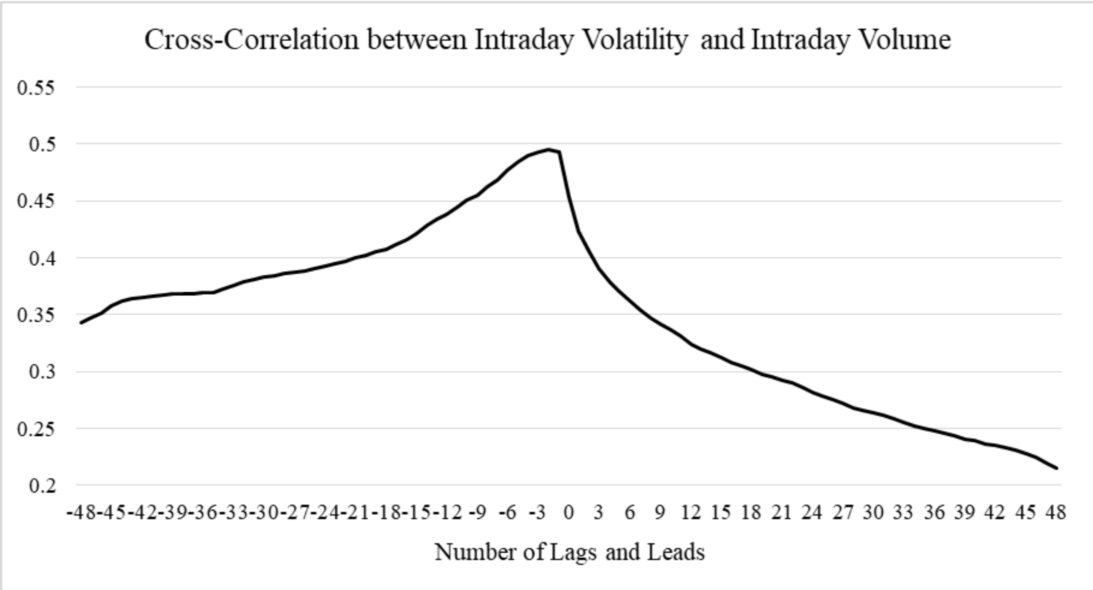
Notes: Table 7 reports the estimation results of equation (10). *, **, and *** denote statistical significance levels at 0.10, 0.05, and 0.01, respectively.

Figure 1: Intraday Dynamics of Bitcoin Spot Market



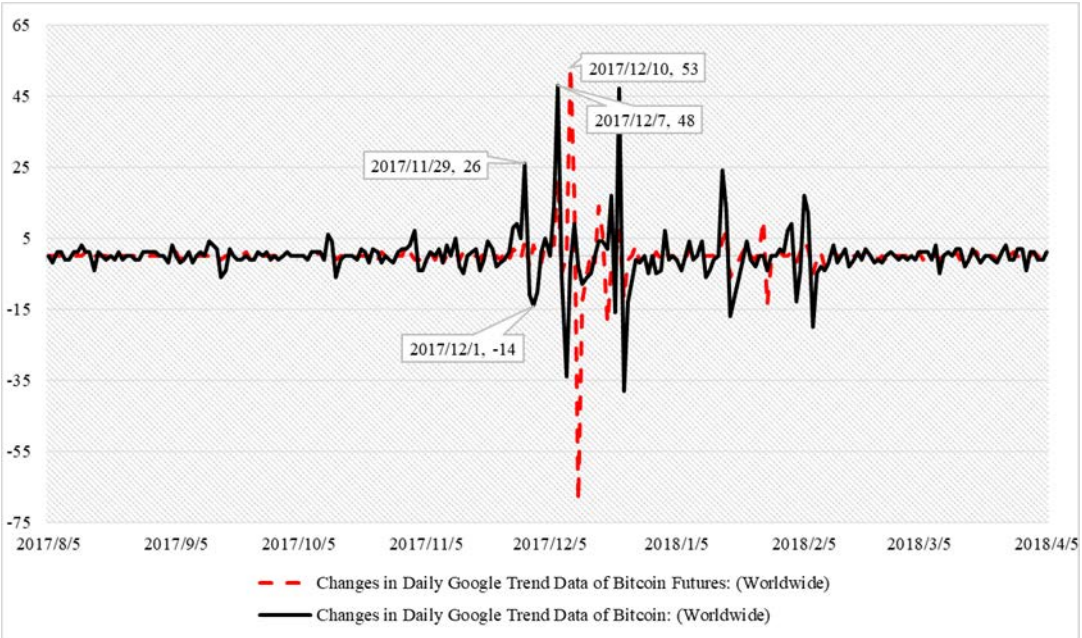
Notes: Figure 1 shows the intraday means of the Bitcoin spot volatility and trading volume. The sample period is from 05/08/2017–05/04/2018.

Figure 2: Cross-Correlation between Volatility and Volume



Notes: Figure 2 indicates the cross-correlation of the intraday volatility and trading volume at different lags, represented by positive numbers; and at different leads, represented by negative numbers. The sample period is from 05/08/2017–05/04/2018.

Figure 3: Changes in Daily Google Trend of "Bitcoin" and "Bitcoin Futures"



Notes: Figure 3 depicts the changes in the daily search volume of two words "Bitcoin" and "Bitcoin Futures" on Google Trends from 05/08/2017–05/04/2018.

Appendix A

Table A: Impact of Futures Trading Ban and Futures Trading on Intraday Spot Volatility

Variable	Coefficient	T-Stat
γ_0	0.026	4.334***
		(0.000)
γ_1	0.002	0.161
		(0.872)
φ_{Ban}^{Return}	0.052	0.931
		(0.352)
$\varphi_{Futures\,Trading}^{Return}$	-0.076	-1.350
		(0.177)
θ_1	0.305	4.106***
		(0.000)
θ_2	0.441	3.825***
		(0.000)
θ_0	0.083	8.153***
		(0.000)
θ_4	0.051	11.934***
		(0.000)
θ_5	0.939	190.485***
		(0.000)
$\boldsymbol{\varphi_{Ban}^{Short\_V}}$	**0.018**	**2.771*** **
		(0.006)
$\boldsymbol{\varphi_{Ban}^{Long\_V}}$	**-0.238**	**-2.741*** **
		(0.006)
$\varphi_{Futures\,Trading}^{Short\_V}$	-0.025	-1.255
		(0.210)
$\varphi_{Futures\,Trading}^{Long\_V}$	1.007	0.846
		(0.210)

Notes: We add a futures trading dummy variable to the AR (1)-CGARCH model described in the equations (3) and (4). Table A reports the estimation results. *, **, and *** denote statistical significance levels at 0.10, 0.05, and 0.01, respectively. P-values are in the parentheses.

Appendix B

Table B: Impact of Futures Trading Ban, Futures Announcement, and Futures Trading on Intraday Spot Volatility

Variable	Coefficient	T-Stat
γ_0	0.026	4.024***
		(0.000)
γ_1	0.002	0.175
		(0.861)
φ_{Ban}^{Return}	0.053	0.993
		(0.321)
$\varphi_{Futures\ Announcement}^{Return}$	0.217	1.506
		(0.132)
$\varphi_{Futures\ Trading}^{Return}$	-0.077	-1.405
		(0.160)
θ_1	0.307	4.125***
		(0.000)
θ_2	0.453	4.160***
		(0.000)
θ_0	0.084	8.056***
		(0.000)
θ_4	0.050	12.092***
		(0.000)
θ_5	0.941	201.121***
		(0.000)
$\boldsymbol{\varphi_{Ban}^{Short\_V}}$	**0.018**	**3.044*** **
		(0.002)
$\boldsymbol{\varphi_{Ban}^{Long\_V}}$	**-0.232**	**-3.032*** **
		(0.002)
$\varphi_{Futures\ Announcement}^{Short\_V}$	-0.038	-3.308***
		(0.001)
$\varphi_{Futures\ Announcement}^{Long\_V}$	-0.110	-0.634
		(0.526)
$\varphi_{Futures\ Trading}^{Short\_V}$	-0.022	-1.292
		(0.196)
$\varphi_{Futures\ Trading}^{Long\_V}$	0.923	0.865
		(0.387)

Notes: We add additional two dummy variables to the AR (1)-CGARCH model in the equations (3) and (4), i.e., futures trading dummy variable and futures announcement dummy variable. Table B reports the estimation results. *, **, and *** denote statistical significance levels at 0.10, 0.05, and 0.01, respectively. P-values are in the parentheses.