Has the Introduction of Extended Trading Hours Enhanced Market Quality?

Liangyi Mu*

January 15, 2020

ABSTRACT

This paper investigates the characteristics of options markets in extended trading hours (ETH) and documents positive liquidity externality with network effect and information spillover. Even with low liquidity and high transaction costs, the probability of informed trading is high during ETH. The introduction of ETH enhances market quality by decreasing the quoted spread and effective spread in the following regular trading hours (RTH). This is due to the decreased adverse selection cost, as the private information is incorporated via informed trading during ETH. The high probability of informed trading and low trading activities are possible explanations for wide quoted and effective spreads during ETH. Moreover, implied volatility in ETH options market contains incremental information to predict realized volatility in the following RTH.

Keywords: Market design; Liquidity; Extended trading hours; Asymmetric information; Informed trading; Predictability.
EFM Classification: 360, 410.

*Liangyi is with the Alliance Manchester Business School, University of Manchester, Oxford Rd, Manchester M13 9PL. Telephone: +44(0)7521654860. Email: liangyi.mu@manchester.ac.uk. I gratefully acknowledge the helpful comments from Yoichi Otsubo, Alexandros Kostakis, and participants in Young Finance Scholar Conference 2019 and annual review panel in Alliance Manchester Business School.

Understanding extended trading hours (ETH)[1] is important for market design as the development of technology has changed financial markets structures. Some traditional 09:30–16:00 markets are becoming 24-hour markets. Since 1999, broker-dealers have placed retail investors' orders into electronic communication networks (ECNs) which allows them to trade during the post regular trading hours. The Chicago Mercantile Exchange (CME) provides S&P 500 futures that trade from 18:00–17:00.[2] From 2015, options have been tradable in ETH as CBOE provides global trading hours for S&P 500 options. ETH is becoming normal in financial markets.

This research is crucial for exchange owners, market participants, and academics. The availability of ETH introduces a new issue in market design: whether financial markets should be extended beyond regular trading hours (RTH). By showing the enhancement in market quality after the ETH was introduced in an options market, this paper provides supporting evidence for ETH. Exchange owners and policymakers may consider introducing ETH markets or introducing ETH for existing options markets based on this paper's empirical results on market quality.

Market participants may recognize the high probability of informed trading and the risk of low liquidity in ETH options markets presented in this paper. Market participants need to consider whether they should trade in ETH and use the information in ETH for the following RTH. This paper suggests that market participants should be cautious of trading in ETH options markets, as they must bear high transaction costs and trade with informed traders. Market participants may have better trading performance by utilizing the information from ETH options markets, given the identified relationship between option implied index level and the market open value and the predictability of ETH IV for the following RTH RV.

Besides the interests of market participants and policymakers, academics have long focused great attention on after-hours markets. Barclay and Hendershott (2003, 2004), Dungey, Fakhrutdinova, and Goodhart (2009) respectively analyze after-hours stock markets and after-hours equity futures markets. This study extends the analysis of after-hours markets to ETH options markets. In after-hours equity markets, such as ECNs, investors' orders are directly linked with each other through the system, which requires no intermediary dealer. Unlike in an after-hours equity market, Lead Market makers (LMMs) continuously provide quotes in an ETH options market. This research contributes insights about ETH in quote-driven options markets. Also, CBOE's introduction of ETH options markets provides a quasi-natural experiment for market design and adverse selection cost tests. Moreover, Barclay and Hendershott (2004) present positive temporal liquidity externality with network effect. This paper further examine the impact of information spillover as the introduction of ETH improves the market quality in RTH.

With tick-by-tick data, this study aims to measure and compare a variety of aspects of market quality during ETH vs. RTH, and before vs. after the introduction of ETH, thereby providing a comprehensive descriptive study for the literature. It shows that an ETH options market is important for incorporating market news and contains information for the following RTH market.

[1] CBOE also refers to ETH as Global Trading Hours.

[2] Unless other specified, all timestamps in this paper are US Eastern Time.

Although market quality in ETH is poor, the market quality in RTH is enhanced after the introduction of ETH. The rest of this paper is organized as four parts. First, it provides insights into options markets around the clock with summary statistics of different measures and presents a detailed description of ETH. Second, it tests market quality around the introduction of ETH through a difference-in-differences analysis on quoted and effective spreads. Third, by applying the spread decomposition model and the probability of informed trading model, this paper explores the factors that explain differences in market quality. Fourth, this paper identifies ETH option implied index level and implied volatility (IV) contains information for the following RTH.

I. Literature review

This research is related to five streams of literature: after-hours trading, market quality and market design, information asymmetry and adverse selection cost, the probability of informed trading, and realized volatility forecasting.

A. After-Hours Trading

ECNs allow investors to place orders and trade without an intermediary which enables investors to trade stocks after RTH (Division of Market Regulation (2000)). Barclay and Hendershott (2003) compare after-hours stock trading with regular-hours stock trading and conclude that although the after-hours trading volume is low, it is important for price discovery. Trades before the opening of regular hours are possibly the most informed as information asymmetry is high before markets open and low after markets close. Pre-open trades on ECNs make a great contribution to price discovery, whereas post-close trades contribute little there.

Dungey et al. (2009) analyze after-hours equity futures markets. They show that the both volume and volatility are highest when macroeconomic news is announced before the opening of regular hours. Moreover, the price impact in the post-close period is greater than that in the pre-open period.

Chen, Yu, and Zivot (2012) find that after-hours high-frequency stock returns can improve the predictive power of GARCH model for next day stock volatility, especially the pre-open realized volatility. Jiang, Likitapiwat, and Mcinish (2012) focus on the after-hours trading around earnings announcements as 95% of announcements are released after-hours. They find the S&P 500 index stocks show an instant price response to earnings announcements and follows strong price discovery.

This paper extends the previous literature on after-hours trading into options markets. Options have no short-sale constraints and greater leverage (Black (1975)) while higher moments can only be extracted from options markets. These advantages allow options markets to provide additional understanding about ETH beyond that obtained from studies of equity and futures markets.

B. Market Quality and Design

Past literature on options market quality mainly focuses on the impact from market maker structure and intermarket competition.

Mayhew (2002) examines the impact of intermarket competition on the quoted spread in options markets. He finds that multiple-listed options have narrower quoted and effective spreads than single-listed options. He also compares the quoted and effective spreads between multiple-listed options and single-listed options, and investigates the influence of the Designated Primary Market-Maker (DPM) structure on options markets. He concludes that interexchange competition reduces the quoted and effective spreads, and the DPM structure performs better for low-volume options than for high-volume options. Battalio, Hatch, and Jennings (2004) examine whether market quality is enhanced and economic efficiency improved by the evolution of equity options markets to a national market system. Their analysis of effective spreads shows a 60 percent fall during 18 months of changing from segmented options markets to a national market. Cross quotes (bid price exceeds offer price), which provide arbitrage opportunities, drop as an indication of better market quality.

Anand and Weaver (2006) evaluate the introduction of the DPM system on options market quality with a quasi-natural experiment design. They find that quoted, current, and effective spreads all decrease after the introduction of a specialized system. Anand, Hua, and McCormick (2016) use the introduction of the make-take structure as an event and find that the execution costs decline after the event.

This paper contributes to the market quality and design literature by examining the impact of the introduction of ETH on both quoted spread and effective spread, providing new insight into market quality from the perspective of ETH.

C. Adverse Selection Cost and Information Asymmetry

Market microstructure literature indicates that adverse selection cost is an important component of bid-ask spread. Madhavan, Richardson, and Roomans (1997) and Huang and Huang and Stoll (1997) propose structure models to decompose quoted spread into its components. Madhavan et al. (1997) decompose quoted spread into adverse selection cost and costs of supplying liquidity while Huang and Stoll (1997) decompose it into adverse selection cost, inventory holding costs, and order processing costs. Lin, Sanger, and Booth (1995) decompose effective spread into adverse selection cost and order processing costs.

Li, French, and Chen (2017) apply three spread decomposition models to analyze S&P 500 options markets and use adverse selection cost as the proxy for informed trading. They find that adverse selection cost was significantly higher in options markets around the 2008 crisis.

Using models developed by Lin et al. (1995), Barclay and Hendershott (2004) find that adverse selection cost is highest in pre-open hours in stock. It is worth researching whether adverse selection cost are changed by introducing ETH in options markets and whether the changes in quoted and effective spreads can be explained by changes in adverse selection cost.

D. *Probability of Informed Trading (PIN)*

The PIN model was originally developed by Easley, Kiefer, O' Hara, and Paperman (1996), and used by Barclay and Hendershott (2003) for after-hours trading analysis. Easley, Hvidkjaer, and O' Hara (2002) extend the original PIN model to allow different arrival rates of buy-initiated trades and sell-initiated trades.

Both the PIN model and extended PIN model have been developed for a single asset. However, options markets have a series of contracts (e.g., different strike prices and different maturities) for the same underlying asset. Cheung, Chou, and Lei (2015) estimate the PIN of all options contracts and summarize the parameters of all contracts. Wu, Liu, Lee, and Fok (2014) use a nearby futures contract instead of an option contract as the proxy for options markets PIN.

However, Gan, Wei, and Johnstone (2017) criticize that the PIN model only weakly fits actual trade data, and suggest that using PIN value as an explanatory variable may result in unreliable results. In this paper, the PIN estimate is not the sole explanatory variable. PIN estimates are combined with other measures, specifically trade size and trade volume, to help explain the spreads in ETH.

E. *Realized Volatility Forecasting*

Corsi (2009) introduces heterogeneous autoregressive model of Realized Volatility (HAR-RV). Although HAR-RV has simple structure, it succeeds to capture features of financial returns.

Recently, Bollerslev, Patton, and Quaedvlieg (2016) incorporate realized quarticity into HAR-RV model to have more accurate estimate of RV.

Busch, Christensen, and Nielsen (2011) present IV has additional information for RV forecasting. RV forecasting model with IV outperforms other return based models in out-of-sample prediction. This paper extends the RV forecasting literature by incorporating ETH IV.

II. Methodology

This study's methodology contains four parts. First, characteristics of ETH options markets are presented with summary statistics of intraday quotes and trades. Second, through the difference-in-differences method with quoted spread and effective spread, the impact of CBOE's introduction of ETH is analyzed. Third, the quoted spread decomposition model (Huang and Stoll (1997)), the effective spread decomposition model (Lin et al. (1995)), and the PIN model (Easley et al. (2002)) are applied to explore the factors causing spreads to differ. Fourth, IV together with HAR-RV and HARQ-RV models is analyzed to identify the information in ETH for predicting RV in RTH.

A. *Descriptive Measures*

The summary statistics of quote changes, volume, trade size, quoted spread, and effective spread are calculated to describe the characteristics of the ETH market. Tick-by-tick best quotes and trades are directly extracted from Thomson Reuter DataScope. Midquote is the average of best bid and best ask.

This study uses dollar quoted spread (formula 1a), percentage quoted spread (formula 1b), dollar effective spread (formula 1c), and percentage effective spread (formula 1d) as proxies for market quality. For each quote update or transaction i, these measures are defined as

$$Spread_{Q,i}(\$) = Ask_i - Bid_i \tag{1a}$$

$$Spread_{Q,i}(\%) = Spread_{Q,i}(\$)/Mid_i \tag{1b}$$

$$Spread_{E,i}(\$) = 2 * |p_i - Mid_i| \tag{1c}$$

$$Spread_{E,i}(\%) = Spread_{E,i}(\$)/Mid_i \tag{1d}$$

where Ask_i, Bid_i, and Mid_i are best ask quote, best bid quote, and midquote respectively, p_i is the transaction price.

Quote-weighted average quoted spread (formula 2a) and volume-weighted effective spread (formula 2b) during time t are calculated as

$$Spread_{Q,t} = \frac{1}{N}\Sigma_{i=1}^{N} Spread_{Q,i} \tag{2a}$$

$$Spread_{E,t} = \Sigma_{i=1}^{N} Spread_{E,i} \frac{Volume_i}{\Sigma_{i=1}^{N} Volume_i} \tag{2b}$$

where $Spread_{Q,i}$ is the tick by tick quoted spread updates during time t, $Spread_{E,i}$ and $Volume_i$ are effective spread and volume of tick by tick transaction during time t, N is total number of quote updates or total number of trades during time t.

B. *Test of Market Quality*

This research aims to test whether the introduction of ETH enhances market quality. On March 9, 2015, CBOE launched ETH for S&P 500 weeklys (SPXW) and S&P 500 traditional (SPX) options. There is no other market structure changes around this event. Before the introduction of ETH options markets, information in ETH is aggregated until the opening of RTH. In the post-open period of RTH, information asymmetry and adverse selection cost may be high due to the accumulated information. Liquidity providers require high compensation given the high level of asymmetric information. Therefore, high quoted spread and high effective spread are expected before the introduction of ETH. After the introduction of ETH, information in ETH can be immediately incorporated into the market. Information asymmetry and adverse selection cost in the following RTH may, thus, decrease. Liquidity providers require low compensation when asymmetric information is low resulting in low quoted spread and effective spread. Quoted and effective spreads are widely used measures for market quality: wide (narrow) quoted and effective spreads indicate high (low) market quality.

Previous literature uses matched samples (Mayhew (2002)), regression (Anand and Weaver (2006)), and categorized difference-in-differences (Anand et al. (2016)) to study the impact of market structure changes on options market quality.

Mayhew (2002) uses a matched sample method to control variables affecting options market quality other than multi-listing and DPM structure. Options contracts are matched by price, volume, and volatility for all stock options in CBOE. The differences in paired option spreads show the impact of market structure changes.

Anand and Weaver (2006) use regression to analyze the impact of the DPM system. They control for the effects of maturity, moneyness, and option price with multiple-listed options. As CBOE has introduced the DPM system whereas other exchanges have not, the interaction variable between CBOE/non-CBOE and Before DPM/Post DPM presents the DPM system's impact on options markets.

Anand et al. (2016) categorize option contracts by their prices and conduct simple difference-in-differences analysis within each options price group. They also apply panel regression with fixed entity effect and fixed date effect to confirm the results from the difference-differences method.

Similar to Anand et al. (2016), and using the introduction of ETH options markets as an event, this study conducts a difference-in-differences analysis with controlled variables between SPXW and SPY options to analyze the impact of the introduction of ETH options markets. SPY options cannot be traded in extended hours but are affected by the same information as SPXW and SPX options. Therefore, the difference-in-differences method with SPXW and SPY options minimizes the impact of extraneous variables.

The treatment group is SPXW options; the control group is SPY options. The characteristics of SPXW and SPY options are similar. The underlying asset of SPXW options is the S&P 500 index while the underlying asset of SPY options is the SPDR ETF. In the long term, the SPDR ETF and the S&P 500 index are highly correlated. Besides, the SPDR ETF price is one-tenth of S&P 500 index level; hence, ten SPY options are approximately the same as one SPXW option plus the early exercise opportunity in American option.

The null hypothesis for the market quality test: The introduction of ETH in options markets does not improve market quality. The market quality changes of SPXW options are not significantly different from the market quality changes of SPY options around the introduction of ETH.

B.1. Determinants of Bid-ask Spreads

To identify the impact of the introduction of ETH on spreads, variables with fixed effects have to be controlled first. Option midquote, trading volume, and time to maturity are the three most relevant control variables in this study.

Mayhew (2002) asserts that option price, options trading volume, and the volatility of the underlying stock are the most important control variables for spread analysis. Anand et al. (2016) also use these control variables in their panel regression. Option price is related to not only the dollar quoted spread but also the percentage quoted spread.

The underlying asset of SPXW and SPY options have similar volatility. Underlying volatility is the same for all S&P 500 options. Also, the daily differences in underlying volatility can be captured by the date fixed effect. Therefore, underlying volatility is not incorporated in this study's analysis.

There is a maturity effect in implied volatility spread, as discussed by Hsieh and Jarrow (2019) and Chong, Ding, and Tan (2003). As maturity near, the implied volatility increases. Anand and Weaver (2006) also use time to maturity as a control variable in their regression. Therefore, this study incorporates time to maturity as a control variable.

B.2. Spreads Around the Introduction of ETH

This study categorizes options contracts by their midquote. Option midquote is a good approximation for intraday option price. As spread is not linearly related to midquote, difference-in-differences regression is conducted in each midquote category.

The difference-in-differences regression equation for market quality analysis is

$$\begin{aligned} Spread_{i,t,m} = \beta_0 + \beta_1 TTM_{i,t,m} + \beta_2 Mid_{i,t,m} + \beta_3 Volume_{i,t,m} \\ + \beta_4 D_t + \beta_5 D_s + \beta_6 (D_t \cdot D_s) + \varepsilon \end{aligned} \tag{3}$$

where $Spread_{i,t,m}$ is the half-hour average spread (quote-weighted average quoted spread or volume-weighted effective spread) of option contract i on day t in midquote category m; D_t is period dummy variable, which equals 1 if after March 9, 2015, and 0 if before February 28, 2015; D_s is the sample dummy variable, which equals 0 for SPY options, and 1 for SPXW options; TTM,Mid,and $Volume$ are the control variables in this study; TTM is the logarithm of days to maturity plus 1, Mid is the bid and ask quotes average for the spread; and $Volume$ is the logarithm of trading volume during one half-hour; β_0 is the intercept; β_1, β_2, and β_3 are the fixed effects of the control variables; β_4 is the fixed effect of time; β_5 is the fixed effect of sample group; β_6 is the impact of the introduction of ETH on options markets.

This regression is conducted for half-hour average spreads in midquote groups during RTH. In each midquote group, dollar quoted spread, percentage quoted spread, dollar effective spread, and percentage effective spread are separately estimated by the regression.

The null hypothesis for spreads is $H_0 : \beta_6 = 0$. If market quality improves with ETH, the null hypothesis will be rejected and β_6 will be significantly negative.

C. Factors Explaining Market Quality

This section analyze the factors explaining the market quality difference between ETH and RTH by PIN model and the market quality difference in RTH before and after the introduction of ETH by spread decomposition models.

C.1. Asymmetric Information Cost Around the Introduction of ETH

This part extends the analysis of spreads into their components by investigating the factors for changes in market quality around the introduction of ETH using spread decomposition models. In the structure spread decomposition models, spreads are decomposed into asymmetric information cost, inventory holding costs, and order processing costs. As ETH allows market information to be immediately incorporated into the market, asymmetric information cost is expected to be lower in the post-introduction period while order processing costs and inventory holding costs may remain unchanged.

The quoted spread decomposition model developed by Huang and Stoll (1997) is specified as

$$\begin{aligned} &E(x_{t-1}|x_{t-2}) = (1-2\varphi)x_{t-2} \\ &\Delta Q_t = (\alpha+\beta)\frac{sp_{t-1}}{2}x_{t-1} - \alpha(1-2\varphi)\frac{sp_{t-2}}{2}x_{t-2} + \varepsilon_t \end{aligned} \tag{4}$$

where t denotes the trade time, x_t is the trade direction, sp_t is the quoted spread, ΔQ_t is the midquote change from time $t-1$ to time t, α is adverse selection cost, β is inventory holding costs, and φ is the probability that trade price reverses from time $t-1$ to time t.

The moments conditions of model (4) for GMM estimation are specified as

$$E\begin{pmatrix} (x_{t-1}-(1-2\varphi)x_{t-2})) \\ (\Delta Q_t - (\alpha-\beta)\frac{sp_{t-1}}{2}x_{t-1} - \alpha(1-2\varphi)\frac{sp_{t-2}}{2}x_{t-2})x_{t-1} \\ (\Delta Q_t - (\alpha-\beta)\frac{sp_{t-1}}{2}x_{t-1} - \alpha(1-2\varphi)\frac{sp_{t-2}}{2}x_{t-2})x_{t-2} \end{pmatrix} = 0 \tag{5}$$

The effective spread decomposition model developed by Lin et al. (1995) is specified as

$$\begin{aligned} &Q_{t+1} - Q_t = \lambda z_t + e_{t+1} \\ &z_{t+1} = \theta z_t + \eta_{t+1} \\ &P_{t+1} - P_t = -\gamma z_t + u_{t+1} \end{aligned} \tag{6}$$

where Q_t is the midquote, z_t is the effective spread, P_t is the trade price, λ is adverse selection cost, γ is order processing costs, and θ is the persistence of order flow; e_{t+1}, η_{t+1}, and u_{t+1} are uncorrelated; parameters λ, θ, γ are estimated by OLS.

Previous literature has different methods to determine the trade direction. Madhavan et al. (1997) use Lee and Ready (1991) algorithm with a 16-second time lag, following Blume and Goldstein (1992) suggestion for the stock market. Savickas and Wilson (2003) compare four classification rules for option trades: quote rule, tick rule, Lee and Ready (1991) rule, and the Ellis, Michaely, and O'Hara (2000) (EMO) rule. Their results show that Lee and Ready (1991) rule is slightly more accurate than EMO rule in options markets. In applying spread decomposition model, Li et al. (2017) use Lee and Ready (1991) rule with the most recent midquote, which means they ignore the time lag. Considering all previous literature, this study adopts a similar approach to Li et al. (2017) by applying Lee and Ready (1991) original algorithm with the most recent midquote to determine buy- or sell-initiated trades.

The transaction price is compared with the most recent midquote. If the transaction price is higher (lower) than the midquote, the trade is buy- (sell-) initiated. If the transaction price is equal to the midquote, the tick direction is used to determine whether the trade is buy- or sell-initiated: upward (downward) tick direction indicates buy- (sell-) initiated trade.

If the null hypothesis that ETH options markets are not important for incorporating information is true, either asymmetric information does not accumulate in the absence of ETH options markets, or ETH options markets are unable to incorporate information immediately and have no effect on information asymmetry in the following RTH markets, the adverse selection costs will not be reduced after the introduction of ETH.

To test this hypothesis, a difference-in-difference regression for components of spreads with control variables similar to equation (3) is conducted:

$$\begin{aligned} y_{i,t} = \beta_0 + \beta_1 TTM_{i,t} + \beta_2 Mid_{i,t} + \beta_3 Volume_{i,t} \\ + \beta_4 D_t + \beta_5 D_s + \beta_6 (D_t \cdot D_s) + \varepsilon \end{aligned} \tag{7}$$

where $y_{i,t}$ is α, β, φ are from model (4) and λ, θ, γ from model (6), respectively, of option contract i on day t, all other variables are the same as defined for equation (3).

The null hypothesis for the regression is $H_0 : \beta_6 = 0$ for adverse selection costs λ and α. If the ETH options market incorporates market news and reduces information asymmetry in the following RTH, the null hypothesis will be rejected and β_6 will be negative.

C.2. Probability of Informed Trading (PIN)

This paper tries to explain the difference of market quality between ETH and RTH using the PIN model. A high probability of informed trading may partially explain the wide quoted spread and effective spread in ETH options markets, as liquidity providers require more compensation given the high probability of informed trading.

Buy and Sell Trades in Options Markets To estimate PIN model, Buy and Sell trades have to be identified first. Instead of estimating PIN for each option contract, this study pools option trades into aggregate trades.

First, based on Lee and Ready (1991) algorithm, all trades are compared with the most recent midquote. If the transaction price is higher (lower) than the midquote, it is regarded as buy-initiated (sell-initiated). If the transaction price is the same as the midquote, the transaction price is compared with the previous transaction price.

Second, this study assumes there is no market segmentation in SPXW options markets. Informed investors will treat SPXW options market as a whole. Therefore, SPXW option trades with different strike prices and time to maturities are aggregated into the two categories of buy- and sell-initiated trades.

Buying a call and selling a put both have a bullish expectation about the market. Buy-initiated call option trades and sell-initiated put option trades are regarded as buy trades in the PIN model. Conversely, selling a call and buying a put both have a bearish expectation about the market. Sell-initiated call option trades and buy-initiated put option trades are regarded as sell trades in the PIN model.

Extended PIN Model In this part, the extended PIN model (Easley et al. (2002)) is applied to analyze informed and liquidity trading after hours in options markets.

Assuming a Poisson arrival process, the likelihood function for one trading period is specified as:

$$\begin{aligned} L((B,S)|\theta) = (1-\alpha)e^{-\epsilon_b T}\frac{(\epsilon_b T)^B}{B!}e^{-\epsilon_s T}\frac{(\epsilon_s T)^S}{S!} \\ + \alpha\delta e^{-\epsilon_b T}\frac{(\epsilon_b T)^B}{B!}e^{-(\mu+\epsilon_s)T}\frac{((\mu+\epsilon_s)T)^S}{S!} \\ + \alpha(1-\delta)e^{-\epsilon_s T}\frac{(\epsilon_s T)^S}{S!}e^{-(\mu+\epsilon_b)T}\frac{((\mu+\epsilon_b)T)^B}{B!} \end{aligned} \tag{8}$$

where B and S are total buy trades and sell trades during the period, (α, δ, μ, ϵ_b, ϵ_s) are the parameter vectors of the model, α is the probability of an information event, δ is the probability of a bad-news day, ϵ_b is the arrival rate of uninformed buy orders, ϵ_s is the arrival order of uninformed sell orders, and μ is the arrival rate of informed orders, assuming that each period on different days are independent, the parameter vector is estimated by MLE.

The probability of informed trading (PIN) is the expected number of private information-based transactions to the expected total number of trades:

$$PIN = \frac{\alpha\mu}{\epsilon_b + \epsilon_s + \alpha\mu} \tag{9}$$

The proportion of informed trading (PIT) is the proportion of informed trades to the total number of trades when there is an information event:

$$PIN = \frac{\mu}{\epsilon_b + \epsilon_s + \mu} \tag{10}$$

Liquidity ratio is the ratio of liquidity rate of buy orders to the liquidity rate of sell orders:

$$liquidity\ ratio = \epsilon_b/\epsilon_s \tag{11}$$

From the results of Barclay and Hendershott (2003), the participation rates of informed traders and liquidity traders are expected to differ in different periods, with a higher proportion of liquidity traders during post-close and a higher proportion of informed traders during pre-open. In this research, the trading time is divided into half-hour intervals, and the PIN of each half-hour is estimated.

D. Predictability

This part tries to evaluate the predictability of option implied information in ETH. If ETH options market incorporates updated information with informed trading, option implied information in ETH may provide forecasting information for the following RTH. This study identifies that ETH options market is able to predict the open value of index level and realized volatility in RTH.

D.1. Put-call Implied Index Level

The underlying of S&P 500 weekly options is S&P 500 index which is not available in ETH. Traded S&P 500 derivatives in ETH include S&P 500 futures and S&P 500 Emini futures. However, the expiry dates of S&P 500 futures and S&P 500 E-mini futures are different from the expiry date of S&P 500 weekly options. The option implied index from put-call parity may provide independent information about S&P 500 index level. This study tests whether the put-call implied S&P 500 index level at the end of ETH predicts S&P 500 index level at the open of the following RTH. Option implied index level $s_{I,t}$ at the close of ETH on day t for S&P index from put call parity is specified as

$$s_{I,t} = (c_t + Xe^{-rT} - p_t)e^{qT} \tag{12}$$

where c_t and p_t are call and put option last midquote from 09:10 to 09:15 on day t respectively, X is the strike price, r is risk-free rate, q is the dividend yield, T is the time to maturity.

The average of put-call parity implied index levels across different moneyness is used as the option implied index level.

The predictive power of option implied index for market open index level is examined by a simple regression

$$r_{M,t} = \alpha + \beta_{I,t} r_{I,t} + \epsilon_t \tag{13}$$

where $r_{I,t}$ is the option implied overnight simple return on day t calculated from option implied index level and previous day close index level, $r_{M,t}$ is the index overnight simple return calculated from open and previous close index level on day t.

Following Gao, Han, Zhengzi Li, and Zhou (2018), the out-of-sample predictability is measured by out-of-sample R^2

$$r^2_{OS} = 1 - \frac{\sum_{t=1}^{T}(r_{M,t} - \hat{r}_{M,t})^2}{\sum_{t=1}^{T}(r_{M,t} - \bar{r}_{M,t})^2} \tag{14}$$

where $r_{M,t}$ is the market index overnight return, $\hat{r}_{M,t}$ is the forecasted index overnight return from regression (equation 13) with coefficients estimated from previous 22 days and current option implied overnight return. $\bar{r}_{M,t}$ is the historical average of 22 forecasted overnight return.

D.2. Option Implied Volatility(IV)

Model free option implied volatility developed by Bakshi, Kapadia, and Madan (2003) is compared with two realized volatility forecasting models, HAR-RV (Corsi (2009)) and HARQ-RV

(Bollerslev et al. (2016)) models for one-day RV forecasting.

Before applying model free implied volatility, option data is filtered by non-arbitrage rule. If call (put) option with higher (lower) strike price has higher or same price, it is excluded from this study.

Then, model free implied volatility is

$$\begin{aligned} M_1 &= e^{rT} - 1 \\ M_2 &= \frac{2}{S_0^2}[\sum_{XP_i} p_i(XP_i - XP_{i-1}) + \sum_{XC_i} c_i(XC_i - XC_{i-1})] \\ IV &= [e^{rT} M_2 - M_1^2]^{\frac{1}{2}} \end{aligned} \tag{15}$$

where S_0 is the option implied index level estimated from formula (12), XP_i and p_i are OTM put option strike price and option price, XC_i and c_i are OTM call option strike price and option price.

Daily realized volatility is estimated as

$$RV_t = sqrt(\sum_{i=1}^{M} r_{t,i}^2) \tag{16}$$

where M is 390 for one-minute return and 78 for five-minute return, $r_{t,i}$ is the logarithm return.

HAR-RV (Corsi (2009)) (equation 17a) and HARQ-RV (Bollerslev et al. (2016)) (equation 17b) are specified as

$$RV_t = \alpha + \gamma_1 RV_{t-1} + \gamma_2 RV_{t-5,t-1} + \gamma_3 RV_{t-22,t-1} + \varepsilon_t \tag{17a}$$

$$RV_t = \alpha + \gamma_1 RV_{t-1} + \gamma_2 RV_{t-5,t-1} + \gamma_3 RV_{t-22,t-1} + \gamma_4 RV_{t-1} RQ_{t-1} + \varepsilon_t \tag{17b}$$

where RV_{t-1} is previous day RV, $RV_{t-5,t-1}$ is average RV in previous five days, $RV_{t-22,t-1}$ is average RV in previous 22 days, $RQ_{t-1} \equiv \frac{M}{3} \sum_{i=1}^{M} r_{t,i}^4$.

Following the idea of Busch et al. (2011), IV is incorporated into HAR-RV and HARQ-RV models to examine whether IV in ETH has additional information for the realized volatility in the following RTH. HAR-RV-IV (equation 18a) and HARQ-RV-IV (equation 18b) are specified as

$$RV_t = \alpha + \gamma_1 RV_{t-1} + \gamma_2 RV_{t-5,t-1} + \gamma_3 RV_{t-22,t-1} + \beta_1 IV_t + \varepsilon_t \tag{18a}$$

$$RV_t = \alpha + \gamma_1 RV_{t-1} + \gamma_2 RV_{t-5,t-1} + \gamma_3 RV_{t-22,t-1} + \gamma_4 RV_{t-1} RQ_{t-1} + \beta_1 IV_t + \varepsilon_t \tag{18b}$$

where IV_t is the model free implied volatility from formula (15).

Besides, IV can be used to forecast RV directly. If RV is assumed to be linearly related to IV, model IV_Q-RV is specified as

$$RV_t = \alpha + \beta_1 IV_t + \varepsilon_t \tag{19}$$

If variance risk is assumed to be zero in one day expectation, Risk-neutral IV can be used to transformed into physical RV directly. (IV_P-RV)

$$RV_t = IV_t + \varepsilon_t \tag{20}$$

Following Patton (2011), mean squared error (MSE) and QLIKE (formula 21) are used to evaluate out-of-sample RV forecasting performance.

$$QLIKE = \frac{\hat{\sigma}^2}{h} - log\frac{\hat{\sigma}^2}{h} - 1 \tag{21}$$

where $\hat{\sigma}^2$ is the market realized volatility, h is the model forecast RV.

III. Data

Tick-by-tick trade data and best-bid-offer data of SPXW and SPY options are extracted from Thomson Reuters DataScope.

There are four types of options related to the S&P 500 index: SPX traditional options, SPXW weekly non-traditional options, SPX mini-options, and SPY options. SPY options are American style options; they are frequently traded in RTH but not traded in ETH. SPY options are used as the control group in this study.

SPX mini-options are one-tenth of the notional size. They may be less preferred by institutional investors, as reflected by their extremely low trading volumes among S&P 500 options. Accordingly, SPX mini-options are excluded from this study.

The settlement time of SPX traditional options is in the morning of the expiry date, while SPXW weekly non-traditional options expire in the afternoon. On settlement day, SPX traditional options do not span the following RTH while SPXW options span. Also, SPX traditional options only have expiry date on third Friday each month while SPXW options have more expiry dates especially in the short terms. Therefore, SPXW rather than SPX options are estimated in this study.

Risk-free rate is the zero-coupon rate from OptionMetrics. Cubic spline interpolation[3] is applied to zero-coupon rate to get the risk-free with the same time to maturity as the option contract. S&P 500 dividend rate is directly extracted from OptionMetrics. S&P 500 E-mini futures tick by tick data from Thomson Reuters DataScope is used to estimate the volatility in ETH.

Three sample periods are estimated for market quality analysis: before the introduction of ETH (December 1, 2014–February 28, 2015); after the introduction of ETH (March 9, 2015–May 31, 2015); and a recent sample (January 1, 2019–March 31, 2019).

For predictability analysis, sample period is from May 1, 2017 to March 31, 2019. From May 1,2017, SPXW contains expiry dates on Monday, Wednesday, and Friday .

[3]Cubic spline interpolation is conducted by MATLAB built-in function *spaps*

IV. Characteristics of Index Option Market Around the Clock

With the introduction of CBOE's ETH options market, which is traded from 03:00 to 09:15 from Monday to Friday with an all-electronic trading environment, index options market is one step closer to a 24 hour market. During ETH, three Lead Market makers (LMMs) continuously provide bid and ask quotes while in RTH there are multiple LMMs. Therefore, informed traders can trade with the LMMs even in the absence of voluntary liquidity traders.

A. Trading Volume

Figure 1 panel A shows the intraday options trading. Trading volumes differ significantly between ETH and RTH, with RTH options trading the absolutely majority for a day.

[Insert Figure 1 panel A]

Figure 1 panel B shows the options trading volumes in ETH. The trading volumes are relatively small overnight and increase sharply in the pre-open session: specifically, they peak about one hour before the market opens, which is the time of scheduled macroeconomic announcements. It should be noted that the trading volumes in both ETH and RTH and U-shaped.

[Insert Figure 1 panel B]

As Figure 2 panel A presents, at-the-money (ATM) options are the most traded in RTH, with OTM options also frequently traded, but ITM options rarely traded. ATM options have the highest Vega, while OTM options have high leverage. It is expected that they are preferred by market participants.

[Insert Figure 2 panel A]

Options trading has a similar pattern in ETH with moneyness that only ATM and OTM options are frequently traded. ATM options trading represents around 50% of total options trading in the ETH market. In the following analysis, this study mainly focuses on the OTM and ATM options.

[Insert Figure 2 panel B]

Figure 3 shows that the trade size in the options market varies substantially from ETH to RTH. Unlike Barclay and Hendershott's (2003) empirical results for the stock market, the average trade size in ETH options market is not larger than the trade size in regular hours. However, there are some large options trades of approximately two to three times the average trade size. Liquidity providers have higher uncertainty in inventory management in ETH.

[Insert Figure 3]

B. 30-minute Realized Volatility and Quote Changes

Based on equation (16) with one-minute return and 30 minute interval, 30-minute realized volatility is estimated from S&P 500 E-mini futures. As there is no index available in ETH, the RV of S&P 500 E-mini futures is the proxy for index volatility.

On average, the RTH market has much higher realized volatility than the ETH market. Similar to the intraday options trading volumes pattern, realized volatility is also U-shaped in both the

ETH and RTH markets. Combining the patterns from low realized volatility, fewer quotes changes, and low trading volume, there are likely fewer information updates and less trading activities in ETH.

[Insert Figure 4]

[Insert Figure 5]

C. The Intraday Patterns of Quoted Spread in Options Markets

The literature contains no consistent conclusion about the intraday options market quoted spread pattern. Chan, Chung, and Johnson (1995) present an L-shaped pattern in options markets, whereas Mishra and Daigler (2014) show a U-shaped pattern in the SPY options market.

Figure 6 shows the intraday dynamics of the quoted spread for both ETH and RTH. There are three intraday patterns of quoted spread in the options markets. First, the overall quoted spread is U-shaped in RTH but more volatile in ETH. Second, there are three peaks of quoted spread at the times of macroeconomic announcements. Third, quoted spread is significantly higher in ETH than RTH.

Previous studies take different approaches to summarizing the intraday pattern of quoted spread. Mishra and Daigler (2014) categorize options by their moneyness and calculate the average quoted dollar spread in each moneyness category at each time of the day. Chan et al. (1995) calculate the quoted dollar spread and quoted percentage spread for each option contract in 15-minute intervals each day. They then subtract the mean and divide the standard deviation of the spreads with each option contract in each day. The averages of the standardized quoted dollar spread and quoted percentage spread at each time of day are presented.

As deep OTM options prices are quite small and close to the minimum tick price, the quoted percentage spread is highly biased by those deep OTM options. Therefore, the quoted percentage spread is not applied in this part.

This study calculates quoted spreads similarly to Chan et al. (1995) as it is only interested in the relative level of the time of day effects in quoted dollar spread. First, the quote-weighted quoted dollar spread is calculated for each contract in 5-minute intervals each day. Second, the spread ratio is the 5-minute average quoted dollar spread divided by the 5-minute average quoted dollar spread at the opening of RTH for each contract each day. In this way, the quoted spread of different options contracts at different time of the day can be summarized, and only the time of day effect in the quoted spread is presented.

This study presents a different quoted spread pattern from previous literature on RTH and provides new insights into ETH. Chan et al. (1995) document that quoted spread is high in the opening hour and low in the closing hour, making an L-shape during the day. By contrast, Mishra and Daigler (2014) find SPY options to present a U-shape, but not SPX options.

The quoted spread in Figure 6 shows that the overall SPXW option quoted spread during RTH is approximately U-shaped. Quoted spread is wider when the market opens narrower during the middle of trading hours. Before market closes, quoted spread is slightly wider than the middle of trading hours. The difference between these results and previous findings may be attributable to two aspects. First, since the study of Chan et al. (1995)), the structure of options markets may have changed. A new trading platform has been introduced and market-maker rules are different. Consequently, the intraday quoted spread patterns may be different over a long period. Second, the difference in summarizing quoted spread from different options between Mishra and Daigler (2014) and this study may explain the absence of a U-shaped SPX option quoted spread. Mishra and Daigler (2014) group the quoted spread by moneyness. Averaging quoted spread from different options contracts may reduce the accuracy of intraday patterns. Besides, in ETH, quoted spread is more volatile and not a typical U-shape. Quoted spread at the open and close in ETH seems slightly wider than in the middle of ETH, but not significantly.

There are three noteworthy peaks across the day: two in RTH and one in ETH. The three peaks in intraday quoted spread are not well documented and analyzed in the literature. The time of each peak matches the time of scheduled macroeconomic news announcements at 08:30, 10:00, and 14:00. Options markets respond to scheduled macroeconomic news immediately. Also, the impact of macroeconomic news on quoted spread lasts no more than 10 minutes, which shows fast price discovery.

Intraday realized volatility and trading volume are also U-shaped in RTH. However, there are no peaks in realized volatility and trading volume at 08:30, 10:00, and 14:00. The abnormal peaks in quoted spread indicate that volatility and volume are unable to explain intraday quoted spread dynamics.

By comparing the quoted spread on announcement days and non-announcement days, it can also be conjectured that scheduled macroeconomic announcements are the reason for the suddenly wider quoted spread. On non-news days, the quoted spread from 08:30 to 08:35 is not significantly different from other periods in ETH. On news days, by contrast, the quoted spread from 8:30 to 8:35 is even wider than the quoted spread at the opening of ETH.

Figure 7 shows that scheduled US Federal Open Market Committee (FOMC) announcements have a significant impact on options markets quoted spreads. Peaks in the daily quoted spread series exactly match the dates of US FOMC announcements. On non-FOMC-announcement dates, the quoted spread is relatively narrower and stable across different days. On FOMC-announcement dates, by contrast, quoted spread is far wider. This pattern is consistent for both SPXW and SPY options.

The last pattern feature is that, in the SPXW options market, quoted spread is much wider in ETH than in RTH. Two possible reasons may explain the wider quoted spread in the ETH market. First, as options trading volume shows that liquidity is much lower in the ETH market, market-makers would require higher compensation for providing liquidity. Second, as suggested by Barclay and Hendershott (2003), the ETH market mainly consists of professional or quasi-professional investors. There is, therefore, a higher possibility that trades in the ETH are informed trades, which is also confirmed by the following empirical results of the PIN model. Market-makers also require higher compensation for informed trades.

[Insert Figure 7]

D. Comparing Effective Spread Between ETH and RTH

As trades may be executed inside the quoted spread, effective spread reflects the real transaction cost, which may have different results from quoted spread. Estimation of effective spread requires the transaction price. However, in ETH, many options are not traded in every 5-minute interval, and ITM options are not frequently traded. The volume-weighted effective spread of all options is calculated within ETH and RTH, respectively. As shown in Table I, similar to quoted spread, the effective spread is also wider in ETH for ATM and OTM options. This confirms the finding with quoted spread that transaction costs are significantly higher in ETH.

[Insert Table I]

E. A Summary of ETH Options Markets

It can be concluded that ETH options markets have low liquidity and high transaction costs, while market quotes are still actively updated in ETH options markets.

Similar to the findings of Barclay and Hendershott (2004), it seems that the options market is in an equilibrium without ETH. Liquidity traders congregate in RTH and have no incentive to change their transactions into ETH even four years after the ETH options market was introduced. This shows the difficulties of introducing ETH for new options markets.

V. Market Quality in RTH

Previous literature has examined the impact on market quality from the introduction of the DPM system, make-take, and multiple-listing. This study presents the impact of the introduction of ETH on market quality in post-open hours. Quoted and effective spreads are used as measures of market quality.

The introduction of ETH options markets may change the market quality in post-open hours. Before ETH is introduced, overnight information is aggregated until the opening of RTH. In the post-open period, information asymmetry and adverse selection costs may be high. After the introduction of ETH, overnight information can be incorporated into the market immediately. Therefore, information asymmetry and adverse selection costs in the post-open period may decrease due to this new market structure.

Table II presents the impact of CBOE's introduction of ETH on quoted spread ($), quoted spread (%), effective spread ($), and effective spread (%). Difference-in-differences regression using equation (3) is conducted in each midquote group during a half-hour interval. Options with midquote less than $3 are excluded because SPXW options have a different minimum tick size from SPY options below $3. Also, options with prices below $3 are very deep OTM options, which are not frequently traded. Options with midquote greater than $100 are also excluded. ATM options are in the midquote group 10<Midquote $\leq$ 30. Options greater than \$100 are ITM options with a long time to maturity, which is not the main focus of options markets.

As the empirical evidence in Table II shows, market quality in terms of liquidity measured by spreads is enhanced after the introduction of ETH. Quoted spread and effective spread in both dollar and percentage terms decrease from the pre-introduction period to the post-introduction period. The impact of the introduction of ETH on spreads is both statistically significant and economically large. The null hypothesis that market quality is not enhanced with ETH is, thus, rejected. This is consistent with the study's expectation. As market information can be incorporated into options markets immediately in ETH, information asymmetry is lower after the introduction of ETH options markets. Market-makers require lower compensation for providing liquidity, so transaction costs are reduced.

[Insert Table II]

This paper also conducts a long term impact analysis of market quality after the introduction of ETH, examining market quality in the first quarter of 2019. The findings indicate that the positive impact of ETH on SPXW options market quality is greater in 2019 than in 2015 (immediately after the introduction of ETH). The ETH trading volume in 2019 is much higher than that in 2015. It is likely that information asymmetry decreases more significantly in 2019 due to more frequent transactions. It seems that the ETH options market enhances market quality over time.

This paper applies normalized quoted spread and normalized effective spread used by Clark-Joseph, Ye, and Zi (2017) as a robustness test. A matched sample is a group of option contracts with the same strike price and same time to maturity. Normalized quoted spread (Normalized effective spread) is calculated as quoted-weighted average quoted spread (volume-weighted effective spread) divided by matched sample mean.

Table III shows the results of difference-in-differences test with normalized spreads. Both normalized quoted and effective spreads decreases significantly after CBOE's introduction of ETH option market, while the placebo test indicates that there is no significant difference before CBOE's introduction. The placebo test aims to examine the parallel assumption in difference-ind-differences test. It the parallel assumption is valid, the difference-in-differences results should not be significant. The only exception is normalized effective spread with call options. Therefore, the parallel assumption in difference-in-differences test is not rejected.

[Insert Table III]

VI. Asymmetric Information Around the Introduction of ETH

Based on the structure models developed by Huang and Huang and Stoll (1997) and Lin et al. (1995), the decrease in quoted spread may due to decrease in its components: adverse selection costs, inventory holding costs, and order processing costs. Relatedly, the change in effective spread may due to decrease in adverse selection costs and order processing costs. This part continues the analysis of spreads in terms of their components, investigating whether enhanced market quality results from decreased adverse selection costs.

Two spread decomposition models are applied to the trades in RTH. For a reliable estimation of the model, the option contract needs to be traded frequently. In the empirical estimation of Madhavan et al. (1997), they require at least 250 trades for each period. Options markets are less frequently traded than equity markets. To have enough observations for each estimation, options with at least 250 trades from 09:30 to 16:00 are considered in this study.

The results reported in table IV show an economically largely and statistically significantly drop in adverse selection costs after the introduction of ETH. In quoted spread, both adverse selection costs and inventory holding costs decrease significantly. In effective spread, dollar order processing costs do not change significantly around the introduction, but dollar adverse selection costs decrease significantly. Decreased adverse selection costs in both quoted and effective spread are consistent with thus study's expectation. The null hypothesis that ETH options markets are not important for incorporating information is, thus, rejected. ETH options markets incorporate market information and reduce information asymmetry in the following RTH. Asymmetric information costs in RTH decrease after the introduction of ETH because less asymmetric information accumulates during the overnight period.

[Insert Table IV]

VII. Informed Ttrading Between ETH and RTH

This part investigates the level of PIN in ETH. Because trading volume is low in ETH, it is not possible to apply the spread decomposition model. The PIN is also a proxy for adverse selection costs. Higher (lower) probability of informed trading results in higher (lower) adverse selection costs.

A. PIN and PIT

PIN and PIT are calculated from equations (9) and (10). Both are significantly higher in ETH, which is consistent with the theoretical expectation. High quoted spread and effective spread in ETH may be explained by a much higher probability of informed trading. However, after the introduction of ETH, neither PIN nor PIT decrease immediately in post-open hours.

[Insert Figure 8 panel A, B]

B. Liquidity Ratio and the Probability of an Event (α)

Unlike PIN and PIT, the liquidity ratio and probability of an event are not significantly different during the day. There are some outlier liquidity ratio estimations in the post-introduction sample. This is because ETH options markets are only available in that sample. The trading volume is too low to have robust estimates. However, in the recent sample, the estimates are stable and robust.

Liquidity ratio and the probability of an event confirm the robustness of PIN estimations. During the estimation periods, there are no market changes resulting in different liquidity ratios or different probabilities of an event.

[Insert Figure 8 panel C, D]

VIII. Predictability

Previous sections show ETH options market is important in incorporating market information and reduce the information asymmetry in the following RTH. This part directly identifies two types of information from ETH options market for the prediction of the following RTH.

First, put-call parity implied S&P 500 index level estimated at 09:15 is accurate in forecasting the open value of S&P 500 index. Regression (13) has $\beta_{I,t}$ as 0.79***, in sample adjusted R^2 as 94.47%, and out-of-sample R^2 as 95.50%.

Second, ETH IV contains additional information for RV forecasting. Figure 9 shows the time series of IV at 09:15 and RV in the following RTH. Panel A and panel B present one-minute RV and five-minute RV respectively. One-minute RV and five-minute RV have similar daily movement. ETH IV is highly correlated with the following RTH RV, especially from low volatility regime to high volatility regime, which is hardly captured by historical RV.

Table V shows ETH IV contains incremental information for RV forecasting. By incorporating IV, both in-sample and out-of-sample predication ability are improved for HAR-RV and HARQ-RV. The only exception is one-minute HARQ-RV model. The out-of-sample predication performance deteriorates after incorporating IV in one-minute HARQ-RV model.

Although in-sample R^2 is low with only using IV, $\mathrm{IV_Q}$ and $\mathrm{IV_P}$ outperform all return based models in out-of-sample forecasting. ETH IV is a better source for one-day RV forecasting.

IX. Conclusion

This paper examined ETH options markets by comparing ETH vs. RTH, SPXW options vs SPY options, and before ETH introduction vs. after ETH introduction. Its findings show that although liquidity traders still congregate in RTH after the introduction of ETH as a result of temporal consolidation of trades, market quality improves significantly in the RTH options market as the ETH options market incorporates information immediately and reduces the information asymmetry in RTH.

This paper has five aspects of findings. First, ETH options markets differ from RTH options markets. They have low liquidity and high transaction costs. Market information is actively incorporated into ETH options markets as quotes update frequently. However, the relatively low quote updates in ETH (compared to RTH) and low realized volatility indicate that ETH options market is less active.

Second, although the trading volume is low in ETH, the introduction of ETH options markets improves market quality, according to difference-in-differences analysis between S&P 500 options and SPY options around CBOE's introduction of ETH. Two market quality proxies, quoted spread and effective spread, show the same conclusion across different option midquote categories during RTH.

Third, the improvement of market quality is due to reduced asymmetric information costs in the post-open period. ETH options markets provide additional instruments to incorporate immediate market information, which can be observed with the temporal increased quoted spread at 08:30—the scheduled US macroeconomic announcement time. The existence of ETH options markets avoids the overnight accumulation of asymmetric information, which reduces the adverse selection costs in RTH.

Fourth, ETH options markets show a significantly high probability of informed trading, low trading volume, and high volatility of trade size, which can explain the high quoted spread and effective spread in ETH. Due to the low turnover of their inventory with low trading volume in ETH, liquidity providers require high compensation for each trade. High uncertainty about trade size also makes inventory management more difficult for liquidity providers; such uncertainty needs to be compensated by a higher quoted spread. Finally, liquidity providers make profit from trading with liquidity demanders and lose money from trading with informed traders. As ETH options markets have a much higher probability of informed trading, liquidity providers require additional compensation for informed trading. Together, a high probability of informed trading, high uncertainty about trade size, and low trading volume result in a high quoted spread and effective spread in ETH options markets.

Fifth, ETH options market contains updated information for the following RTH. Put-call parity implied index level in ETH shows the open value of RTH. ETH IV contains incremental information than return based models for one-day RV forecasting.

REFERENCES

Anand, A., J. Hua, and T. McCormick, 2016, Make-take structure and market quality: Evidence from the U.S. options markets, *Management Science* 62, 3271–3290.

Anand, Amber, and Daniel G. Weaver, 2006, The value of the specialist: Empirical evidence from the CBOE, *Journal of Financial Markets* 9, 100–118.

Bakshi, Gurdip, Nikunj Kapadia, and Dilip Madan, 2003, Stock Return Characteristics, Skew Laws, and the Differential Pricing of Individual Equity Options, *The Review of Financial Studies* 16, 101–143.

Barclay, Michael J., and Terrence Hendershott, 2003, Price Discovery and Trading After Hours, *The Review of Financial Studies* 16, 1041–1073.

Barclay, Michael J., and Terrence Hendershott, 2004, Liquidity Externalities and Adverse Selection: Evidence from Trading after Hours, *Journal of Finance* 59, 681–710.

Battalio, Robert, Brian Hatch, and Robert Jennings, 2004, Toward a National Market System for U.S. Exchange–listed Equity Options, *Journal of Finance* 59, 933–962.

Black, Fischer, 1975, FACT AND FANTASY IN THE USE OF OPTIONS, *Financial Analysts Journal* 31, 36.

Blume, Marshall E, and Michael A Goldstein, 1992, Displayed and effective spreads by market, *Available at SSRN 979084* .

Bollerslev, Tim, Andrew J Patton, and Rogier Quaedvlieg, 2016, Exploiting the errors: A simple approach for improved volatility forecasting, *Journal of Econometrics* 192, 1–18.

Busch, Thomas, Bent Jesper Christensen, and Morten Ørregaard Nielsen, 2011, The role of implied volatility in forecasting future realized volatility and jumps in foreign exchange, stock, and bond markets, *Journal of Econometrics* 160, 48–57.

Chan, Kalok, Y. Peter Chung, and Herb Johnson, 1995, The Intraday Behavior of Bid-Ask Spreads for NYSE Stocks and CBOE Options, *Journal of Financial and Quantitative Analysis* 30, 329–346.

Chen, Chun-Hung, Wei-Choun Yu, and Eric Zivot, 2012, Predicting stock volatility using after-hours information: Evidence from the NASDAQ actively traded stocks, *International Journal of Forecasting* 28, 366–383.

Cheung, William M., Robin K. Chou, and Adrian C. H. Lei, 2015, Exchange-Traded Barrier Option and VPIN: Evidence from Hong Kong, *Journal of Futures Markets* 35, 561–581.

Chong, Beng-Soon, David Ding, and Kok-Hui Tan, 2003, Maturity Effect on Bid-Ask Spreads of OTC Currency Options, *Review of Quantitative Finance and Accounting* 21, 5–15.

Clark-Joseph, Adam D., Mao Ye, and Chao Zi, 2017, Designated market makers still matter: Evidence from two natural experiments, *Journal of Financial Economics* 126, 652–667.

Corsi, Fulvio, 2009, A Simple Approximate Long-Memory Model of Realized Volatility, *Journal of Financial Econometrics* 7, 174–196.

Division of Market Regulation, 2000, Special Study: Electronic Communication Networks and After-Hours Trading.

Dungey, Mardi, Luba Fakhrutdinova, and Charles Goodhart, 2009, After-hours trading in equity futures markets, *Journal of Futures Markets* 29, 114–136.

Easley, David, Soeren Hvidkjaer, and Maureen O' Hara, 2002, Is Information Risk a Determinant of Asset Returns?, *Journal of Finance* 57, 2185–2221.

Easley, David, Nicholas M. Kiefer, Maureen O' Hara, and Joseph B. Paperman, 1996, Liquidity, Information, and Infrequently Traded Stocks, *Journal of Finance* 51, 1405–1436.

Ellis, Katrina, Roni Michaely, and Maureen O'Hara, 2000, The Accuracy of Trade Classification Rules: Evidence from Nasdaq, *The Journal of Financial and Quantitative Analysis* 35, 529–551.

Gan, Quan, Wang Chun Wei, and David Johnstone, 2017, Does the Probability of Informed Trading Model Fit Empirical Data?, *Financial Review* 52, 5–35.

Gao, L., Y. Han, S. Zhengzi Li, and G. Zhou, 2018, Market intraday momentum, *Journal of Financial Economics* 129, 394–414.

Hsieh, Peilin, and Robert Jarrow, 2019, Volatility Uncertainty, Time Decay, and Option Bid-Ask Spreads in an Incomplete Market, *Management Science* 65, 1833.

Huang, Roger D., and Hans R. Stoll, 1997, The Components of the Bid-Ask Spread: A General Approach, *The Review of Financial Studies* 10, 995–1034.

Jiang, Christine X., Tanakorn Likitapiwat, and Thomas H. Mcinish, 2012, Information Content of Earnings Announcements: Evidence from After-Hours Trading, *The Journal of Financial and Quantitative Analysis* 47, 1303–1330.

Lee, Charles M. C., and Mark J. Ready, 1991, Inferring Trade Direction from Intraday Data, *Journal of Finance* 46, 733–746.

Li, Wei-Xuan, Joseph J. French, and Clara Chia-Sheng Chen, 2017, Informed trading in S&P index options? Evidence from the 2008 financial crisis, *Journal of Empirical Finance* 42, 40–65.

Lin, Ji-Chai, Gary Sanger, and G Booth, 1995, Trade size and components of the bid-ask spread, *Review of financial studies* 8, 1153–1183.

Madhavan, Ananth, Matthew Richardson, and Mark Roomans, 1997, Why Do Security Prices Change? A Transaction-Level Analysis of NYSE Stocks, *The Review of Financial Studies* 10, 1035–1064.

Mayhew, Stewart, 2002, Competition, Market Structure, and Bid-Ask Spreads in Stock Option Markets, *Journal of Finance* 57, 931–958.

Mishra, Suchismita, and Robert T. Daigler, 2014, Intraday Trading and Bid–Ask Spread Characteristics for SPX and SPY Options, *The Journal of Derivatives* 21, 70.

Patton, Andrew J, 2011, Volatility forecast comparison using imperfect volatility proxies, *Journal of Econometrics* 160, 246–256.

Savickas, Robert, and Arthur J Wilson, 2003, On Inferring the Direction of Option Trades, *Journal of Financial and Quantitative Analysis* 38, 881–902.

Wu, Wei-Shao, Yu-Jane Liu, Yi-Tsung Lee, and Robert C.W. Fok, 2014, Hedging costs, liquidity, and inventory management: The evidence from option market makers, *Journal of Financial Markets* 18, 25–48.

Table I. Comparison of the effective spread ($) between ETH and RTH.
This table shows the mean of hourly volume-weighted effective spread ($). Moneyness is the round value of the option strike price divided by index close level in previous day. A simple t test is used to compare the mean. The sample period is from March 9, 2015 to May 31, 2015.

Mean of effective spread ($) in ETH and RTH					
	Moneyness	Mean (ETH)	Mean (RTH)	Diff	t stats
call	0.9	1.54	1.14	0.4	2.22
	1	0.34	0.2	0.15	4.71
	1.1	0.63	0.09	0.55	2.47
Put	0.6	2.25	0.1	2.15	5.3
	0.7	2.68	0.1	2.58	2.08
	0.8	3.05	0.1	2.94	2.65
	0.9	0.37	0.09	0.29	4.69
	1	0.36	0.24	0.11	4.2

Table II. Impact of CBOE's introduction of ETH options market on Spreads.
This table reports the difference-in-differences analysis results on the impact of CBOE's introduction of ETH options markets on quoted spread ($), quoted spread (%), effective spread ($), and effective spread (%) respectively. The treatment group is SPXW options; the control group is SPY options. The controlled difference-in-differences regression formula is $Spread_{i,t,m} = \beta_0 + \beta_1 TTM_{i,t,m} + \beta_2 Mid_{i,t,m} + \beta_3 Volume_{i,t,m} + \beta_4 D_t + \beta_5 D_s + \beta_6 (D_t \cdot D_s) + \varepsilon$ (equation 3). This table shows the impact of CBOE's introduction of ETH on spreads (β_6). Values in panel A and C are in dollar term. Values in panel B and D are in percentages. The pre-introduction sample period is from December 1, 2014 to February 28, 2015; the post-introduction sample period is from March 9, 2015 to May 31, 2015. The whole sample is categorized by midquote and 30-minute intervals. Significance tests use standard errors clustered on option class[4] and date. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. Adjusted R^2 is the average adjusted R^2 of different midquote groups.

Panel A: Quoted spreads ($)	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00
3<Midquote≤5	-0.01	-0.04	-0.05	-0.07***	-0.07***	-0.07***	-0.06***	-0.06***	-0.09**	-0.08**	-0.08***	-0.07***	-0.08***
5<Midquote≤10	-0.04	-0.07**	-0.07**	-0.11***	-0.1***	-0.1***	-0.09***	-0.09***	-0.13***	-0.12***	-0.11***	-0.1***	-0.11***
10<Midquote≤30	-0.08*	-0.11***	-0.1***	-0.15***	-0.14***	-0.13***	-0.11***	-0.13***	-0.16***	-0.22***	-0.16***	-0.14***	-0.15***
30<Midquote≤50	-0.2***	-0.22***	-0.22***	-0.25***	-0.25***	-0.23***	-0.19***	-0.21***	-0.23***	-0.31*	-0.23***	-0.24***	-0.23***
50<Midquote≤100	-0.08*	-0.07	-0.12***	-0.15***	-0.15***	-0.12***	-0.11***	-0.1***	-0.12***	-0.15	-0.11	-0.13**	-0.12***
Adjusted R^2	0.49	0.55	0.56	0.55	0.54	0.54	0.54	0.53	0.39	0.27	0.47	0.52	0.54

[4]Options with the same underlying are classified into one class.

Panel B: Quoted spreads (%)

	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00
3<Midquote≤5	-0.35	-1.15	-1.2	-1.92 ***	-1.88 ***	-1.82 ***	-1.62 ***	-1.65 ***	-2.29 **	-1.75 *	-2.11 ***	-1.87 ***	-1.96 ***
5<Midquote≤10	-0.49	-0.99 **	-0.98 **	-1.59 ***	-1.49 ***	-1.39 ***	-1.25 ***	-1.35 ***	-1.82 ***	-1.6 ***	-1.6 ***	-1.37 ***	-1.56 ***
10<Midquote≤30	-0.41	-0.61 ***	-0.55 ***	-0.84 ***	-0.79 ***	-0.74 ***	-0.63 ***	-0.72 ***	-0.9 ***	-1.13 ***	-0.87 ***	-0.75 ***	-0.8 ***
30<Midquote≤50	-0.54 ***	-0.58 ***	-0.58 ***	-0.66 ***	-0.65 ***	-0.6 ***	-0.5 ***	-0.55 ***	-0.59 ***	-0.8 *	-0.61 ***	-0.61 ***	-0.58 ***
50<Midquote≤100	-0.13 *	-0.11	-0.18 ***	-0.23 ***	-0.23 ***	-0.19 ***	-0.17 ***	-0.16 ***	-0.18 ***	-0.23	-0.17 *	-0.21 **	-0.18 ***
Adjusted R^2	0.43	0.48	0.49	0.49	0.48	0.48	0.48	0.47	0.36	0.23	0.41	0.45	0.48

Panel C: Effective spreads ($)

	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00
3<Midquote≤5	-0.0	-0.03 ***	-0.02 ***	-0.02 ***	-0.02 ***	-0.02 **	-0.02 ***	-0.02 ***	-0.04 ***	-0.07	-0.02 ***	-0.01 **	-0.02 ***
5<Midquote≤10	-0.0	-0.03 ***	-0.02 ***	-0.03 ***	-0.04 ***	-0.0	-0.03 ***	-0.04 ***	-0.02 ***	-0.06	-0.03 ***	-0.02 ***	-0.03 ***
10<Midquote≤30	-0.25 ***	-0.07 ***	-0.04 ***	-0.05 ***	-0.04 ***	-0.04 ***	-0.05 ***	-0.07 ***	-0.03 **	-0.11 **	-0.04 ***	-0.06 ***	-0.07 ***
30<Midquote≤50	-0.04	-0.05	-0.07 **	-0.08 ***	-0.06 ***	-0.08 ***	-0.07 ***	-0.05 *	-0.04 ***	0.02	-0.07 ***	-0.01	-0.04 ***
50<Midquote≤100	0.1 *	0.12 ***	-0.01 ***	-0.01 ***	0.04 ***	-0.06 ***	-0.05 **	-0.02 ***	-0.08 ***	0.36 ***	0.46 ***	-0.09 ***	-0.04 ***
Adjusted R^2	0.03	0.06	0.09	0.11	0.11	0.12	0.1	0.11	0.1	0.02	0.07	0.1	0.1

Panel D: Effective spreads (%)													
	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00
3<Midquote≤5	-0.02	-0.71 ***	-0.62 ***	-0.59 ***	-0.62 ***	-0.43 **	-0.57 ***	-0.52 ***	-0.89 ***	-0.53 ***	-0.63 ***	-0.27 *	-0.61 ***
5<Midquote≤10	-0.08	-0.37 ***	-0.33 ***	-0.3 ***	-0.56 ***	-0.07	-0.36 ***	-0.52 ***	-0.32 ***	-0.41	-0.41 ***	-0.27 ***	-0.4 ***
10<Midquote≤30	-0.24 ***	-0.38 ***	-0.19 ***	-0.26 ***	-0.23 ***	-0.18 **	-0.27 ***	-0.34 ***	-0.14	-0.49 **	-0.21 ***	-0.31 ***	-0.34 ***
30<Midquote≤50	-0.12	-0.16	-0.19 **	-0.21 ***	-0.17 ***	-0.22 ***	-0.18 ***	-0.15 **	-0.1 ***	0.02	-0.19 ***	-0.03	-0.12 ***
50<Midquote≤100	0.17*	0.21 ***	-0.02 ***	-0.01 ***	0.08 ***	-0.08 ***	-0.05 *	-0.04 ***	-0.13 ***	0.66 ***	0.81 ***	-0.16 ***	-0.05 ***
Adjusted R^2	0.04	0.05	0.06	0.06	0.07	0.07	0.06	0.07	0.06	0.02	0.04	0.06	0.05

Table III. This table reports the results of difference-in-differences test with normalized quoted spread and normalized effective spread in 30-minute interval. Panel A,B,C,D report the results in 09:30-10:00 interval. Panel E,F,G,H report the difference-in-differences coefficients in all intervals. In Panel A, B, E, F, Pre-event sample period is from Dec 1, 2014 to Feb 28, 2015 and After-event sample period is from Mar 9, 2015 to May 31, 2015. In Panel C, D, G, H, Pre-event sample period is from Dec 1, 2014 to Jan 15, 2015 and After-event sample period is from Jan 16, 2015 to Feb 28, 2015. Only call options with moneyness from 97.5% to 122.5% and put options with moneyness from 77.5% to 102.5% are included. The maximum time to maturity in this estimation is 250 business days. All values are in percentages. Significant tests use standard errors clustered on option class and date. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Category	Pre-event			After-event			Diff-in-Diffs
	SPXW	SPY	Difference	SPXW	SPY	Difference	
Panel A: Difference-in-differences Results of normalized quoted spreads around CBOE introduction event							
Call	96.46	93.20	3.26	102.89	107.61	-4.72	-7.97***
Put	117.99	112.42	5.57	86.09	87.26	-1.17	-6.74**
Panel B: Difference-in-differences Result of normalized effective spreads around CBOE introduction event							
Call	90.38	88.62	1.76	108.51	112.35	-3.84	-5.61*
Put	120.24	112.90	7.34	80.41	86.72	-6.31	-13.65***
Panel C: Placebo difference-in-differences Results of normalized quoted spreads							
Call	99.29	99.35	-0.06	100.63	100.67	-0.04	0.02
Put	100.36	100.44	-0.08	99.66	99.56	0.10	0.18
Panel D: Placebo Difference-in-differences Results of normalized effective spreads							
Call	98.06	100.33	-2.27	101.92	99.67	2.25	4.53*
Put	99.20	99.53	-0.33	100.84	100.47	0.37	0.71

Category	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00
Panel E: Difference-in-differences Results of normalized quoted spreads around CBOE introduction event													
Call	-7.97 ***	-9.65 ***	-10.43 ***	-9.0 ***	-8.16 ***	-8.28 ***	-7.9 ***	-6.72 ***	-9.07 ***	-11.13 ***	-8.87 ***	-8.65 ***	-8.12 ***
Put	-6.74 **	-8.65 ***	-10.11 ***	-9.77 ***	-8.19 ***	-7.95 ***	-6.89 ***	-7.04 ***	-10.26 ***	-9.88 ***	-10.77 ***	-9.51 ***	-8.95 ***
Panel F: Difference-in-differences Result of normalized effective spreads around CBOE introduction event													
Call	-5.61 *	2.19	3.03	4.62 ***	5.04 ***	2.16	5.47 ***	1.33	3.9 **	1.6	6.95 ***	-3.22	1.88
Put	-13.65 ***	-25.23 ***	-26.1 ***	-23.9 ***	-24.0 ***	-17.6 ***	-21.25 ***	-20.4 ***	-21.92 ***	-22.25 ***	-21.69 ***	-23.27 ***	-19.97 ***
Panel G: Placebo difference-in-differences Results of normalized quoted spreads													
Call	0.02	-0.23	-1.01	-0.06	0.22	-0.69	0.97	0.03	-2.68	3.65	1.61	-0.08	1.22
Put	0.18	0.99	0.24	0.81	2.06	0.39	1.72	0.87	-1.91	4.39	2.02	0.49	0.87
Panel H: Placebo Difference-in-differences Results of normalized effective spreads													
Call	4.53 *	-5.98 **	5.99	-2.88	2.27	-3.06	-6.96 ***	-5.92 *	-0.11	7.0	2.82	-0.38	1.32
Put	0.71	-5.44	1.37	3.74	1.89	-2.96	2.53	1.3	-0.53	1.84	-2.57	-8.91 **	-2.48

Table IV. This table reports the components of quoted spread and effective spread estimated by the models of Huang and Stoll (1997) and Lin et al. (1995), respectively. Quoted spread is decomposed into adverse selection costs (α) and inventory holding costs (β). φ is the probability that trade price reverses from time t-1 to time t. Effective spread is decomposed into adverse selection costs (λ) and order processing costs (γ). θ is the persistence of order flow. The controlled difference-in-differences regression formula is $y_{i,t} = \beta_0 + \beta_1 TTM_{i,t} + \beta_2 Mid_{i,t} + \beta_3 Volume_{i,t} + \beta_4 D_t + \beta_5 D_s + \beta_6 (D_t \cdot D_s) + \varepsilon$ (equation 7). The treatment group is SPXW options; the control group is SPY options. The before sample period is from December 1, 2014 to February 28, 2015; the after sample period is from March 9, 2015 to May 31, 2015. Only options with over 250 trades in RTH are considered. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

		SPXW Options			SPY Options			Diff-in-Diff
		Before	After	Difference	Before	After	Difference	
Panel A: The decomposition of quoted spread								
α	(¢)	2.5	1.7	-0.8**	3.6	3.4	-0.3	-0.3
	(%)	8.00%	5.60%	-2.3%**	15.80%	17.60%	1.8%**	-4.6%**
β	(¢)	4.7	3	-1.6***	5.9	5.6	-0.3*	-0.6
	(%)	12.80%	10.00%	-2.8%**	24.80%	26.40%	1.6%**	-4.3%**
φ		45.20%	44.30%	-0.8%**	45.70%	45.20%	-0.5%**	-0.60%
Panel B: The decomposition of effective spread								
λ	(¢)	2	1.5	-0.5***	3	3.1	0.1	-0.5***
	(%)	33.80%	28.00%	-5.7%***	36.10%	39.80%	3.7%***	-9.7%***
γ	(¢)	2.9	2.5	-0.4**	3.8	3.5	-0.4***	0
	(%)	50.30%	56.00%	5.7%***	48.00%	46.10%	-1.8%***	7.8%***
θ		16.60%	16.80%	0.20%	16.70%	14.70%	-2.0%***	2.2%**

Table V. Realized volatility forecasting.

This table shows the results of different realized volatility forecasting models for one-day realized volatility forecasting. Standard errors are in parentheses. Adj. R^2 is the adjusted R^2 for the im-sample regression. MSE and QLIKE are measures for out-of-sample prediction accuracy with 22 days rolling window. Panel A and B use one-minute and five-minute returns to calculate realized volatility respectively.

Panel A: One-minute frequency

Model	Const	$RV_{t-22,t-1}$	$RV_{t-5,t-1}$	RV_{t-1}	$RQ_{t-1} \cdot RV_{t-1}$	IV_t	Adj. R^2 (%)	MSE (*10-6)	QLIKE
HAR-RV	0.0004 (0.0002)	-0.1386 (0.0536)	1.0751 (0.0736)	0.0000 (0.0525)			75.0	11.2	0.0818
HAR-RV-IV	-0.0002 (0.0002)	-0.1407 (0.0462)	0.7500 (0.0684)	-0.0869 (0.0457)		0.5023 (0.0398)	81.5	8.8	0.0710
HARQ-RV	0.0001 (0.0002)	-0.1738 (0.0534)	0.9782 (0.0761)	0.2084 (0.0726)	-60.0123 (14.6969)		75.8	17.2	0.0926
HARQ-RV-IV	-0.0004 (0.0002)	-0.1630 (0.0463)	0.6988 (0.0699)	0.0488 (0.0644)	-38.2649 (12.8821)	0.4859 (0.0398)	81.8	18.9	0.1043
IV_Q	0.0001 (0.0002)					0.9530 (0.0269)	72.4	7.1	0.0575
IV_P						1		5.8	0.0482

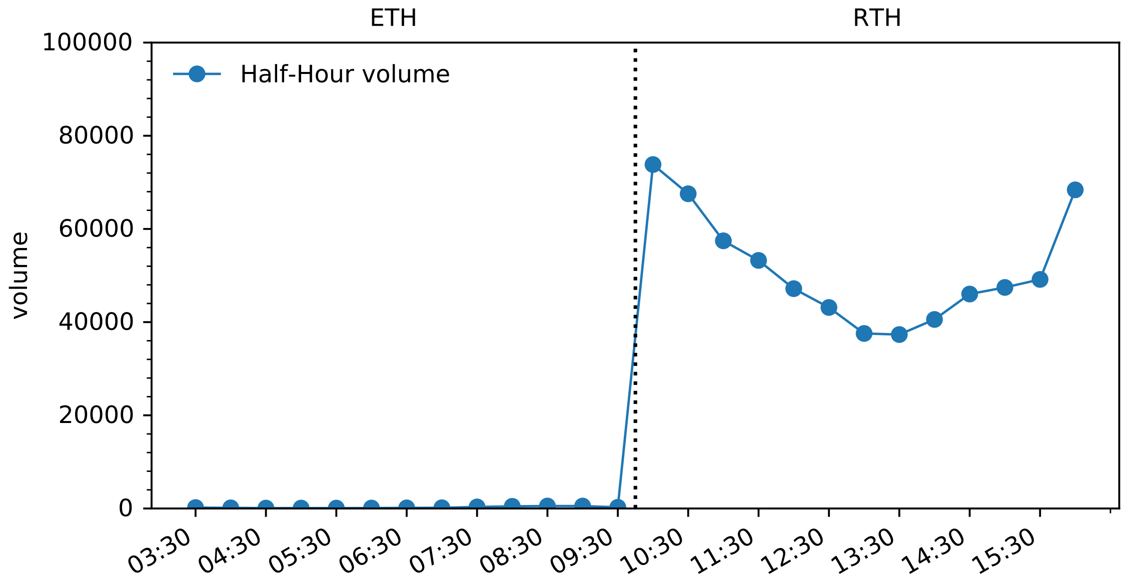
Panel B: Five-minute frequency

Model	Const	$RV_{t-22,t-1}$	$RV_{t-5,t-1}$	RV_{t-1}	$RQ_{t-1} \cdot RV_{t-1}$	IV_t	Adj. R^2 (%)	MSE (*10-6)	QLIKE
HAR-RV	0.0004	-0.1353	1.0532	0.0197			75.3	9.7	0.0905
	(0.0002)	(0.0533)	(0.0738)	(0.0528)					
HAR-RV-IV	-0.0002	-0.1322	0.7821	-0.0604		0.4294	80.0	8.7	0.0822
	(0.0002)	(0.0479)	(0.0713)	(0.0481)		(0.0410)			
HARQ-RV	0.0001	-0.1551	1.0113	0.1540	-111.1393		75.5	12.2	0.1555
	(0.0003)	(0.0535)	(0.0753)	(0.0749)	(44.2427)				
HARQ-RV-IV	-0.0003	-0.1401	0.7702	-0.0057	-44.1012	0.4219	80.0	11.2	0.0982
	(0.0002)	(0.0484)	(0.0721)	(0.0696)	(40.5658)	(0.0419)			
IV_Q	0.0003					0.9363	68.9	7.8	0.0620
	(0.0002)					(0.0288)			
IV_P						1		6.6	0.0530

Table VI. Comparison of S&P 500 options

S&P 500 Options	S&P 500 PM-settled Traditional	S&P 500 3rd Fridays Options	S&P 500 weeklys options	SPDR Mini options	SPDR ETF options
Option Root Ticker	SPX	SPXPM	SPXW	XSP	SPY
Underlying	S&P 500 index	S&P 500 index	S&P 500 index	1/10 S&P 500 index	SPDR ETF
Settlement type	AM-settled	PM-settled	PM-settled	PM-settled	PM-settled
Settlement Date	3rd Fridays	3rd Fridays	Monday, Wednesday, Friday weeklys. End of the month	Fridays	Fridays or End of Quarters
Settlement Type	Cash	Cash	Cash	Cash	Physical ETH
Exercise Style	European	European	European	European	American
ETH Available	Yes	Yes	Yes	No	No
GTH volume on July 24th, 2019	831	3180		0	0
Daily Volume on March 9th, 2015	572370	2290	176393	1338	375071
Note		SPXPM ticker merged to SPXW on May 1st, 2017	SPX Monday Weeklys - Launched August 15th, 2016 SPX Wednesday Weeklys - Launched February 23rd, 2016		

Panel A: Daily average half-hour trading volume of all SPXW options



Panel B: Daily average half-hour trading volume of all SPXW options in ETH.

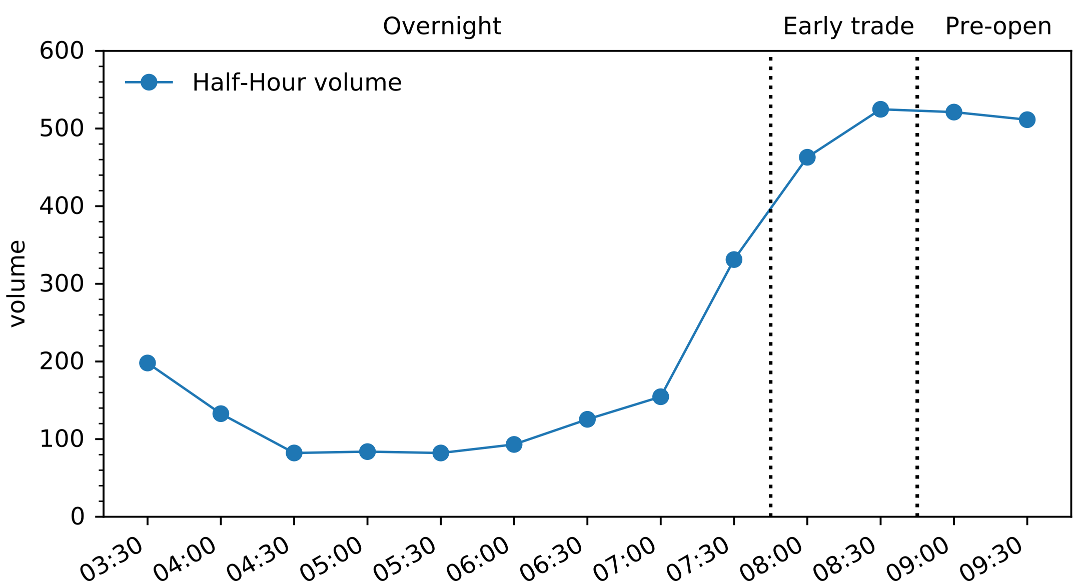
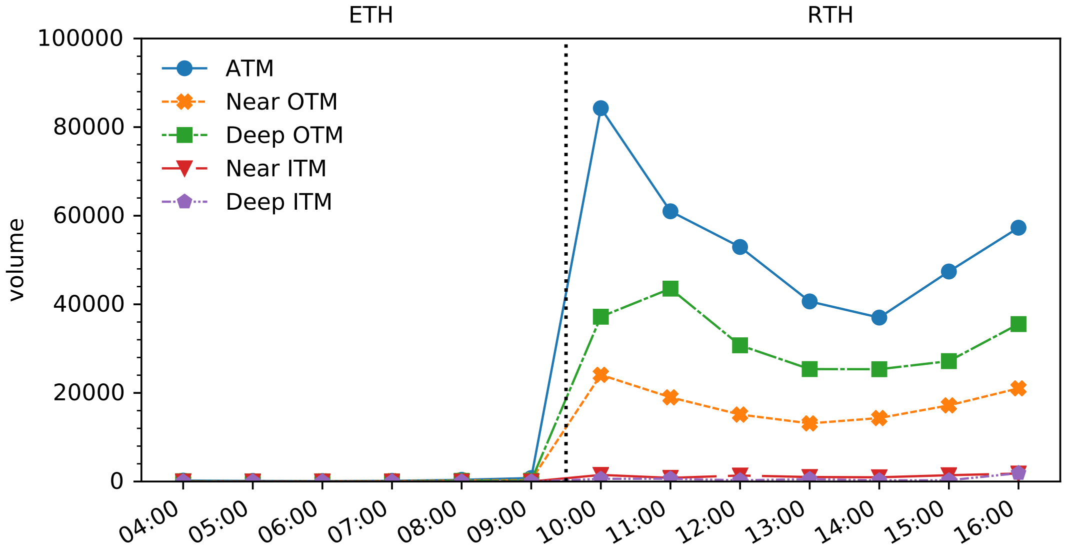


Figure 1. Daily average half-hour trading volume of all SPXW options.
This figure shows the aggregate trading volume of all SPXW options in different periods of the day. Taking half-hour intervals between 03:00 and 16:15, the trading volumes are aggregated. The sample period is from January 1, 2019 to March 31, 2019.

Panel A: The moneyness preference for options trading during ETH and RTH.



Panel B: The moneyness preference for options trading during ETH.

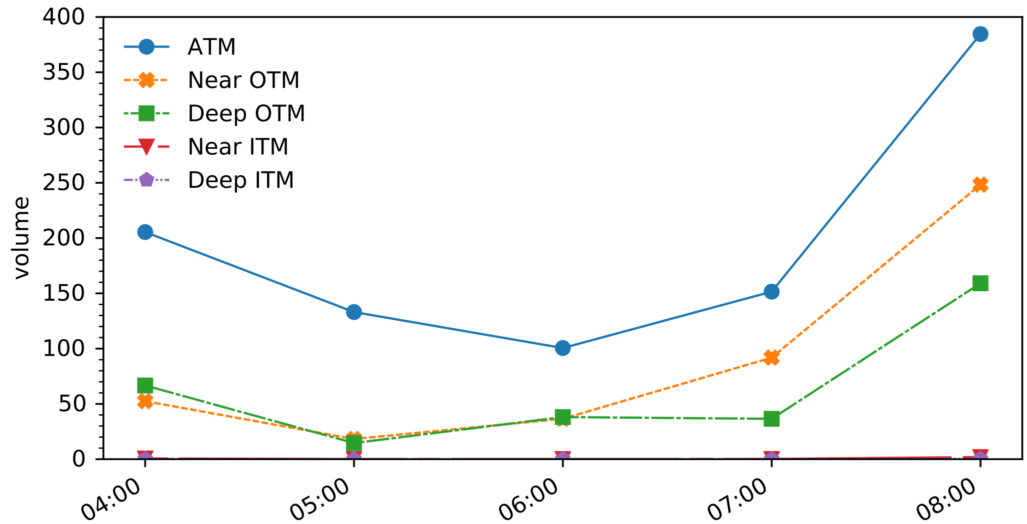


Figure 2. The moneyness preference for option trading.
This figure shows the trading volume of options with different moneyness during the day.[5] The sample period is from January 1, 2019 to March 31, 2019.

[5] ATM options have moneyness from 0.975 to 1.025. Near ITM (OTM) options are call (put) options with moneyness from 0.95 to 0.975 and put (call) options with moneyness from 1.025 to 1.05. Deep ITM (OTM) options are call (put) options with moneyness greater than 0.95 and put (call) options with moneyness greater than 1.05.

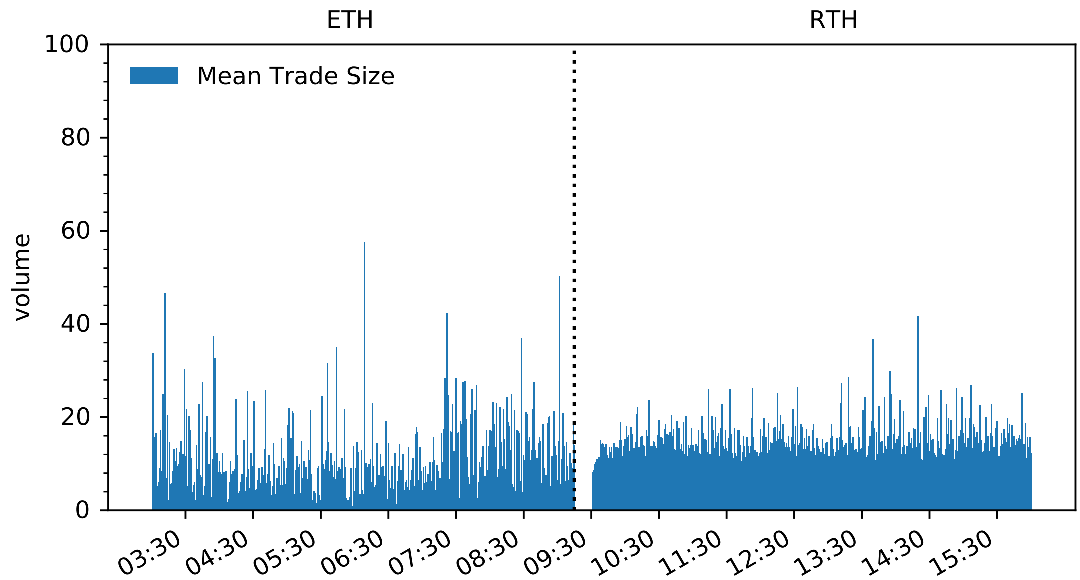


Figure 3. Option trade size in ETH and RTH.
This figure shows the intraday average one-minute trade size of all SPXW options. The sample period is from January 1, 2019 to March 31, 2019.

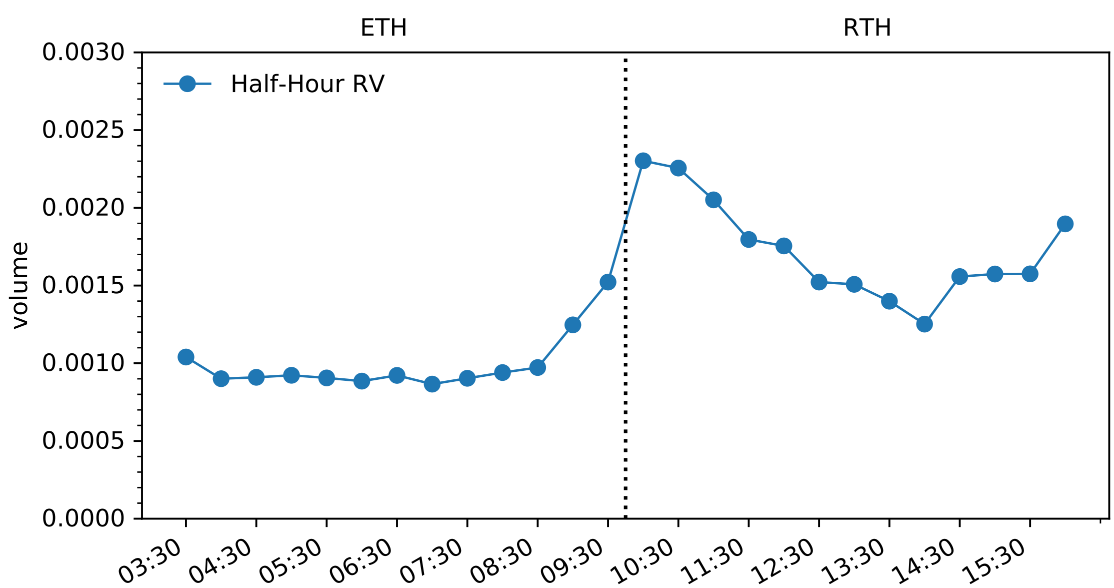


Figure 4. Realized volatility in ETH and RTH.
This figure shows the average 30-minute realized volatility (RV) of nearest-expiry S&P 500 E-mini futures. The sample period is from January 1, 2019 to March 31, 2019.

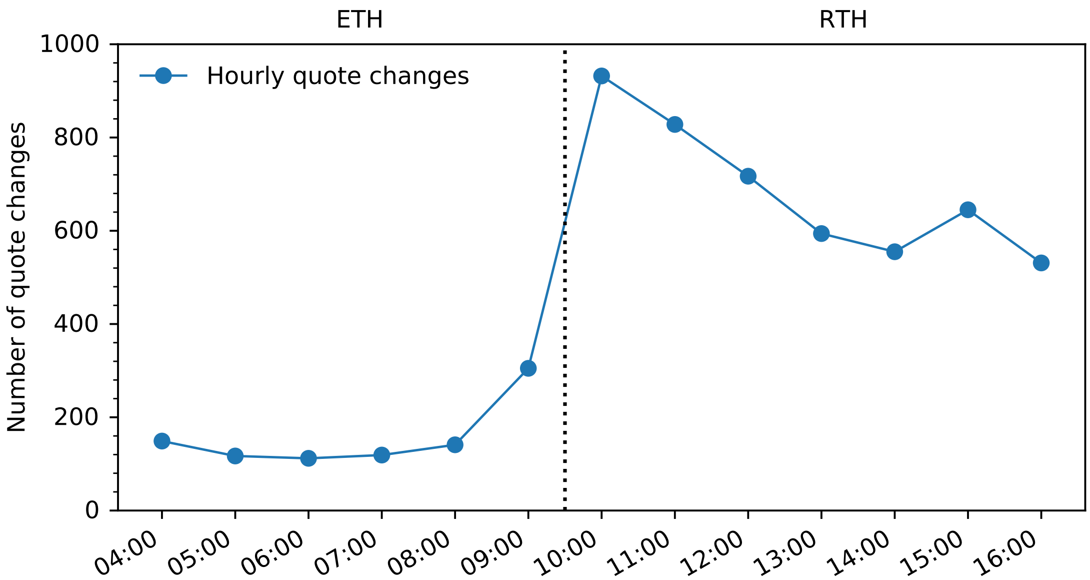
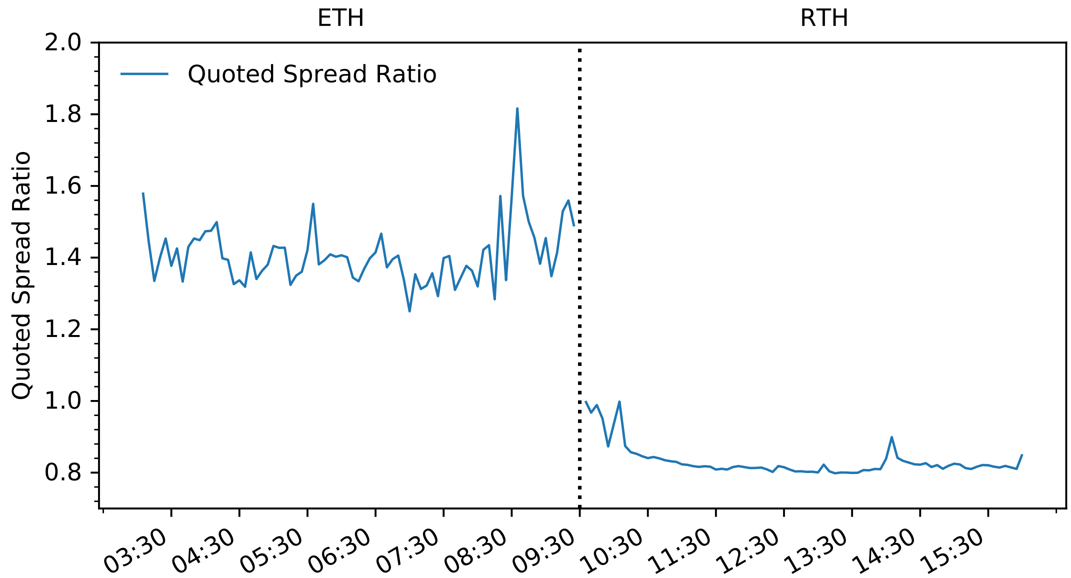


Figure 5. Quote changes in options markets.
This figure shows the average number of quote changes of SPXW option contracts during one-hour intervals.

Panel A: Intraday quoted spread ratio



Panel B: Quoted spread ratio on news days and non-news days

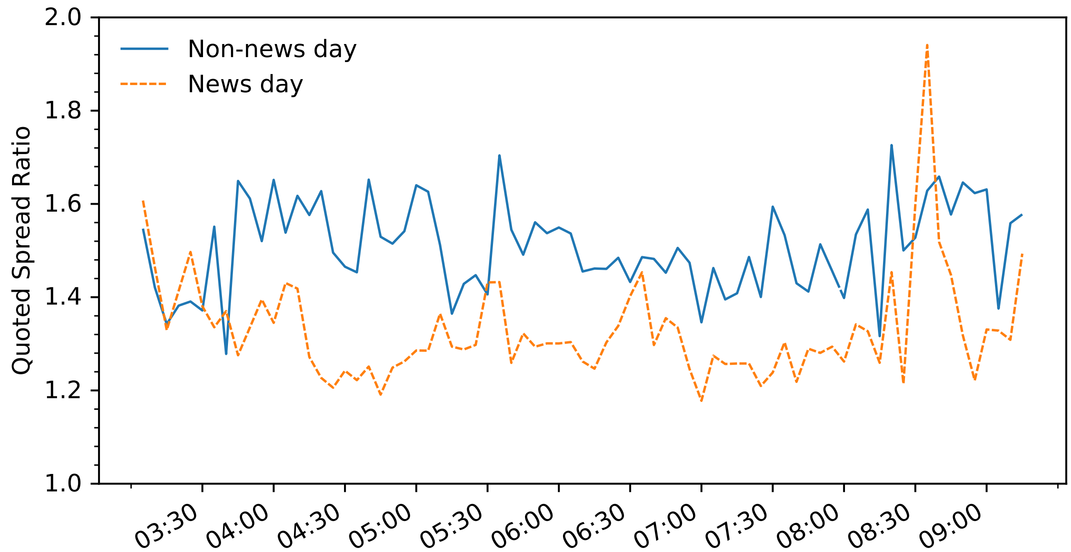


Figure 6. Intraday quoted spread pattern.
This figure shows the intraday quoted spread pattern. Quoted spread ratio is the quote-weighted average quoted spread of each contract in 5-minute interval divided by quote-weighted average quoted spread from 09:30 to 09:35. The sample period is from March 9, 2015 to May 31, 2015.

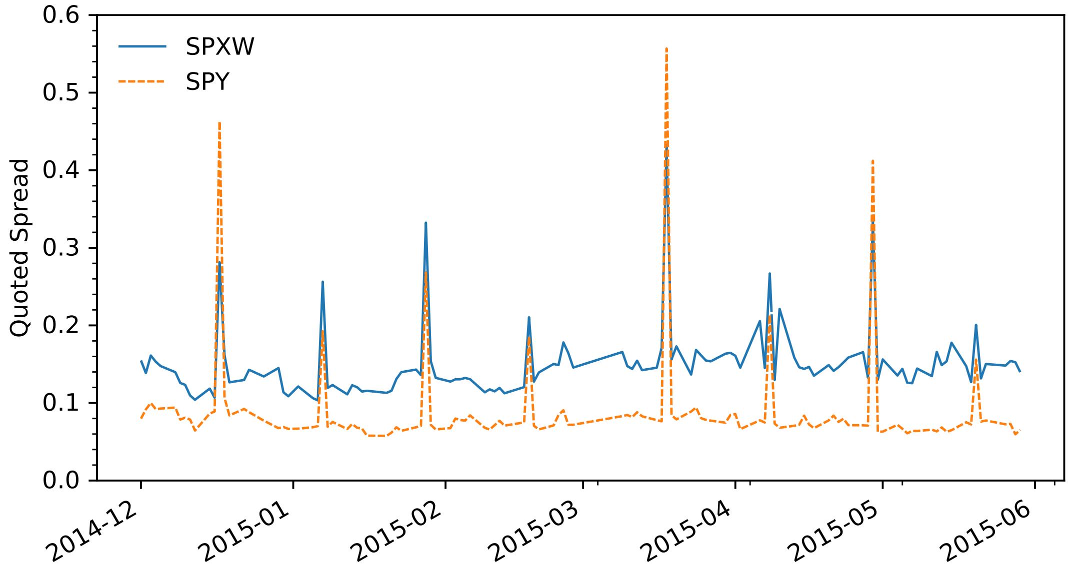
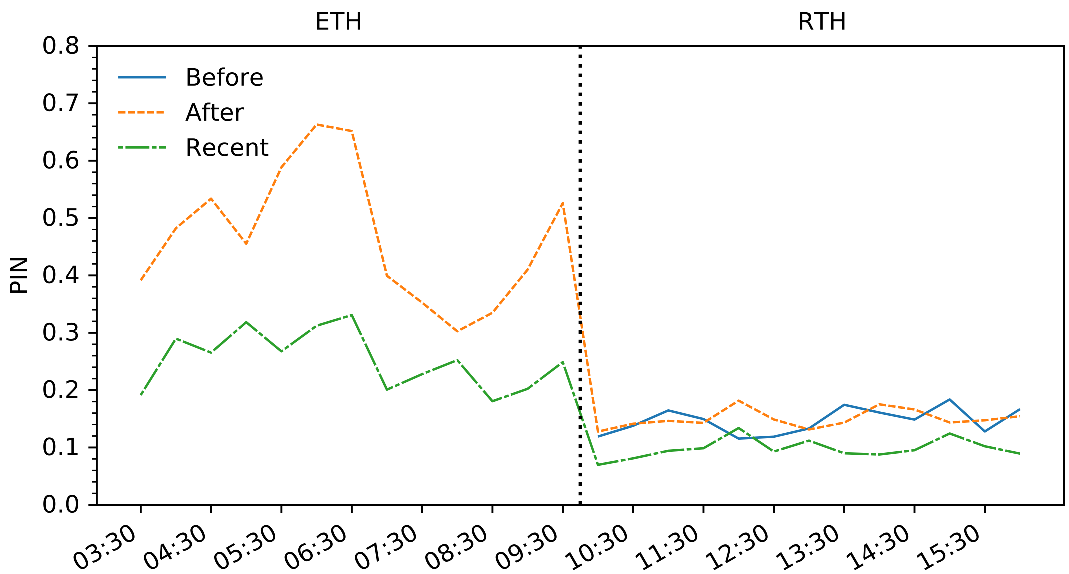
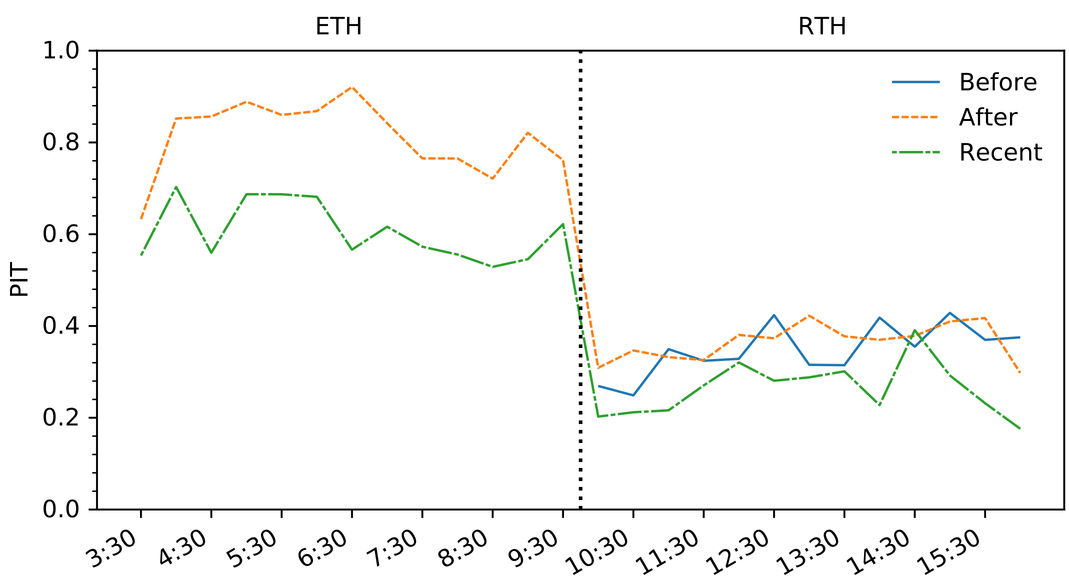


Figure 7. FOMC announcements' impact on quoted spread.
This figure shows the daily average quoted spread (%) from 14:00 to 14:05. US FOMC announcements are released at 14:00 on scheduled dates. The sample period is from December 1, 2014 to May 31, 2015..

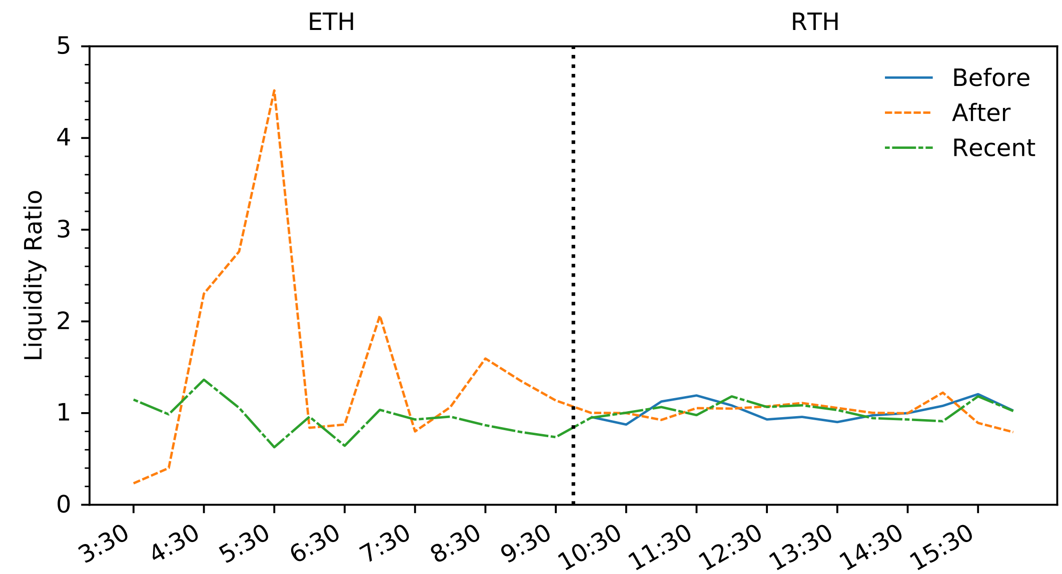
Panel A: Intraday probability of informed trading (PIN)



Panel B: Intraday dynamics of proportion of informed trading (PIT)



Panel C: Intraday dynamics of liquidity ratio



Panel D: Intraday dynamics of the probability of an event

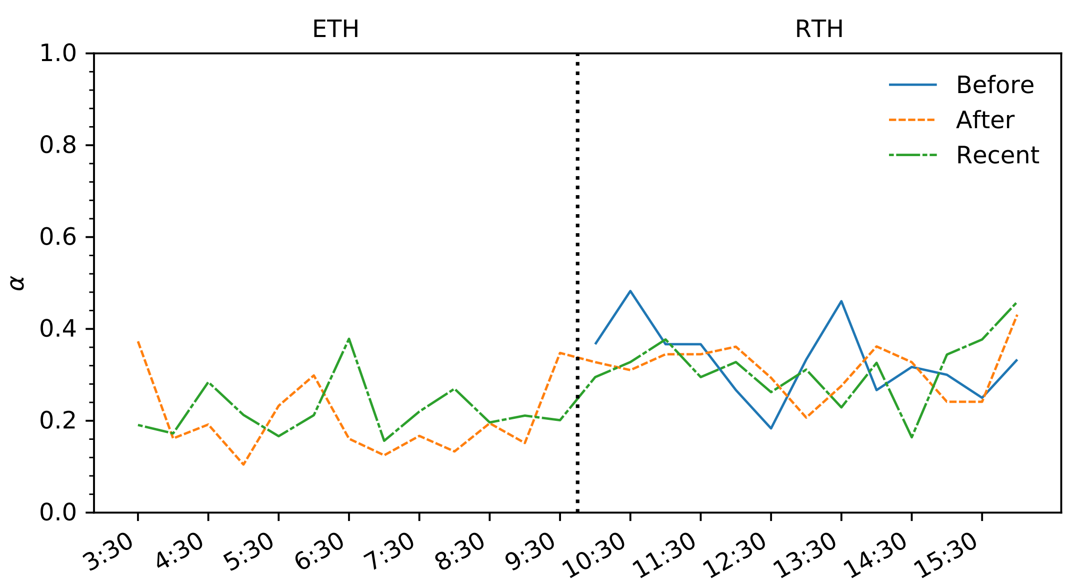
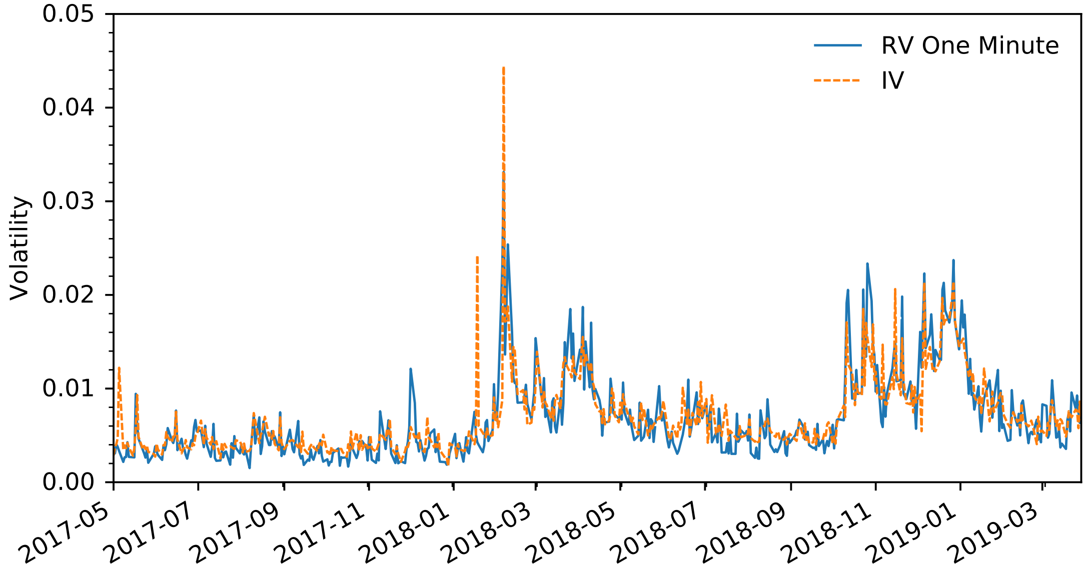


Figure 8. Results of PIN model.
These charts show estimations from the PIN model (Easley et al., 2002). Panel A, B, C, D show the probability of informed trading, the proportion of informed trading, liquidity ratio, and the probability of an event in each period respectively. The Before sample period is from December 1, 2014 to February 28, 2015. The After sample period is from March 1, 2015 to May 31, 2019. The Recent sample period is from January 1, 2019 to March 31, 2019.

Panel A: One-minute RV with IV



Panel B: Five-minute RV with IV

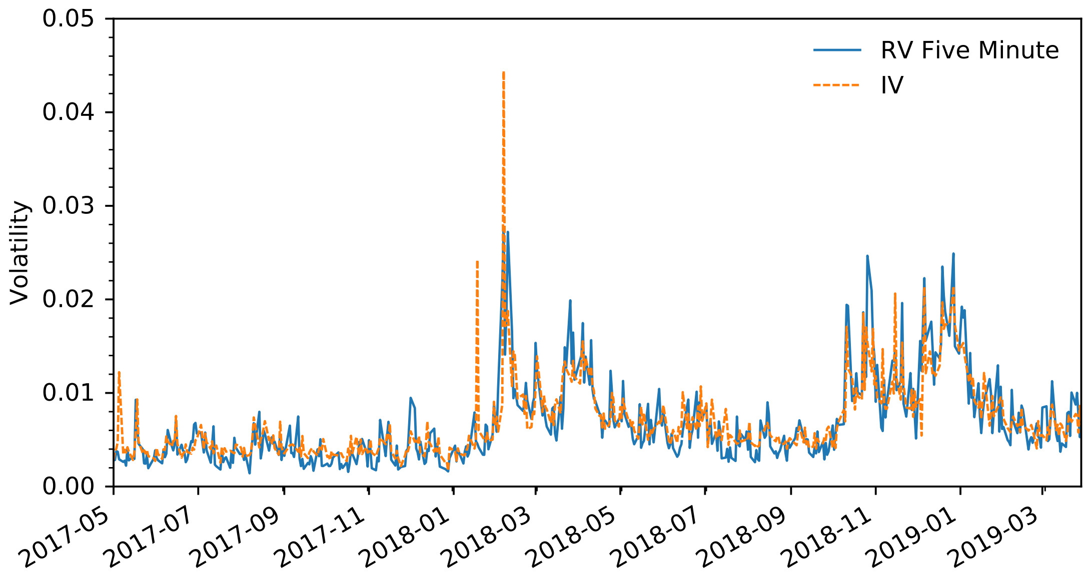


Figure 9. Daily dynamics of realized volatility and implied volatility.
Panel A and B plot the realized volatility estimated from one-minute and five-minute returns respectively. Implied volatility is estimated by model free volatility (Bakshi, Kapadia, & Madan, 2003) with the last midquote from 09:10 to 09:15. Sample period is from May 1, 2017 to March 31, 2019.