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Impacts of Zero-Commission Trading on Stock Market Liquidity

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IMPACTS OF ZERO-COMMISSION TRADING ON STOCK MARKET LIQUIDITY

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This thesis is approved as a creditable and independent investigation by a candidate for the master's degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department.

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ABSTRACT

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With the elimination of commission fees of retail brokers, zero-commission trading became the new normal after October 2019. This study employs DTAQ data to calculate ten different market liquidity measures and finds that the implementation of zero-commission trading significantly improves market liquidity. This effect is also significant after related factors including trading volume, price volatility, market performance, opening effect, and closing effect are controlled. By explicitly modeling the simultaneity nature among market liquidity measures, trading volume, and price volatility, this study finds that there is a positive relationship between spread and price volatility. The implementation of zero-commission trading decreases price volatility which causes an indirect negative effect on spread. This study also finds that the proportion of retail orders in the stock market increased significantly after the implementation of zero-commission trading. The asymmetric model on market microstructure predicts that noise traders tend to decrease the adverse selection cost of market makers and contribute to the decrease of spread. The findings of increased retail trading and improved market liquidity in this thesis is consistent with the prediction of an asymmetric information model, implying that retail investors tend to be noise traders. This study concludes that the implementation of zero-commission trading benefits retail investors from both commission costs and liquidity costs perspectives.

CHAPTER 1 INTRODUCTION

1.1 Background

After Robinhood, an online broker with a relatively no-frills platform, pioneered the idea of commission-free stock trading a few years ago, in late 2019, many major brokerages such as Charles Schwab, E-Trade, Interactive Brokers and TD Ameritrade announced in quick succession they were eliminating trading fees for online stock, ETF and option trades. These commission-free trades are unlimited, and no inactivity fees will be charged. Zero-commission trading, referring to this phenomenon, has become the new normal. In this thesis, I research the impact of zero-commission trading on market liquidity and try to identify the underlying causes of the impact.

Commission fees have been one significant component of trading costs. Brokers charge clients commission fees as compensation for executing trades on their behalf. Commission fees are usually quoted on a per-trade basis. Another important component of trading costs is the bid-ask spread (BAS) of market makers/dealers/liquidity providers[1]. They sell at a high (ask) price and buy at a low (bid) price to earn a spread profit as compensation for standing ready to provide immediate liquidity (Fleming, Ostdiek and Whaley (1996)). Bid-ask spreads in liquid markets are usually smaller than those in less liquid markets.

Zero-commission trading tends to have a greater impact on retail investors than on institutional investors. Institutional investors refer to companies or organizations investing money on behalf of other people. Retail investors refer to individual people who invest on their own accounts. Retail investors are an important part of the financial

[1] We use these three words interchangeably in this paper.

market. In past five years, more than 37% of the US equities are owned by individual investors (SIFMA (2020)). Compared to institutional investors, retail investors usually trade a smaller amount of capital per order, which results in a high proportion of commission fees on a per dollar value basis. Therefore, it benefits individual investors most from this standpoint.

Zero-commission trading could increase market liquidity, which may further decrease other aspects of trading costs for retail investors. The implementation of zero-commission trading attracts more retail investors to enter the financial market and stimulates retail trading activities. Retail brokerage firms including E-Trade, Interactive Brokers and TD Ameritrade all experienced increased trading in October 2019. The number of new brokerage accounts increased most considerably for Charles Schwab.[2] Charles Schwab was the first major retail broker announcing the application of zero commission on October 1, 2019. Its active brokerage accounts increased by 182,000 in the following three months after the announcement of eliminating online trading fees (Schwab (2019)). In addition, Citadel Securities is a financial company providing liquidity and trade execution to retail and institutional clients as a market maker. It handles about 40% of retail trading volume. Joe Mecane, Citadel Securities' head of execution services, argued that the proportion of retail trading increased to 15% of the stock market at the end of 2019 compared to historically 10%, as a result of the implementation of zero-commission trading (Mecane (2020)). If market makers wish to compete for higher volumes, they would have to decrease spreads as long as the upside from higher volume outweighs the downside caused by lower spreads per trade.

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[2] Refer to the article: https://www.cnbc.com/2019/11/14/the-move-to-free-stock-trading-led-to-a-big-jump-in-new-accounts-for-charles-schwab.html

However, it is also possible that zero-commission trading leads to decreased market liquidity, which may cause the increase of trading costs. Zero-commission trading causes brokers to lose their revenue from commissions. They mostly offset the loss through payment for order flow (PFOF) from wholesalers, who usually also serve as market makers in the financial market. PFOF refers to the operation that brokers sell their order flows coming from their retail customers to wholesalers instead of routing them to stock exchanges or other trading venues. By doing this, wholesalers acquire more trading volume without competing with other market makers on stock exchanges. Meanwhile, wholesalers need to pay retail brokers for retail order flow. PFOF increases the cost of wholesalers/market makers. They may widen spreads or at least slow down the decreasing trend of spreads to offset the increased cost.

In addition, ‘toxicity’ is a term often used in the financial market to categorize the order flow that adversely selects the market makers. Institutional investors are often considered as “high” in toxicity while retail investors are usually considered “low” or “no toxicity” (Mittal and Berkow (2021)). From the toxicity of order flow perspective, on the one hand, the increased proportion of retail investors will decrease the overall toxicity in the financial market, which in general will decrease the adverse selection cost of dealers and give them the motivation to decrease spreads. On the other hand, zero-commission trading may also stimulate the practice of payment for order flow. It is possible that most of the increased order flow from new retail investors are sold to wholesalers instead of interacting with the volume trading on exchanges. Furthermore, in order to obtain payment for order flows to offset the loss of profits caused by the implementation of zero commissions, some retail brokers who originally sent retail order flows to exchanges may start to sell order flows to wholesalers too. Even though retail orders increased in the market, these orders do not interact with volume trading on exchanges, and exchanges can lose some of their original retail orders to wholesalers. This situation will lead to the decreased proportion of retail orders on public exchanges and higher overall toxicity of the financial market. As a result, market makers could increase spreads to offset the increased adverse selection cost.

1.2 Research Objective

The overall objective of this thesis is to assess the impact of zero-commission trading on stock market liquidity and identify the possible causes of the impact. The specific objectives are to:

i. Analyze how zero-commission trading changes stock market liquidity including quoted spread, effective spread, realized spread, and quoted depth.

ii. Examine the quantified effect of zero-commission trading on different liquidity measures while controlling the related factors including trading volume, realized price volatility, and market performance.

iii. Identify the retail trades and analyze how zero-commission trading changes the proportion of retail orders.

iv. Analyze the characteristics of retail orders such as trade size and the proportion of odd lots and compare them with those characteristics of the entire stock market.

Zero-commission trading is a new phenomenon in the financial market. There are only a few research that have studied the impact of zero-commission trading. This study contributes to enrich literature twofold: (a) as the first paper to document that the implementation of zero-commission trading results in better liquidity by explicitly considering the simultaneity nature among market liquidity, trading volume, and price volatility; (b) this study concludes that zero-commission trading benefits individual investors from both commission cost and liquidity cost perspectives.

The remainder of this thesis is organized as follows. I review the relevant literature in chapter 2. I document the empirical methodology in chapter 3 and describe the data in chapter 4. I present empirical results and provide discussions in chapter 5. Finally, chapter 6 concludes the thesis.

CHAPTER 2 LITERATURE REVIEW

This section covers literature related to retail investors, trading costs, and determinants of market liquidity. The literature on market microstructure is inclusive on whether retail investors behave as uninformed or noise traders and how retail investors' trading activities affect market liquidity. As for trading costs, three measures are widely researched including commission fees, bid-ask spread, and price impact. Generally speaking, lower trading costs are always welcomed because higher trading costs always reduce strategy profitability (Novy-Marx and Velikov (2016)). The prior literature supports that market liquidity, trading volume, and price volatility are simultaneously determined, and market performance is a significant determinant of market liquidity.

2.1 Retail Investors

Some literature finds that retail investors are commonly considered as noise traders due to their lack of expertise and skills (Kaniel, Saar and Titman (2008)). Foucault, Sraer and Thesmar (2011) use a reform of the French stock market which discourages the trading costs of retail investors for some stocks. They find that retail trading activity increases the volatility of stock returns and retail investors are noise traders. They find no significant difference between quoted bid-ask spreads of stocks affected by the reform and of stocks not affected by the reform.

Other literature argues that retail investors are informed traders, and their trading can be used to predict future stock returns. Kaniel, Saar and Titman (2008) use a unique data set containing detailed individual buy/sell order information provided by the NYSE and find that retail investor orders can be used to forecast future returns. They document that positive (negative) excess returns can be expected after intense retail buying (selling) on a per-stock basis. However, this predicting power does not exist at the market level portfolio. They use the same data and find evidence of informed trading by retail investors around earnings announcements (Kaniel, et al. (2012)). However, they do not research how retail trading will affect the market liquidity.

Eaton, et al. (2021) use the Robinhood platform outages to isolate the effect of zero-commission trading on market quality and find that zero-commission trading tends to attract younger and less wealthy retail investors. They also find that retail orders do not have significant power in predicting future stock returns, and they conclude that retail investors motivated by the implementation of zero-commission behave as uniformed noise traders. They also document that these noise traders contribute to market volatility and create liquidity-reducing inventory risks, resulting in lower market liquidity.

By contrast, Peress and Schmidt (2020) use the sensational U.S. news to investigate the effect of noise traders' attention on markets. Sensational U.S. news is exogenous to the financial market and leads to temporary reduction of attention of noise investors to the financial market. They find that for stocks mostly owned by retail investors, "in which noise trading is expected to be more pronounced", their trading activity, liquidity, and volatility all decrease on days of distraction. These findings are consistent with noise traders mitigating the adverse selection risk of market makers, which means noise trading contributes to better market liquidity.

2.2 Trading Costs

Trading costs in the security market contain at least three components: commission fee, bid-ask spread, and market-impact cost (Fleming, Ostdiek and Whaley (1996)). The first component is commission fee charged by brokers. Retail brokerage firms usually charge a fixed commission fee per trade, while full-service brokerage firms tend to have higher fees with a more complicated commission structure. In late 1999, the commission fee for a trade with a full-service broker is $80-$100, while the cheapest retail brokers charge just $5-$8 per trade (Bakos, et al. (2000)), and this number was further reduced to zero after the implementation of zero-commission trading. Bakos, et al. (2000) also document that for trading volume of 100 share lots, the commission is the dominant component of trading costs.

The second component is the market maker's bid-ask spread. The literature has documented that various spread measures decline over time. For example, Jones (2002) finds that percent quoted bid-ask spreads on Dow Jones stocks surged during market turmoil, such as in 1932, when the Great Depression was at its worst. But overall, they have kept declining in the 20th century (1900-2000) and dropped sharply in the last two decades of the 20th century. In addition, Novy-Marx and Velikov (2016) estimate round-trip effective bid-ask spreads of all stocks traded in the market over 5 decades from 1960s to 2000s by using the Bayesian Gibbs sampler proposed by Roll (1984) and generalized and improved by Hasbrouck (2009). They document that effective spreads are much greater for small-cap stocks. Overall, effective spreads decrease over time. The downward trend is most obvious over the last decade for small-cap stocks. They also document that idiosyncratic volatility is positively related to effective spread, and firm size is negatively related to effective spread. In addition, the relationship between firm size and effective spread is concave rather than linear. Hasbrouck (2009) finds that firm size also affects the time-series volatility of effective spread. More specifically, the volatility decreases with firm size. However, these relationships are found at the individual stock level instead of at the aggregate market level.

The third component is market-impact cost in the form of a price concession for large trades. For a large institutional trader, market impact cost tends to dominate the full costs of trading (Kyle (1985)). Frazzini, Israel and Moskowitz (2018) use unique trade execution data from a large institutional money manager and find that market impact costs have exhibited a steady decline over the sample period: a 19-year period from August 1998 to June 2016. Similar to the finding of Novy-Marx and Velikov (2016) on effective spreads, Frazzini, Israel and Moskowitz (2018) find market impact costs also increase with idiosyncratic volatility and decrease with firm size. In addition, they find that trade size is the most significant determinant of market impact costs.

2.3 Determinants of Market Liquidity

Prior to 2000, the literature on liquidity mainly focuses on the liquidity of individual securities and uses short-term data (one year or less) (Chordia, Roll and Subrahmanyam (2000)). Chordia, Roll and Subrahmanyam (2001) is the first to study the aggregate market liquidity and trading activities using an extended time sample (11 years). They find that market performance is the most significant variable affecting market liquidity. Market liquidity plummets in a down market, while it increases weakly in an up market. However, they fail to consider the endogeneity among bid-ask spreads, trading volume, and market volatility. Wang and Yau (2000) take into consideration the potential endogeneity of these three measures. They use a three-equation simultaneous structural model on four financial and metal futures. They find that bid-ask spread is negatively related to trading volume, positively related to price volatility, while trading volume and price volatility are positively related. However, this research is conducted on the futures market instead of on the stock market.

CHAPTER 3 METHODOLOGY

In this thesis, I first investigate the timeline of main brokers implementing zero-commission trading and determine the cut-off time between pre- and post-zero commission periods. Then I calculate different measures of market liquidity and compare their magnitude before and after the implementation of zero-commission trading. I also conducted an autocorrelation-adjusted Welch's t-test to confirm the significance of the difference between the two periods. Next, I follow the methodology proposed by Wang and Yau (2000) to set up a three-equation simultaneous structural model, and include the market performance, open effect, and close effect as the control variables to investigate the quantified effect of zero-commission trading on different market liquidity measures. Finally, I follow the methodology introduced by Boehmer, et al. (2017) to identify retail orders from the market and investigate possible causes of the zero-commission trading's impact on the market liquidity. This section covers five related methodologies including the identification of pre- and post-zero commission trading cut-off time, liquidity measures, autocorrelation-adjusted Welch's t-test, three-equation simultaneous structural model, and identification of retail trades.

3.1 Pre- and Post-Zero Commission Trading Cut-Off Time

Robinhood is a private online broker company, founded in 2013, and started to provide zero-commission trading service for stocks and exchange-traded funds (ETF) in 2015. Other online brokers successively announced the elimination of online trading commission fees in October 2019. On September 26, 2019, Interactive Brokers announced that it was rolling out a new "lite" version (IBKR Lite) of its trading platform with free, unlimited trading for U.S. equities in October 2019. Charles Schwab was the first online broker announcing their zero-commission trading service for online stock, ETF, and option trading on October 1, 2019. It started the zero-commission trend in earnest. Charles Schwab's zero-commission trading policy took effect on October 7, 2019 (Schwab (2019)). Later that day, on October 1, 2019, TD Ameritrade also announced its zero-commission trading service, and it took effect on October 3, 2019 (Ameritrade (2019)). The next day, on October 2, 2019, E-Trade announced it would offer the zero-commission trading service on October 7, 2019. About two weeks later, on October 12, 2019, Fidelity Investments said that it would eliminate trading commissions. On October 21, 2019, Merrill Lynch, an investment company owned by Bank of American, announced to expand its loyalty program to offer unlimited free stock, ETF, and options trades for customers who qualify for free trades under a relationship-based Preferred Rewards (PR) program based on their use of other Bank of America products and services[3].

In general, as summarized in Figure 1, the implementation of zero-commission trading by different online brokers was mainly concentrated in the first three weeks of October 2019. Considering that the financial market needs some time to digest the news and see the impact of this new policy, I assume transactions occurred before and in October as pre-zero commission trading and transactions occurred in November and thereafter as post-zero commission trading.

[3] Refer to the news: https://www.advisorhub.com/merrill-edge-wont-mimic-schwabs-zero-commission-offer-executive/.

Figure 1 Implementation Timetable of Zero-Commission Trading

3.2 Liquidity Measures

From the market microstructure perspective, the essence of stock trading comes down to the interaction between liquidity suppliers and liquidity demanders. Market liquidity presents the profit (cost), quantity, and time of a trade to the liquidity supplier (demander) (Holden, Jacobsen and Subrahmanyam (2014)). This thesis focuses on the cost and quantity dimensions of market liquidity. The standard measures of the cost dimension include quoted spread, effective spread, realized spread, and price impact. The standard measure of the quantity dimension is quoted depth.

I first measure quoted spread in U.S. dollars and percentage at time t, which are defined as

$$Dollar\ Quoted\ Spread_t = O_t - B_t,$$

$$Percent\ Quoted\ Spread_t = \log(O_t) - \log(B_t),$$

where O_t is the best (lowest) offer price in National Best Bid and Offer (NBBO) at time t, B_t is the best (highest) bid price in NBBO at time t. Both quoted spreads presented above measure the theoretical cost of liquidity demanders to conduct a round-trip transaction, which means buying a given stock at O_t and simultaneously selling the same stock at B_t. Equivalently, it can also be viewed as the profit of liquidity providers to sell a stock at O_t and simultaneously buy the same stock at B_t. I aggregate these two quoted spread measures into a daily interval and 15-min intervals respectively for each stock by calculating their time-weighted average as follows:

$$Qtuoed\ Spread_i = \frac{\sum_{t=1}^{N_i}(T_t * Quoted\ Spread_t)}{\sum_{t=1}^{N_i} T_t}, i \in \{daily, 15 - \min intervals\},$$

where N_i is the final time stamp of the corresponding time interval i, T_t is the valid time period of the corresponding $Quoted\ Spread_t$.

I next measure the effective spread in U.S. dollars and percentage for the k^{th} trade, which is defined as

$$Dollar\ Effective\ Spread_k = 2 \times D_k(P_k - M_k),$$

$$Percent\ Effective\ Spread_k = 2 \times D_k[\log(P_k) - \log(M_k)],$$

where D_k is a buy-sell indicator variable that equals +1 if the k^{th} trade is the liquidity demander's buy and equals -1 if the k^{th} trade is the liquidity demander's sell. P_k is the transaction price of the k^{th} trade and M_k is the midpoint between the prevailing best offer price and prevailing best bid price in NBBO at the moment when the k^{th} trade occurs. Effective spread measures the actual liquidity cost for the liquidity demander to implement this trade (Chordia, Roll and Subrahmanyam (2000)). I aggregate these two effective spread measures into a daily interval and 15-minutes intervals respectively for each stock by calculating their equal-weighted average as follows:

$$Effective\ Spread_i = \frac{\sum_{k=1}^{N_i}(Effective\ Spread_k)}{N_i}, i \in \{daily, 15 - \min intervals\},$$

where N_i is the number of trades, equivalently, the number of $Effective\ Spread$ within the corresponding time interval i.

In this paper, I use three conventions to determine, from the liquidity demander's perspective, whether the given trade is a buy ($D_k = +1$) or a sell ($D_k = -1$). The first method is to use Lee and Ready (1991) convention (LR), which defines a trade as a buy when $P_k > M_k$, and a sell when $P_k < M_k$. When $P_k = M_k$, the tick test classifies a trade as a buy if $P_k > P_{k-1}$, otherwise a sell. P_{k-1} is the trading price of the most recently previous trade with a different trading price. The second method is to use the Ellis, Michaely and O'Hara (2000) convention (EMO), which specifies a trade as a buy if $P_k = O_k$, and a sell if $P_k = B_k$, where O_k is the prevailing best offer price and B_k is the prevailing best bid price in NBBO at the moment when the k^{th} trade occurs. Otherwise, the same tick test is implemented to determine the value of D_k. The third method is to use the Chakrabarty, et al. (2007) convention (CLNV), which defines a trade as a buy when $P_k \in [0.3B_k + 0.7O_k, O_k]$, and a sell when $P_k \in [B_k, 0.7B_k + 0.3A_k]$, otherwise the same tick test is implemented to determine the value of D_k. None of these three indication methods is perfect, they all have different advantages and disadvantages. LR convention is proposed and tested based on data of NYSE-listed firms. Lee and Ready (1991) report an overall 93% agreement between the actual order and LR's algorithmic inference. Both EMO and CLNV conventions are proposed and tested based on NASDNQ trades. Ellis, Michaely and O'Hara (2000) and Chakrabarty, et al. (2007) find that EMO and CLNV conventions have better classification accuracy rate for trades executed inside the quotes. This study determines the value of D_k as the value that is supported by at least two conventions. For example, if D_k determined by LR convention and EMO convention is equal to $+1$ while D_k determined by CLNV method is equal to -1, this study uses $D_k = +1$.

The third liquidity measure of the cost dimension is realized spread. I measure realized spread in U.S. dollars and percentage for k^{th} trade, which is defined as

$$Dollar\ Realized\ Spread_k = 2 \times D_k(P_k - M_{k+5}),$$

$$Percent\ Realized\ Spread_k = 2 \times D_k[\log{(P_k)} - \log{(M_{k+5})}],$$

where M_{k+5} is the midpoint 5 minutes after the midpoint M_k. Realized spread is the temporary component of effective spread, and it measures the actual liquidity profit for the liquidity supplier to implement this trade, net the adverse selection costs. I aggregate these two realized spread measures into daily interval and 15-minutes interval respectively for each stock by calculating their equal-weighted average.

The last liquidity measure in the cost dimension is price impact. I measure the price impact in U.S. dollars and percentage for k^{th} trade, which is defined as

$$Dollar\ Price\ Impact_k = 2 \times D_k(M_{k+5} - M_k),$$

$$Percent\ Price\ Impact_k = 2 \times D_k[(\log(M_{k+5}) - \log(M_k)].$$

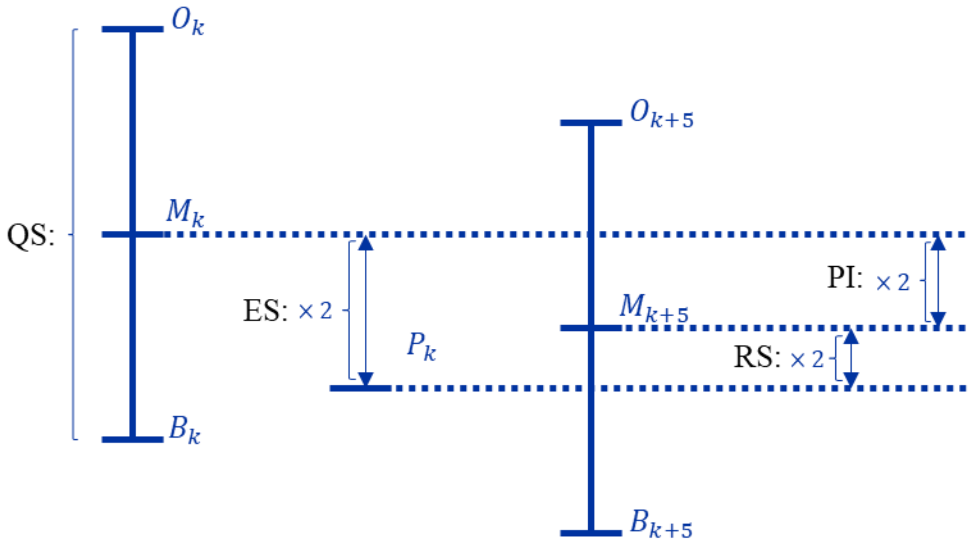
Price impact is the permanent component of effective spread, it measures the adverse selection costs of liquidity suppliers (Hendershott and Moulton (2011)). I aggregate these two price impact measures into a daily interval and 15-minute intervals respectively by calculating their equal-weighted average.

Effective spread can be decomposed to realized spread and price impact as follows:

$$Dollar\ (Percent)\ Effective\ Spread_t = Dollar\ (Percent)\ Realized\ Spread_t + Dollar\ (Percent)\ Price\ Impact_t.$$

Figure 2 also illustrates the relationship among quoted spread, effective spread, realized spread and price impact.

Figure 2 Visualization of Liquidity Measures



The last liquidity measure is in the quantity dimension, quoted depth. I measure the best offer depth and best bid depth at time t. Best offer depth in shares for a given stock at time t, denoted as $BOSD_t$, is defined as the number of shares provided at the best offer price at time t in the NBBO. Best bid depth in shares for a given stock at time t, denoted as $BBSD_t$, is defined as the number of shares provided at the best bid price at time t in the NBBO. Similarly, I also define the best offer and bid depth in dollars, which is the number of dollars calculated by multiplying $BOSD_t$ and corresponding best offer price, denoted as $BODD_t$, and the number of dollars calculated by multiplying $BBSD_t$ and corresponding best bid price, denoted as $BBDD_t$. For simplicity, in this study, I calculate the average of offer and bid depth measured in share and dollar, respectively. They are defined as follows:

$$Average\ Share\ Depth\ = (BOSD_t + BBSD_t)/2,$$

$$Average\ Dollar\ Depth\ = (BODD_t + BBDD_t)/2.$$

As with the quoted spread, I aggregate Average Share Depth and Average Dollar Depth into a daily interval and 15-minute intervals for each stock by calculating their time-weighted average.

In summary, in this study, I calculate ten different measures of market liquidity. Eight of them are in the cost dimension of market liquidity including Dollar Quoted Spread, Dollar Effective Spread, Dollar Realized Spread, Dollar Price Impact, Percent Quoted Spread, Percent Effective Spread, Percent Realized Spread, and Percent Price Impact. Later in this paper, I will collectively refer to these eight measures as Spreads.

Dollar Spreads are related to stock prices. For example, the minimum tick size of stocks with prices greater than 1 dollar is 0.01 cent, which means Dollar Quoted Spread and Dollar Effective Spread of these stocks are usually greater than 0.01 cent. But the minimum tick size of stocks with prices less than 1 dollar is much smaller. For instance, the minimum tick size of penny stocks is 0.0001 cent. Dollar Quoted Spread and Dollar Effective Spread of penny stocks could be much less than 0.01 cent. By contrast, Percent Spreads are unitless and independent of stock prices.

Another two measures are in the quantity dimension of market liquidity including Average Share Depth and Average Dollar Depth. Later in this paper, I will collectively refer to these two measures as Depths.

3.3 Autocorrelation-Adjusted Welch's t-test

Welch's t-test assumes two random samples have two different variances and they are drawn independently from two approximately normal populations. While our data is approximately normally distributed (15-min interval data is mildly right-skewed), they are autocorrelated[4], which violates the assumption of independent samples. Thus, I use the method proposed by Yilmaz and Aktas (2017) to define a new standard error by taking the autocorrelation into consideration. Their method is an extension of the Box-Hunter approach by allowing unequal sample sizes between two groups (Box, Hunter and Hunter (1978)). The adjusted standard error of the difference between two autocorrelated samples is defined as follows:

$$SE = \sqrt{\left|\frac{s_1^2}{2n_1}\left(1 + \frac{2n_1-3}{n_1} r_1^X\right) + \frac{s_2^2}{2n_2}\left(1 + \frac{2n_2-3}{n_2} r_1^Y\right)\right|},$$

where s_1 and s_2 are standard errors, n_1 and n_2 are sample sizes, and r_1^X and r_1^Y are lag-1 autocorrelations in two samples, respectively. The method of calculating the degree of freedom is the same as in the Welch's t-test. The formula is also provided below:

$$v = \frac{\left(\frac{s_1^2}{n_1}+\frac{s_2^2}{n_2}\right)^2}{\frac{\left(\frac{s_1^2}{n_1}\right)^2}{n_1-1}+\frac{\left(\frac{s_2^2}{n_2}\right)^2}{n_2-1}}.$$

3.4 Three-Equation Simultaneous Structural Model

Wang and Yau (2000) use the Hausman (1978) tests of specification and confirm that trading volume, bid–ask spread, and price volatility are jointly determined. In this paper, I follow their methodology to use the three-equation simultaneous structural model to accommodate the endogeneity of trading volume, bid–ask spread, and price volatility. Previous literature ((Demsetz (1968)), (Epps (1976)), (Benston and Hagerman (1974)), (Berkman (1992)), and (George and Longstaff (1993))) all conclude that bid-ask spreads are positively related to price volatility and negatively related to trading volume.

[4] Liquidity measures are widely documented to be autocorrelated. The autocorrelation plots of liquidity measures of daily data and 15-min interval data are provided in the appendix.

Our empirical model is written as follows:

$$BAS = \beta_0 + \beta_1 lag(BAS) + \beta_2 TV + \beta_3 PV + \beta_4 M + \beta_5 Z + \beta_6 OE + \beta_7 CE + e_b \quad (1)$$

$$TV = \alpha_0 + \alpha_1 lag(TV) + \alpha_2 BAS + \alpha_3 PV + \alpha_4 M + \alpha_5 Z + \alpha_6 OE + \alpha_7 CE + e_t \quad (2)$$

$$PV = \gamma_0 + \gamma_1 lag(PV) + \gamma_2 BAS + \gamma_3 TV + \gamma_4 M + \gamma_5 Z + \gamma_6 OE + \gamma_7 CE + e_p \quad (3)$$

where BAS is quoted spread (QS), effective spread (ES), realized spread (RS), price impact (PI) measured in Dollar and Percent forms, and average depth measured in Share (ASD) and Dollar (ADD) forms, respectively. TV is trading volume, and PV is price volatility. $lag(BAS), lag(TV), and\ lag(PV)$ are $BAS, TV, and\ PV$ lagged by 1-time period, respectively. For example, in daily data, the $lag(BAS)$ means the BAS lagged by one day; and in 15-min interval data, the $lag(BAS)$ means the BAS lagged by 15 minutes. Lagged variables entered here as instrumental variables of corresponding original variables.

This thesis constructs an equal-share portfolio using the total 100 stocks in the data and sum all stocks prices at each minute to simulate the portfolio price history. When some stocks do not have trading occurring at the specified minute, I use the nearest stale trading prices of that stock as the substitution of corresponding trading prices. I calculate the absolute difference between the highest price and the lowest price of the portfolio for each time interval and use it as the proxy for the price volatility of the portfolio. Z is the indicator variable of zero commission. $Z = 1$ when zero-commission trading is implemented, otherwise $Z = 0$. M is the indicator variable of market performance. $M = 1$ when concurrent market return (daily return for daily data, and 15-min return for 15-min interval data) is positive, otherwise $M = 0$. I also include two indicator variables to account for the intra-day seasonality effects in spread, trading volume, and price volatility. OE is the indicator variable of market open effect. $OE = 1$ when the data is within 15 minutes after the market opens, otherwise $OE = 0$. CE is the indicator effect on market close effect. $CE = 1$ when the data is within 15 minutes before the market closes, otherwise $CE = 0$.

I find the data are heavily autocorrelated and right-skewed, thus I use generalized method of moments (GMM) instead of common estimation methods such as least squares and maximum likelihood method to estimation equation parameters. GMM has the advantage of not imposing any restriction on the distribution of the data.

3.5 Identify Retail Order Flows

Regulation National Market System (Reg NMS) prohibits executions at fractions of tick size (one cent for most stocks whose price is greater than or equal to $1, and 0.01 cent for remaining stocks whose price is less than $1) on exchanges (Rule 612). One exception is that when orders in exchange are hidden orders priced at midpoint, it is possible for them to be executed at fractions of tick size. The actual execution price depends on the corresponding NBBO. For example, if the corresponding best bid in NBBO is $5.01 and the corresponding best ask in NBBO is $5.02, the execution price of that hidden order priced at midpoint will be at $5.015, which is the average of best bid and best ask in NBBO. Under this situation, the execution price of orders in exchanges is also at fractional cent, in this case 0.5 cents. If the best bid and ask are $5.01 and $5.03, respectively, the execution price will be $5.02, which is at round cent.

However, this rule (Rule 612) does not apply to off-exchange orders. Thus, market makers often provide tiny price improvement, at fractions of cents, at off-exchange venues to acquire more orders. Common price improvement amounts are 0.01, 0.1, and 0.2 cents (Boehmer, et al. (2017)). For example, a buy order with NBBO of $5.01 and $5.02 is likely to receive an execution price of $5.019, improving $5.02 by 0.1 cent. By contrast, a sell order with the same NBBO is more likely to receive an execution price of $5.011, improving $5.01 by 0.1 cent.

In the Unites States, most institutional orders are sent to exchanges and dark pools, where fractional cents execution prices are not allowed, except for half penny execution. However, most marketable orders initiated by retail investors are rarely sent to exchanges, they are instead often sent to wholesalers or executed via internalization. These orders are filled from broker's own inventory (Boehmer, et al. (2017)). For example, Battalio, Corwin and Jennings (2016) examine the SEC Rule 606 filings of ten popular retail brokers including Charles Schwab, Ameritrade, E-Trade, and Interactive Brokers etc. They document that eight out of ten retail brokers route more than 95% of their market orders directly to wholesalers instead of exchanges, and they also route about 50% of their limit orders to the market makers, the majority of which are more likely to be marketable limit orders. Both wholesalers and internalization are off-exchange operations, and execution price improvement at fractional cent commonly occurs. As discussed above, an off-exchange retail buy (sell) order tends to be executed slightly below (above) a round penny due to the price improvement. Thus, I define the order as a retail buy if its fractional cents of the execution price fall into the interval of $(\$0.005,\ \$0.01)$, and as a retail sell if its fractional cents of the execution price fall into the interval of $(\$0.000,\ \$0.005)$[5]. Following Boehmer, et al. (2017), transactions

[5] Our data contain three stocks: APND, FCEL, and SNDE whose prices are less than $1 in some trading sessions. When their prices are less than $1, their tick size is at 0.01 cent. Thus, when their prices are less than $1, the interval used to assign them as retail buy is ($0.00005, $0.0001) and as retail sell is ($0.00000, $0.00005).

occurred at round penny or at half-penny are more likely to be institutional orders, thus I do not include them into the retail category. Admittedly, this identification method is conservative, because some retail orders may not receive this kind of price improvement and do not have an execution price at fractional cent, although not many. Therefore, the identified retail orders may slightly underestimate the actual number of retail orders in the market.

3.6 Hypotheses Development

This study tests four main hypotheses related to our four objectives. As stated in Chapter 1, the implementation of zero-commission trading could increase retail trading volume, reduce the adverse selection cost of market makers. Thus, zero-commission trading could induce a more liquid market. It also has the possibility to increase the practice of PFOF and increase the cost of market makers. Meanwhile, retail orders on public exchanges could decrease due to the practice of PFOF. As a result, market makers face higher adverse selection risks on public exchanges and may widen their spreads. Market liquidity could be affected by the implementation of zero-commission trading in either direction. Thus, the first hypothesis is that market liquidity, measured by Spreads and Depths, has changed significantly after the implementation of zero-commission trading. The second hypothesis is that the change market liquidity is still significant after controlling for related factors such trading volume and price volatility.

Because commission fees are the dominant component of trading costs for retail investors compared to other components like liquidity costs, the elimination of commission fees can attract more retail investors to participate in the financial market, and it can induce retail investors to trade more frequently without the concern of commission fees. Therefore, the third hypothesis is that the proportion of retail orders in the stock market increased significantly after the implementation of zero-commission trading.

Because with positive commissions, investors prefer to aggregate trades to reduce the number of trade executed. This strategy helps avoid generating multiple commission fees, which are charged by brokers on a per trade basis. This strategy also results in a relatively large trade size. But after the implementation of zero-commission trading, the concern of commission fees disappears. Investors have the ability to divide their orders into any number of trades they would like. Smaller trade size per trade has the advantage of reducing price impact, which is preferred by investors. Another factor that could lead to the decrease of trade size per trade is speculative trading. With positive commission fees, investors who have no confidence in a stock will not consider trading it. While after the implementation of zero-commission trading, it is attractive to submit a trade of small size such as one or two shares to participate in the market and have fun, especially for novice investors. Formally, the fourth hypothesis is that after the implementation of zero-commission trading, average trade size decreased.

In summary, this thesis tests four hypotheses as follows:

H1: After the implementation of zero-commission trading, market liquidity changed significantly.

H2: The effect of zero-commission trading on market liquidity is still significant after controlling for related factors such as trading volume and price volatility.

H3: After the implementation of zero-commission trading, the proportion of retail orders increased significantly.

H4: After the implementation of zero-commission trading, average trade size decreased.

CHAPTER 4 DATA AND SUMMARY STATISTICS

4.1 Data Description and Processing

This thesis uses the New York Stock Exchange DTAQ (Daily Trade and Quote). Data period ranges from the first trading day of September (09/03/2019) to the last trading day of November (11/28/2019) to cover the time period of the pre and post zero-commission trading. I exclude data on 11/29/2019 because the stock market opened only for half day and closed at 1:00 pm on that day, which is not a normal market session. In total, the data contain 62 trading days.

This study selects a random sample of 100 actively traded stocks. They meet following three criterions: (a) It must be a common stock; (b) It must be actively traded in U.S. throughout the sample period; (c) It cannot change primary exchange or ticker symbol during the sample period. These criterions generate 4070 stocks, and I rank them by their market capitalizations as of 09/30/2020. Finally, I randomly choose 20 stocks in each quintile (20%, 40%, 60%, 80%, 100%), and they form the random sample of 100 actively traded stocks.

This study uses data during the continuous trading session (9:30am to 16:00pm) and excludes opening and closing auction volume. For trading data records, I only keep normal trades (Trade Correction Indicator = ‘00’ in DTAQ) with positive trading prices, because negative or zero trading prices are usually due to reporting errors. In normal markets, National Best Offer price is supposed to be greater than National Best Bid price, otherwise it will provide arbitrary opportunities. In this paper, before calculating liquidity measures, I remove quote data records where $O_t < B_t$, which is commonly referred to as a crossed quote. I also exclude data where $O_t = B_t$, which is commonly referred to as a locked quote. I also remove data where $O_t - B_t > \$5$, which is commonly caused by reporting errors (Holden and Jacobsen (2014)). After screening, the data have 93.7 million NBBO quote records and 38.4 million trade records (Table 1). Quote records are almost 2.5 times more than trade records, which is reasonable because NBBO is updated very quickly and a lot of NBBO quotes are outdated before any trade occurs. I also provide the number of observations of raw data for each quintile. For example, quintile 1 (Q1) consists of 20 stocks whose market capitalization is in the largest 20%, and quintile 5 (Q5) consists of 20 stocks whose market capitalization is in the smallest 20%. Both types of data are unbalanced. More than 50% of records are associated with the stocks in the first quintile, and only 2.5% of quote records and 6.4% of trade records are associated with stocks in the fifth quintile. This is reasonable because stocks with a large market capitalization tend to be traded more actively than stocks with a smaller market capitalization.

Table 1: Number of Observations of Raw Data

Data Type	Full Sample (100 stocks)	Q1 (20 stocks)	Q2 (20 stocks)	Q3 (20 stocks)	Q4 (20 stocks)	Q5 (20 stocks)
Quote	93,710,573 (100%)	52,918,432 (56.5%)	23,367,668 (24.9%)	8,738,026 (9.3%)	6,390,245 (6.8%)	2,296,202 (2.5%)
Trade	38,357,156 (100%)	20,495,149 (53.4%)	9,066,037 (23.6%)	3,681,547 (9.6%)	2,663,262 (6.9%)	2,451,161 (6.4%)

Data is at nanosecond time stamps. I first calculate all measures for each transaction level record. Then I aggregate transaction level data across all trades in each stock for the designated time interval. The aggregation is based on time-series average for market liquidity measures and time-series sum for trading volume and number of trades. Trade size is calculated by dividing trading volume by number of trades. In this paper, I investigate daily and 15-minute intervals. Finally, I find the cross-sectional equal-weighted average across all 100 stocks to generate one representative observation for each time interval (day and 15 minutes respectively). Daily data has the advantages of smoothing noise and making it easier to detect the overall trend. Daily data contains limited observations which may adversely affect the parameters estimation result of GMM, because GMM may perform poorly in small samples (Chaussé (2010)). While 15-min interval data are more volatile and contain intra-day seasonality, it enables the construction of a sample composed of more observations and allows for implementing a robust test about results obtained from daily data. In this paper, because daily data loses the simultaneity nature among market liquidity measures, trading volume, and price volatility, I only use the 15-min interval data to construct the three-equation simultaneous structural model. Aggregating data at long intervals, such as daily intervals, may cause the data to fail to capture the signal, but this needs to be further investigated.

4.2 Summary Statistics

Tables 2 and 3 show the time-series summary statistics on market liquidity measures in the daily data and in the 15-min interval data. Dollar Spreads are presented in cents, and Percent Spreads are presented in basis points (bps). Average Share Depth is presented in shares and Average Dollar Depth is presented in dollars. In addition to the overall result, I also provide the summary statistics for each quintile.

Table 2 shows the time-series average of Dollar Quoted Spread at the daily interval is 10.87 cents, greater than the time-series average of Dollar Effective Spread, 4.72 cents. About half of the Dollar Effective Spread is decomposed as Dollar Realized Spread (2.23 cents) and another half is decomposed as Dollar Price Impact (2.49cents). Percent Spreads show a similar pattern. The time-series average of Percent Quoted

Spread is the largest (73 bps), followed by Percent Effective Spread (39bps). But more than half of the Percent Effective Spread is decomposed as Percent Realized Spread (21 bps) and less than half is decomposed as Percent Price Impact (19 bps). This discrepancy is more obvious in the 15-min interval data. The time-series average of Average Share Depth is 860 shares, and the time-series average of Average Dollar Depth is $10,218. Table 3 shows a similar pattern for 15-min interval data. One exception is that daily data is more normally distributed while 15-min interval data is more right-skewed (their mean values are much greater than their corresponding median values). The difference in normality between daily data and 15-min interval data is clearly demonstrated in Figures 3 and 4. Figure 3 plots the distributions of Spreads and Figure 4 plots the distributions of Depths in the daily data and 15-min interval data, respectively.

Comparing the liquidity measures across quintiles, stocks with greater market capitalization generally have higher liquidity (smaller Spreads and greater Depths). This finding is consistent with the study of Novy-Marx and Velikov (2016) which documents that bid-ask spreads are much greater for small-cap stocks. Figure 5 plots the time-series average of Spreads and Depths by quintiles in the daily data. The mean value of Spreads increases with the increase of stock quintiles. By contrast, the time-series average of Depths in the higher quintiles tends to be greater than that in the lower quintiles. However, one interesting phenomenon is that stocks with extreme small market capitalization, such as in the fourth and fifth quintiles, have unusually low Dollar Quoted Spread, low Dollar Price Impact, and unusually high Average Share Depth. This abnormality may be due to the relatively low stock prices in these two quintiles. The right graph in the first row of Figure 5 plots time-series average of Percent Spreads which are unitless and independent of stock prices. It does not show any abnormality. The relatively low stock prices make higher quoting depth more affordable compared to stocks with higher trading prices. Liquidity measures in the 15-min interval data show very similar patterns as seen in Figure 6.

Table 2: Summary Statistics of Daily Data

Variable: Full Sample (100 Stocks)	No. of Obs.	Mean	Med.	Std. Dev.	Max.	Min.
Dollar Quoted Spread (cents)	62	10.87	10.64	1.05	13.93	9.12
Dollar Effective Spread (cents)	62	4.72	4.65	0.44	5.82	3.90
Dollar Realized Spread (cents)	62	2.27	2.25	0.33	3.25	1.55
Dollar Price Impact (cents)	62	2.45	2.42	0.31	3.28	1.89
Percent Quoted Spread (bps)	62	73	74	6	87	62
Percent Effective Spread (bps)	62	39	39	4	48	31
Percent Realized Spread (bps)	62	21	21	3	29	14
Percent Price Impact (bps)	62	18	18	3	27	12
Average Share Depth (shares)	62	860	850	90	1118	694
Average Dollar Depth (dollars)	62	10218	10070	937	13773	8456
Variable: Q1 (20 stocks in the first Quintile)	No. of Obs.	Mean	Med.	Std. Dev.	Max.	Min.
Dollar Quoted Spread (cents)	62	8.26	8.21	1.25	11.25	5.85
Dollar Effective Spread (cents)	62	3.39	3.34	0.51	4.73	2.57
Dollar Realized Spread (cents)	62	0.82	0.87	0.35	1.60	0.15
Dollar Price Impact (cents)	62	2.57	2.48	0.45	4.34	1.80
Percent Quoted Spread (bps)	62	7	7	1	9	5
Percent Effective Spread (bps)	62	3	3	0.4	4	3
Percent Realized Spread (bps)	62	1	1	0.3	1	0
Percent Price Impact (bps)	62	3	3	0.4	4	2
Average Share Depth (shares)	62	365	363	34	564	311
Average Dollar Depth (dollars)	62	23043	22843	2135	34616	19582
Variable: Q2 (20 stocks in the second Quintile)	No. of Obs.	Mean	Med.	Std. Dev.	Max.	Min.
Dollar Quoted Spread (cents)	62	10.36	10.07	1.82	14.48	6.65
Dollar Effective Spread (cents)	62	3.91	3.85	0.64	5.85	2.90
Dollar Realized Spread (cents)	62	1.60	1.48	0.47	2.92	0.70
Dollar Price Impact (cents)	62	2.31	2.29	0.42	3.64	1.66
Percent Quoted Spread (bps)	62	18	18	2	23	14
Percent Effective Spread (bps)	62	8	8	0.8	11	7
Percent Realized Spread (bps)	62	2	2	0.7	5	1
Percent Price Impact (bps)	62	6	6	0.8	8	4
Average Share Depth (shares)	62	443	441	43	567	365
Average Dollar Depth (dollars)	62	11105	11109	1061	14667	9359

Variable: Q3 (20 stocks in the third Quintile)	No. of Obs.	Mean	Med.	Std. Dev.	Max.	Min.
Dollar Quoted Spread (cents)	62	12.17	12.05	1.62	16.12	9.42
Dollar Effective Spread (cents)	62	4.89	4.77	0.61	6.29	3.84
Dollar Realized Spread (cents)	62	1.75	1.77	0.50	3.12	0.47
Dollar Price Impact (cents)	62	3.14	3.10	0.59	5.18	1.52
Percent Quoted Spread (bps)	62	45	45	5	56	35
Percent Effective Spread (bps)	62	18	18	2	23	15
Percent Realized Spread (bps)	62	7	6	2	14	2
Percent Price Impact (bps)	62	12	12	2	21	4
Average Share Depth (shares)	62	253	248	24	345	207
Average Dollar Depth (dollars)	62	5861	5770	614	8202	4649
Variable: Q4 (20 stocks in the fourth Quintile)	No. of Obs.	Mean	Med.	Std. Dev.	Max.	Min.
Dollar Quoted Spread (cents)	62	12.10	11.95	2.24	18.66	8.76
Dollar Effective Spread (cents)	62	5.44	5.45	0.84	7.84	3.88
Dollar Realized Spread (cents)	62	3.07	3.24	1.12	4.98	-2.72
Dollar Price Impact (cents)	62	2.37	2.15	1.14	9.15	0.88
Percent Quoted Spread (bps)	62	96	94	12	122	75
Percent Effective Spread (bps)	62	50	50	6	65	38
Percent Realized Spread (bps)	62	24	26	11	41	-42
Percent Price Impact (bps)	62	26	25	10	91	16
Average Share Depth (shares)	62	2065	1904	489	3570	1474
Average Dollar Depth (dollars)	62	7493	6361	2740	17492	4882
Variable: Q5 (20 stocks in the fifth Quintile)	No. of Obs.	Mean	Med.	Std. Dev.	Max.	Min.
Dollar Quoted Spread (cents)	62	11.44	11.40	1.65	15.72	7.89
Dollar Effective Spread (cents)	62	5.97	5.84	0.89	8.55	4.50
Dollar Realized Spread (cents)	62	3.93	3.75	1.25	7.14	1.93
Dollar Price Impact (cents)	62	2.04	1.80	1.01	5.13	-0.68
Percent Quoted Spread (bps)	62	200	199	23	276	163
Percent Effective Spread (bps)	62	116	113	18	162	87
Percent Realized Spread (bps)	62	70	69	19	120	30
Percent Price Impact (bps)	62	46	43	19	117	7
Average Share Depth (shares)	62	1172	1161	252	1797	722
Average Dollar Depth (dollars)	62	3590	3460	715	5650	2437

Table 3: Summary Statistics of 15-Min Interval Data

Variable: Full Sample (100 Stocks)	No. of Obs.	Mean	Med.	Std. Dev.	Max.	Min.
Dollar Quoted Spread (cents)	1612	10.35	8.66	5.48	44.11	4.78
Dollar Effective Spread (cents)	1612	4.85	4.01	2.81	23.86	2.27
Dollar Realized Spread (cents)	1612	2.56	2.13	1.80	16.41	-2.29
Dollar Price Impact (cents)	1612	2.29	1.95	1.34	16.22	0
Percent Quoted Spread (bps)	1612	65	56	27	215	34
Percent Effective Spread (bps)	1612	34	29	17	193	16
Percent Realized Spread (bps)	1612	21	19	10	81	-2
Percent Price Impact (bps)	1612	12	10	9	128	-2
Average Share Depth (shares)	1612	849	805	220	2352	483
Average Dollar Depth (dollars)	1612	10382	9856	2370	38973	7160
Variable: Q1 (20 stocks in the first Quintile)	No. of Obs.	Mean	Med.	Std. Dev.	Max.	Min.
Dollar Quoted Spread (cents)	1612	8.27	6.55	5.95	52.86	2.45
Dollar Effective Spread (cents)	1612	3.72	2.99	2.46	22.89	1.46
Dollar Realized Spread (cents)	1612	1.02	0.82	1.84	20.50	-19.69
Dollar Price Impact (cents)	1612	2.70	2.21	2.03	40.04	-0.81
Percent Quoted Spread (bps)	1612	7	6	5	40	3
Percent Effective Spread (bps)	1612	4	3	2	17	2
Percent Realized Spread (bps)	1612	1	1	1	13	-10
Percent Price Impact (bps)	1612	3	2	2	25	0
Average Share Depth (shares)	1612	365	336	136	2818	206
Average Dollar Depth (dollars)	1612	23047	21607	6799	159139	15043
Variable: Q2 (20 stocks in the second Quintile)	No. of Obs.	Mean	Med.	Std. Dev.	Max.	Min.
Dollar Quoted Spread (cents)	1612	10.23	8.33	6.62	47.98	2.89
Dollar Effective Spread (cents)	1612	4.47	3.54	3.00	30.41	1.13
Dollar Realized Spread (cents)	1612	2.17	1.63	2.41	25.11	-4.21
Dollar Price Impact (cents)	1612	2.29	1.87	1.65	12.38	-4.91
Percent Quoted Spread (bps)	1612	18	15	11	84	7
Percent Effective Spread (bps)	1612	9	7	5	45	4
Percent Realized Spread (bps)	1612	3	3	3	30	-6
Percent Price Impact (bps)	1612	6	5	3	31	-1
Average Share Depth (shares)	1612	443	408	161	1272	230
Average Dollar Depth (dollars)	1612	11095	10394	3166	28034	6904

Variable: Q3 (20 stocks in the third Quintile)	No. of Obs.	Mean	Med.	Std. Dev.	Max.	Min.
Dollar Quoted Spread (cents)	1612	12.10	9.84	7.90	65.28	3.87
Dollar Effective Spread (cents)	1612	5.86	4.75	4.07	36.88	1.98
Dollar Realized Spread (cents)	1612	2.38	1.82	2.97	31.72	-4.94
Dollar Price Impact (cents)	1612	3.48	3.01	2.02	17.10	0.43
Percent Quoted Spread (bps)	1612	45	36	29	228	16
Percent Effective Spread (bps)	1612	22	18	15	130	8
Percent Realized Spread (bps)	1612	9	7	11	110	-20
Percent Price Impact (bps)	1612	13	12	8	69	1
Average Share Depth (shares)	1612	253	235	74	1133	164
Average Dollar Depth (dollars)	1612	5864	5518	1403	21639	4065
Variable: Q4 (20 stocks in the fourth Quintile)	**No. of Obs.**	**Mean**	**Med.**	**Std. Dev.**	**Max.**	**Min.**
Dollar Quoted Spread (cents)	1612	11.50	9.78	6.23	57.08	3.42
Dollar Effective Spread (cents)	1612	5.40	4.36	3.66	30.14	0.95
Dollar Realized Spread (cents)	1612	3.89	3.20	3.13	31.34	-2.89
Dollar Price Impact (cents)	1612	1.51	1.12	1.57	15.20	-10.75
Percent Quoted Spread (bps)	1612	92	79	43	382	45
Percent Effective Spread (bps)	1612	50	43	31	629	21
Percent Realized Spread (bps)	1612	31	27	21	188	-55
Percent Price Impact (bps)	1612	19	16	18	514	-3
Average Share Depth (shares)	1612	2091	1925	796	9294	741
Average Dollar Depth (dollars)	1612	7286	6336	3604	29872	3074
Variable: Q5 (20 stocks in the fifth Quintile)	**No. of Obs.**	**Mean**	**Med.**	**Std. Dev.**	**Max.**	**Min.**
Dollar Quoted Spread (cents)	1612	9.62	8.98	3.67	29.20	2.98
Dollar Effective Spread (cents)	1612	4.72	4.08	2.84	33.89	0.86
Dollar Realized Spread (cents)	1612	3.64	3.09	2.37	23.48	1.47
Dollar Price Impact (cents)	1612	1.07	0.69	1.75	25.85	-6.70
Percent Quoted Spread (bps)	1612	182	169	57	529	75
Percent Effective Spread (bps)	1612	100	92	43	451	33
Percent Realized Spread (bps)	1612	76	72	34	28	-25
Percent Price Impact (bps)	1612	25	18	29	296	-40
Average Share Depth (shares)	1612	1181	1039	606	7782	365
Average Dollar Depth (dollars)	1612	3223	2910	1393	12267	917

Figure 3: Distribution of Spread in Daily Data and 15-Min Interval Data

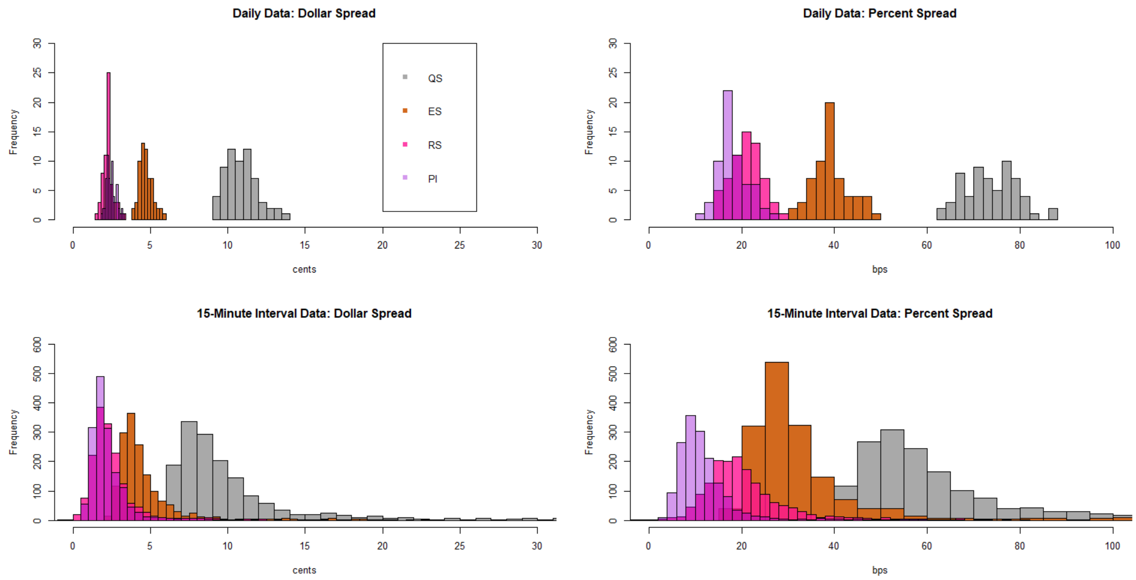


Figure 4: Distribution of Depth in Daily Data and 15-Min Interval Data

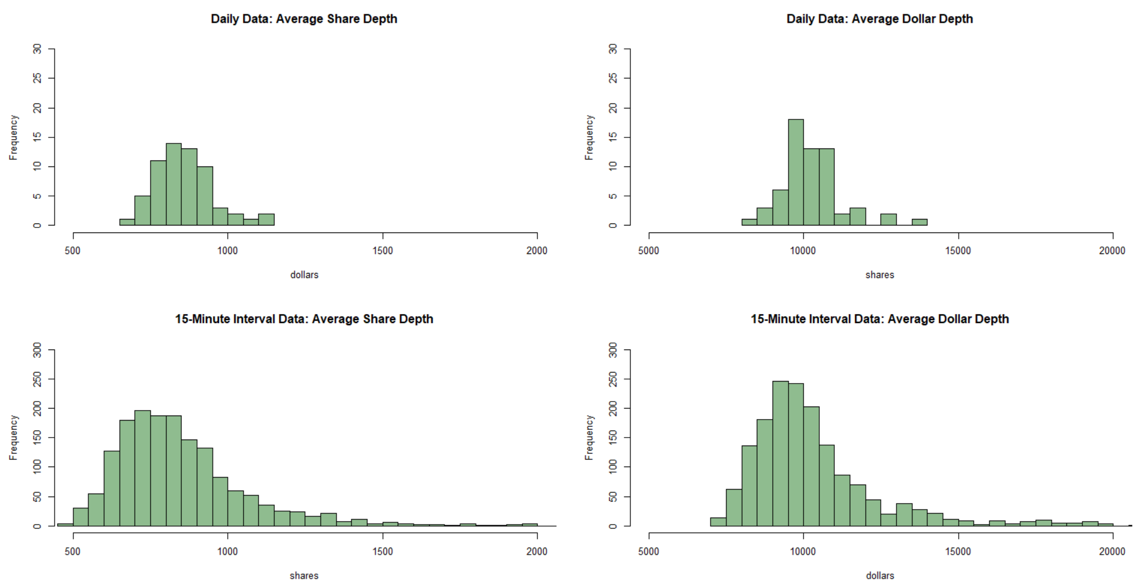


Figure 5: Mean Value of Spread and Depth by Quintiles in the Daily Data

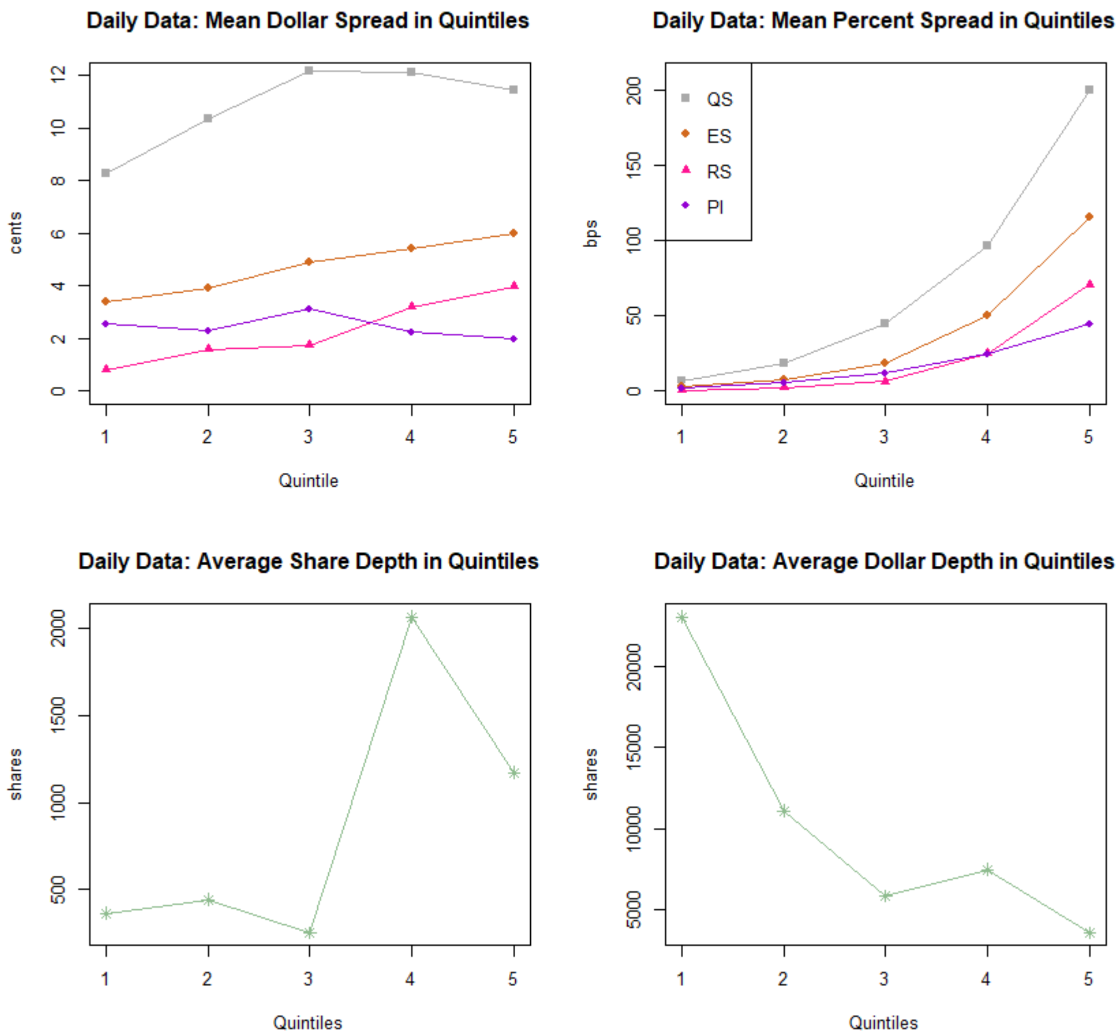
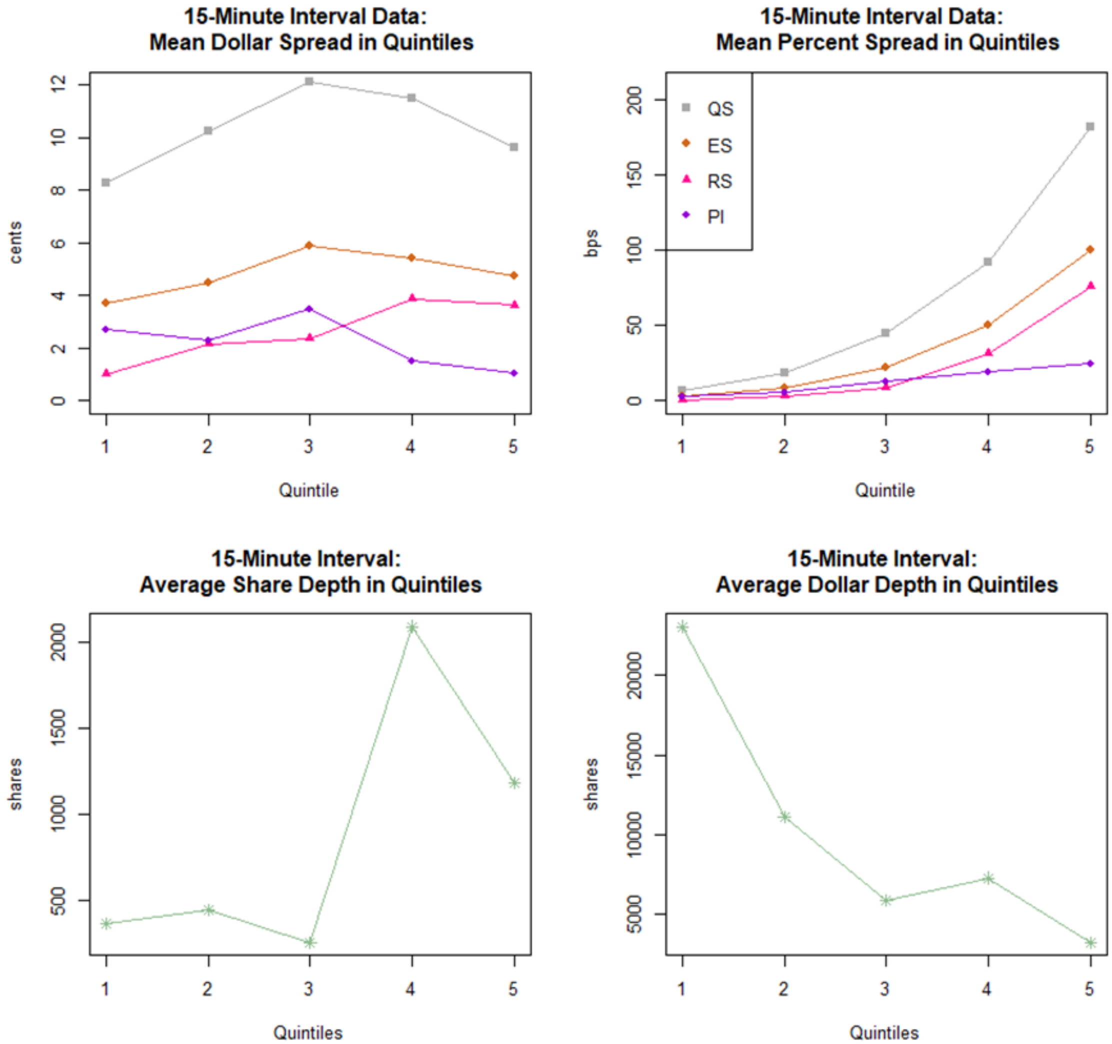


Figure 6: Mean Value of Spread and Depth by Quintiles in the 15-Min Interval Data



CHAPTER 5 RESULTS AND DISCUSSIONS

In this chapter, the time-series plots of Dollar Spreads show an overall downward trend. The Percent Spreads are relatively constant before the implementation of zero-commission trading, but show a clear downward trend after the implementation of zero-commission trading. Both Average Depths show a clear upward trend after the zero-commission event. Autocorrelation-adjusted Welch's t-tests on the differences of mean values of most liquidity measures before and after the implementation of zero-commission trading are significant at 5% significance level. In 15-min interval data, all market liquidity measures, trading volume, and price volatility show clear intra-day seasonality. Next, 15-min interval data are used to set up a three-equation simultaneous structural model. The model is used to investigate the relationship among market liquidity measures, trading volume, and price volatility and to examine the quantified impact of zero-commission trading on them. Finally, the Welch's t-test confirms that the proportion of retail orders in the stock market increased significantly. However, the trade size is found to be unchanged.

5.1 Time-Series Plots and T-test

Figures 7 and 8 show the time-series plots of Spreads and Depths in the Daily Data and the 15-Min Interval Data, respectively. In each figure, the first column contains Dollar Spreads and Average Share Depth, and the second column contains Percent Spreads and Average Dollar Depth. They are sequentially Quoted Spread (gray color), Effective Spread (chocolate color), Realized Spread (dark pink color), Price Impact (dark violet color), and Average Depth (dark green color) respectively. The vertical dashed line (dark color) denotes the point in time when the implementation of zero-commission trading is completed.

Figure 7 shows an overall downward trend for Dollar Quoted Spread, Dollar Effective Spread, and Dollar Price Impact. Before the implementation of zero-commission trading, they all experience a temporary increase and then returned to the downward trend. Percent Quoted Spread, Percent Effective Spread, and Percent Price Impact also show a similar pattern. Before the implementation of zero-commission trading, they all fluctuate around a certain value: 75 bps for Percent Quoted Spread, 40 bps for Percent Effective Spread, and 20 bps for Percent Price Impact. However, after the implementation of zero-commission trading, they all exhibit a downward trend. Neither Dollar Realized Spread nor Percent Realized Spread shows a clear trend change before and after the implementation of zero-commission trading. During the sample period, they fluctuate around 23 cents and 22 bps, respectively. After the implementation of zero-commission trading, both Average Share Depth and Average Dollar Depth show a clear upward trend, which confirms our hypothesis that zero-commission trading motivates more traders to quote at NBBO and both Average Share Depth and Average Dollar Depth increase after the implementation of zero-commission trading.

Figure 8 shows that the 15-min interval data are more volatile than daily data. As with daily data, there is a downward trend in spreads and an upward trend in depths, although with varying degrees.

Figure 9 plots the intra-day seasonality of market liquidity measures, trading volume, and price volatility in the 15-min interval data. There are 26 15-min intervals in each day. The first 15-min interval spans from 9:30 am to 9:45 am, and the 26^{th} 15-min interval spans from 3:45 pm to 4:00 pm. The solid line in each graph plots the time-series average of the corresponding variable across 62 trading days for each 15-min interval. And the shaded area shows the 95% confidence interval. Figure 9 shows that Spreads and price volatility are highest right after the market opens. Depths are highest right before the market closes. Trading volumes exhibit a U shape, higher at the market open and at the close than the rest of the day.

Figure 7: Time-Series Plots of Spread and Depth in Daily Data

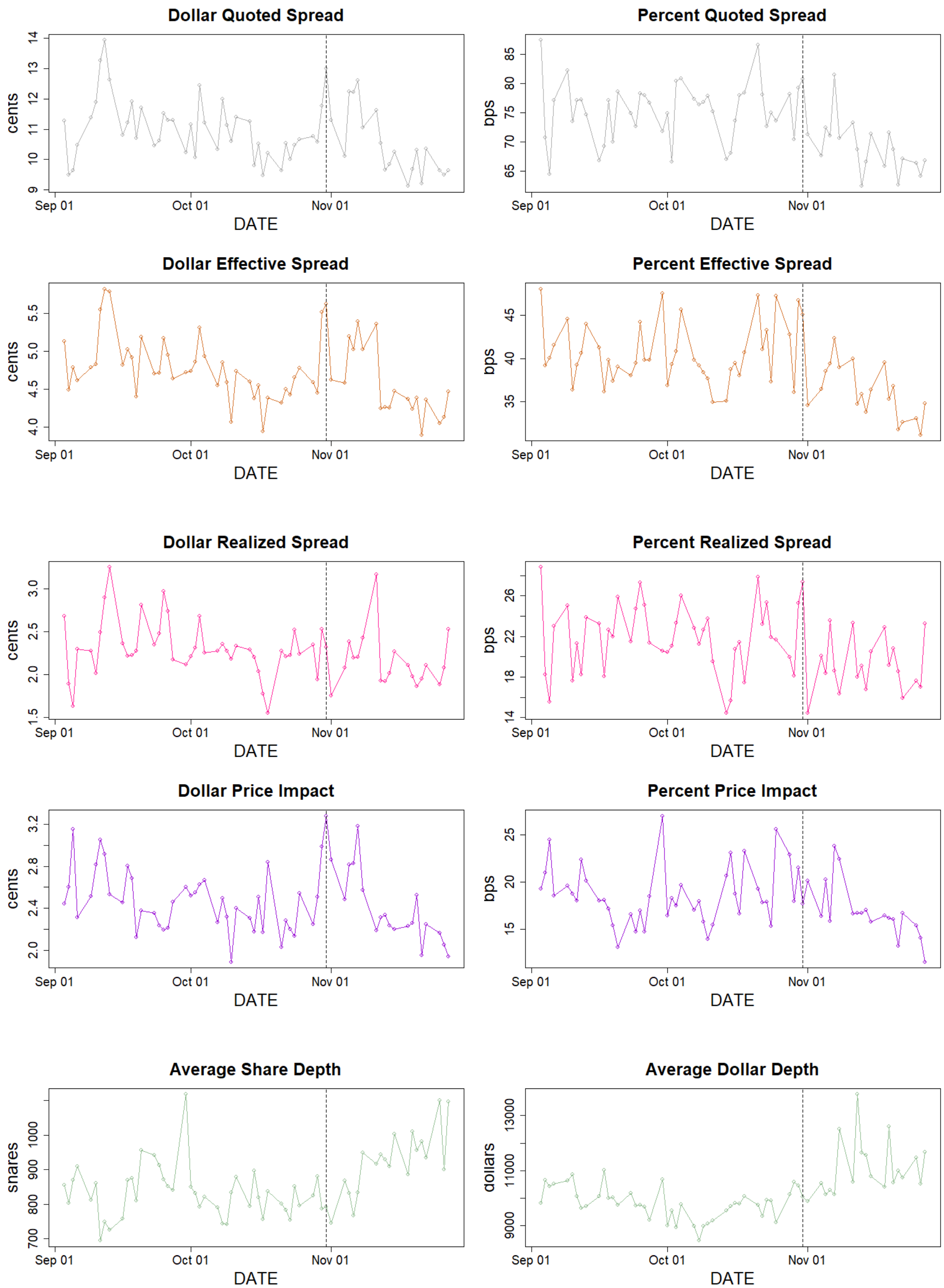


Figure 8: Time-Series Plots of Spread and Depth in 15-Min Interval Data

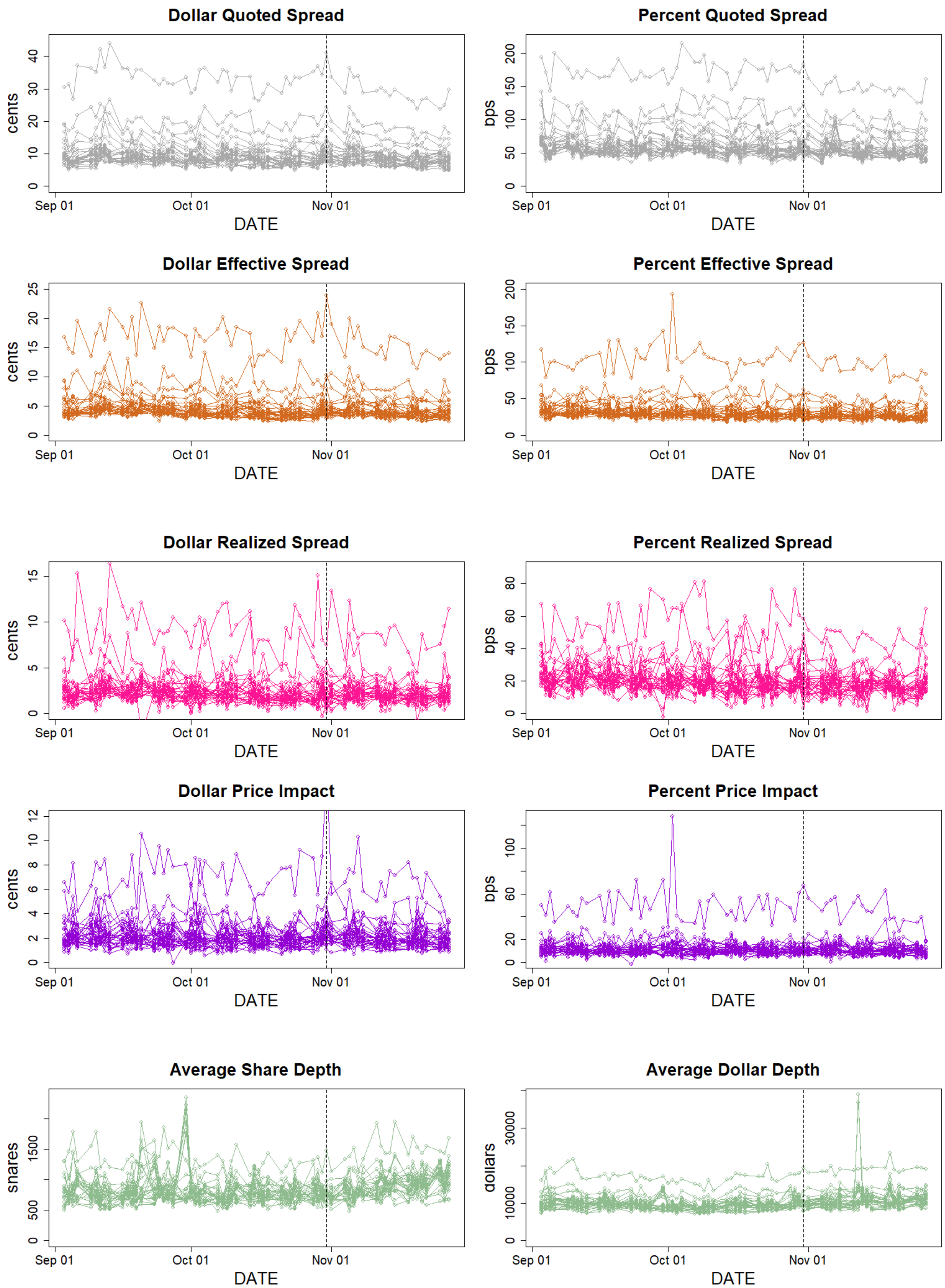
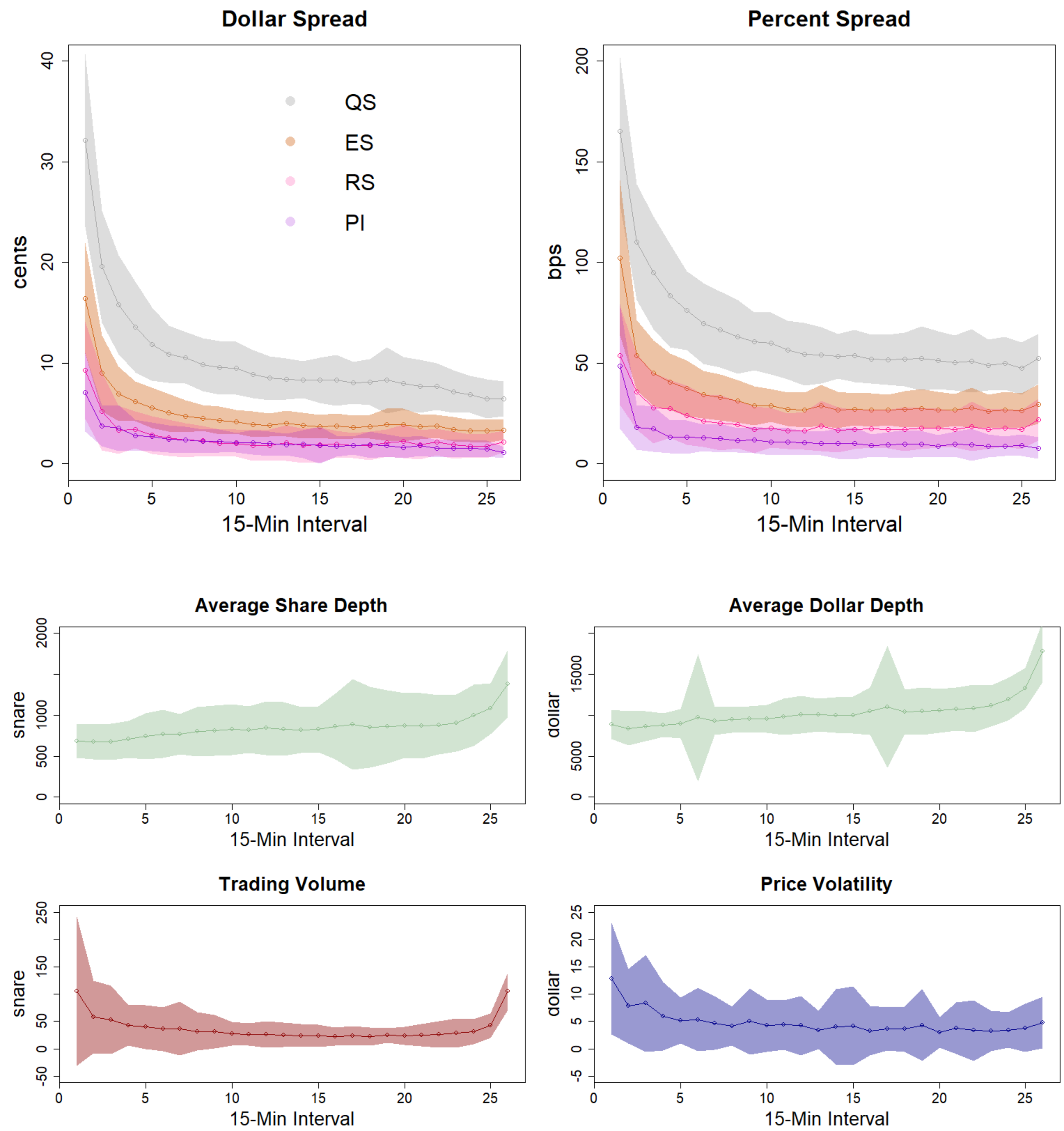


Figure 9: Intra-day Seasonality of Market Liquidity Measures & Trading Volume & Price Volatility



The autocorrelation-adjusted Welch's t-test results are shown in Tables 4 and 5. The null hypothesis in the t-test is that the mean values of Spreads/Depths before the implementation of zero-commission trading is same as that after the implementation of zero-commission trading. For Spreads, the alternative hypothesis is that the mean value of Spreads before the implementation of zero-commission trading is greater than that after the implementation of zero-commission trading. For Depths, the alternative hypothesis is that the mean value of Depths before the implementation of zero-commission trading is less than that after the implementation of zero-commission trading.

Tables 4 and 5 show the t-test results of the daily data and the 15-min interval data, respectively. $\bar{X}_0$ is the sample estimation of mean of liquidity measure before the implementation of zero-commission trading, and $\bar{X}_1$ is the sample estimation of mean of liquidity measure after the implementation of zero-commission trading. SE is the autocorrelation-adjusted standard error of the mean difference of the liquidity measure between before and after the implementation of zero-commission trading. The last column shows the t-statistics and their corresponding significance levels. Table 4 shows that all liquidity measures are significant at the 5% level, except for Dollar Price Impact and Percent Price Impact. Table 5 shows that all liquidity measures are significant at the 1% level, except for Dollar Price Impact and Percent Price Impact. The t-test results are consistent with the visual findings in Figures 7 and 8. These results overall confirm the first hypothesis that after the implementation of zero-commission trading, market liquidity improved significantly.

Majority of the previous literature points to the evidence that stock market liquidity in November is slightly worse than that in summer. This strengthens the finding in this study that zero-commission trading contributes to the improved market liquidity. Chordia, Sarkar and Subrahmanyam (2005) research U.S. stock and bond market liquidity. They document that in both markets, bid-ask spreads are lower in the summer months of July and August compared to the rest of the year. Hameed, Kang and

Viswanathan (2010) document the similar finding that in U.S. stock market, bid-ask spreads are lower from May to September relative to other months. By contrast, Hong and Yu (2009) research the bid-ask spreads in 51 stock exchanges around the globe and find that for most Europe countries, bid-ask spreads are higher in summer months (July, August, and September) compared to other seasons of the year. But for the U.S. stock market, their results show that bid-ask spreads in the summer months are relatively low, although it is not statistically significant. Overall, the literature supports that in this study, the improved market liquidity in November 2019 can be attributed to the implementation of zero-commission trading rather than the month-of-the-year effect of November.

Table 4: T-test of Liquidity Measures in Daily Data

Variables	$\bar{X}_0$	$\bar{X}_1$	SE	T-statistic	
Dollar Quoted Spread (cents)	11.043	10.47	0.291	1.967	**
Dollar Effective Spread (cents)	4.8	4.544	0.122	2.101	**
Dollar Realized Spread (cents)	2.315	2.151	0.075	2.194	**
Dollar Price Impact (cents)	2.483	2.389	0.087	1.084	
Percent Quoted Spread (bps)	75.439	68.932	1.054	6.175	***
Percent Effective Spread (bps)	40.646	36.094	0.813	5.598	***
Percent Realized Spread (bps)	21.983	19.171	0.552	5.094	***
Percent Price Impact (bps)	18.655	16.899	0.715	2.456	*
Average Share Depth (shares)	831.175	924.269	20.382	-4.567	***
Average Dollar Depth (dollars)	9830.06	11096.9	175.095	-7.235	***
*** p<0.01, ** p<0.05, * p<0.1					

Table 5: T-test of Liquidity Measures in 15-Min Interval Data

Variables	$\bar{X}_0$	$\bar{X}_1$	SE	T-statistic	
Dollar Quoted Spread (cents)	10.587	9.824	0.269	2.834	***
Dollar Effective Spread (cents)	4.968	4.576	0.134	2.936	***
Dollar Realized Spread (cents)	2.645	2.366	0.084	3.307	***
Dollar Price Impact (cents)	2.322	2.207	0.06	1.919	**
Percent Quoted Spread (bps)	66.537	60.537	1.341	4.474	***
Percent Effective Spread (bps)	34.711	30.873	0.763	5.033	***
Percent Realized Spread (bps)	22.074	18.776	0.479	6.882	***
Percent Price Impact (bps)	12.638	12.088	0.365	1.507	*
Average Share Depth (shares)	817.016	919.748	11.551	-8.893	***
Average Dollar Depth (dollars)	10008.607	11226.376	131.068	-9.291	***
*** p<0.01, ** p<0.05, * p<0.1					

5.2 Three-Equation Simultaneous Structural Model

To formally test the quantitative effect of the implementation of zero-commission trading on liquidity measures, I construct a regression model to control the related factors including trading volume, observed price volatility, market performance, market open effect and market close effect. I construct a three-equation simultaneous structural model to address potential endogeneity problems. I use the generalized method of moments to obtain consistent and efficient coefficient estimates and standard errors. Table 6 presents estimation results of the three-equation simultaneous structural model using the 15-min interval data. Panels 1-3 report the coefficient estimates for Equation 1-3, respectively. The equations and variable definitions are reproduced below for convenience:

$$BAS = \beta_0 + \beta_1 lag(BAS) + \beta_2 TV + \beta_3 PV + \beta_4 M + \beta_5 Z + \beta_6 OE + \beta_7 CE + e_b;$$

$$TV = \alpha_0 + \alpha_1 lag(TV) + \alpha_2 BAS + \alpha_3 PV + \alpha_4 M + \alpha_5 Z + \alpha_6 OE + \alpha_7 CE + e_t;$$

$$PV = \gamma_0 + \gamma_1 lag(PV) + \gamma_2 BAS + \gamma_3 TV + \gamma_4 M + \gamma_5 Z + \gamma_6 OE + \gamma_7 CE + e_p.$$

BAS is quoted spread (QS), effective spread (ES), realized spread (RS), price impact (PI) measured in Dollar and Percent forms, and average depth measured in Share (ASD) and Dollar (ADD) forms, respectively. TV is trading volume, and PV is price volatility. $lag(BAS), lag(TV), and\ lag(PV)$ are $BAS, TV, and\ PV$ lagged by 1-time period, respectively.

Table 6 shows that the coefficient estimates of all instrument variables, which are lag (BAS), lag (TV), and lag (PV) are significant at the 1% level. This implies that the instrument variables are valid in the three-equation simultaneous structural model.

Panel 1 of Table 6 shows that the effect of trading volume (TV) on market liquidity measures (QS, ES, RS, PI, ASD, ADD) are mixed. Trading volume has no significant effect on Dollar Quoted Spread, Dollar Effective Spread, and Dollar Realized Spread. By contrast, percent spreads are more responsive to trading volume. Trading volume has a significant negative effect on Percent Quoted Spread, which is consistent with the finding of Wang and Yau (2000) in the futures market. In addition, trading volume has a significant positive effect on Percent Effective Spread and Percent Realized Spread. Trading volume also has a significant positive effect on both Dollar Price Impact and Percent Price Impact, while it has no significant effect on either Average Share Depth (ASD) nor Average Dollar Depth (ADD). As for the magnitude of the effect of trading volume on liquidity measures, it is relatively small compared to the effect of other variables on liquidity measures. For example, the coefficient estimation of TV is 0.01 when I use Dollar Price Impact as the target variable. Because Dollar Spread is measured in cents and Trading Volume is measured in thousand shares, the coefficient of TV should be interpreted as that an increase in trading volume of one thousand shares will lead an increase in Dollar Price Impact by 0.01 cent.

The effect of price volatility on liquidity are consistent across different measures. Price volatility has a significant positive effect on all Dollar Spread measures and Percent Spread measures, and it has a significant negative effect on both Average Share Depth and Average Dollar Depth. This is consistent with the finding of Wang and Yau (2000) in the futures market. The magnitude of the effect of price volatility on liquidity measures are relatively large compared to the effect of trading volume on liquidity measures. For example, the coefficient of PV is 0.10 when Dollar Price Impact is used as the target variable. Because price volatility is measured in US dollars, the coefficient of PV should be interpreted as that an increase in price volatility of one dollar will lead to an increase in Dollar Price Impact by 0.1 cent.

Market performance (M) has a positive effect on both Dollar Quoted Spread and Percent Quoted Spread. It also has a positive effect on Dollar Realized Spread. And it has a negative effect on Average Share Depth. A positive (negative) market return coincides with wider (narrower) Dollar and Percent Quoted Spreads, and less (more) Average Share Depth. The effect of market performance on all other liquidity measures are not significant. This contradicts the finding of Chordia, Roll and Subrahmanyam (2001) which states that market liquidity plummets in a down market, while it increases weakly in a up market. This inconsistency could be caused by the different methodologies applied between them and us. Chordia, Roll and Subrahmanyam (2001) do not explicitly consider the simultaneity among spreads, trading volume, and price volatility when investigating the effect of market performance on market liquidity.

The implementation of zero-commission trading (Z) has a negative effect on Percent Quoted Spread, Percent Effective Spread, and Percent Realized Spread. This is consistent with the visual findings in Figures 7 and 8. However, zero-commission trading has no significant effect on all Dollar Spread, Percent Price Impact, and both Average Depth. The discrepancy may be due to fact that percent (relative) measures are more responsive to the change in commissions, especially for low-priced stocks. The magnitude of the effect of the implementation of zero-commission trading on liquidity measures are greater than the effect of trading volume, price volatility, and market performance. For example, coefficient estimation of Z is -2.07 when Percent Effective Spread is used as the target variable. Because Percent Spread measures are measured in basis point, there is a reduction of 2.07 basis point in Percent Effective Spread due to the implementation of zero-commission transactions.

Open Effect has a significant positive effect on all Dollar Spread and Percent Spread, it also has a significant negative effect on Average Share Depth. Close Effect tends to have a significant negative effect on Spread measures and a significant positive effect on Depth measures. These findings imply that the market is the least liquid within 15 minutes after the market opens and it is the most liquid within 15 minutes before the market closes. This is consistent with the visual findings of intra-day seasonality in the bid-ask spreads in Figure 9.

Panel 2 of Table 6 shows that the effect of both Dollar Spread and Percent Spread on trading volume are negative and significant. The effect of both Average Share Depth and Average Dollar Depth on trading volume are positive and significant. Overall, it shows that a more liquid market tends to stimulate trading activities. This is consistent with the finding of Wang and Yau (2000) in the futures market that bid-ask spreads and trading volume are negatively related. As for the magnitude, the change of Price Impact has the greatest effect on trading volume among all liquidity measures. For example, the coefficient of Dollar Price Impact in Equation (2) is -7.28. An increase in Dollar Price Impact by 1 cent will result in a decrease of 7280 shares in trading volume. The coefficient of Percent Price Impact is -2.55 in Equation (2). An increase in Percent Price Impact by 1 basis point will result in a decrease of 2550 shares in trading volume.

However, with the exception of using Percent Price Impact as a liquidity measure in the Equation (2), the effect of price volatility on trading volume is barely significant. Market performance has no significant effect on trading volume. Regardless of the type of liquidity measurement used in Equation (2), the implementation of zero-commission trading has a significant positive impact on trading volume. As for the magnitude, the coefficient estimation ranges from 4.5 to 5.7 when different liquidity measures are used in Equation (2). For example, the coefficient of Z is 5.72 when Dollar Quoted Spread is used as the liquidity measure in Equation (2). The implementation of zero-commission increased trading volume by 5720 shares. The coefficients of Open Effect and Close Effect are positive and significant regardless of the types of liquidity measures used. Compared with other periods during market operation, trading activities within 15 minutes after market opening and within 15 minutes before market closing are more active. This is consistent with the market intra-day seasonality plots in Figure 9.

Panel 3 of Table 6 shows the effect of both Dollar Spread and Percent Spread on price volatility are positive and significant. The effect of both Average Share Depth and Average Dollar Depth on price volatility are negative and significant. Overall, it shows that a more liquid market tends to make the market less volatile. This is consistent with the finding of Wang and Yau (2000) in the futures market that bid-ask spreads and price volatility are positively related. As for the magnitude, the change of Dollar Price Impact has the greatest effect on price volatility among all liquidity measures. For example, the coefficient of Dollar Price Impact in Equation (3) is 1.33. An increase in Dollar Price Impact by 1 cent will result in a decrease of 1.33 dollars in price volatility.

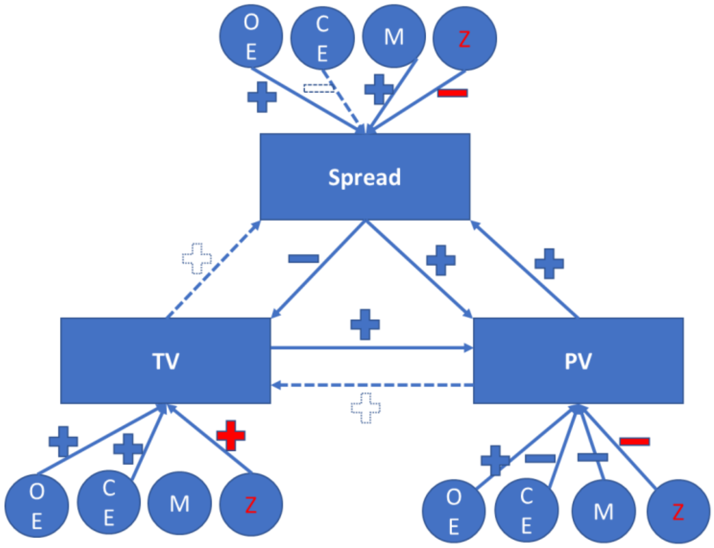
Trading volume has a significant positive effect on price volatility with the exception of using Dollar Quoted Spread, Dollar Effective Spread, and Dollar Price Impact as the liquidity measure in Equation (3). It shows that the market tend to be more volatile when trading activity is active. This is also consistent with the finding of Wang and Yau (2000) in the futures market that trading volume and price volatility are positively related. The magnitude of the coefficient of TV in Equation (3) ranges from 0.1 to 0.3. An increase of one thousand shares in trading volume tends to increase the price volatility by around 0.1 to 0.3 dollars. Market performance has a negative effect on price volatility. It means the concurrent positive market return can make the market less volatile compared to a negative or zero concurrent market return. The implementation of zero-commission trading has a negative effect on price volatility regardless of the types of liquidity measures used. The magnitude of coefficient of Z in Equation (3) ranges from -0.67 to -0.97. The implementation of zero-commission trading reduced the price volatility by around 0.67 ~ 0.97 US dollars. Among ten different liquidity measures, Open Effect has a significant and positive coefficient when eight of them are used as the liquidity proxy in Equation (3), while Close Effect has a significant and positive coefficient when four of them are used as the market liquidity proxy. The magnitude of the coefficient of Open Effect is considerably greater than the coefficient of Close Effect. Overall, it shows that the market is the most volatile within 15 minutes after the market opens, followed by within 15 minutes before the market closes, and other period of market operation has less volatility. This is consistent with the visual findings of intra-day seasonality in the price volatility in Figure 9.

In summary, as depicted in Figure 10, Spreads including four Dollar Spread measures and four Percent Spread measures, tend to have a positive relationship with price volatility. By contrast, the relationship between Spreads and trading volume is mixed. Spreads have a clear negative effect on trading volume, and trading volume has a positive effect on most Spread measures except for Percent Quoted Spread. The relationship between trading volume and price volatility are positive too. However, the effect of price volatility on trading volume is only significant when Percent Price Impact is used as the liquidity measure in Equation (2).

Market Open has a positive effect on Spreads, trading volume, and price volatility. Market Close has a positive effect on trading volume, a negative effect on price volatility and Spreads with exception that it has a positive effect on Percent Quoted Spread. Market performance has a positive effect on Spreads, a negative effect on price volatility, and no effect on trading volume.

Finally, the implementation of zero-commission has a direct negative effect on Spreads, but this effect is only captured by Percent Spread measures. It has a clear negative effect on price volatility, and this leads to an indirect decrease in Spreads through the positive relationship between Spreads and price volatility. In addition, the implementation of zero-commission has a clear positive effect on trading volume, but its indirect effect on Spreads is unclear because the relationship between Spreads and trading volume is mixed. It confirms the second hypothesis that the effect of zero-commission trading on market liquidity is still significant after controlling for simultaneous effect of trading volume and price volatility.

Figure 10: Visualization Summary of Table 6



Notes:
the plus symbol presents a positive effect, and the minus symbol presents a negative effect. The solid arrow means that the effect is consistent across various liquidity measures. The dashed arrow means the effect is mixed across liquidity measures, where the dashed symbol presented are the effect across most liquidity measures.

Table 6: Coefficient Estimates in 15-Min Interval Data

Panel 1: Coefficient Estimates of Equation (1)

	Dollar Spread (cent)				Percent Spread (bps)				Depth (shares/dollars)	
	QS	ES	RS	PI	QS	ES	RS	PI	ASD	ADD
Cons.	3.03 ***	1.66 ***	0.47 ***	0.91 ***	21.84 ***	16.27 ***	8.24 ***	6.71 ***	346.9 ***	6928.8***
	(0.23)	(0.14)	(0.17)	(0.10)	(0.91)	(0.77)	(0.67)	(0.51)	(53.08)	(1536.1)
Lag	0.48 ***	0.36 ***	0.25 ***	0.24 ***	0.57 ***	0.30 ***	0.29 ***	0.14 ***	0.68 ***	0.45 ***
(#)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.03)	(0.05)	(0.13)
TV	0.00	0.00	0.00	0.01 ***	-0.05 **	0.03 *	0.03 **	0.03 **	-0.09	5.89
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.01)	(0.34)	(5.24)
PV	0.30 ***	0.18 ***	0.23 ***	0.10 ***	0.65 *	0.85 ***	1.00 ***	0.44 ***	-15.25***	-331.6***
	(0.08)	(0.04)	(0.05)	(0.04)	(0.35)	(0.24)	(0.24)	(0.15)	(5.17)	(83.73)
M	0.17 **	0.07	0.11 *	0.00	0.75 *	0.22	0.51	-0.17	-11.26 *	-49.98
	(0.07)	(0.05)	(0.06)	(0.03)	(0.39)	(0.31)	(0.34)	(0.23)	(6.48)	(85.17)
Z	-0.06	-0.07	0.03	-0.05	-1.17 *	-2.07 ***	-1.50 ***	-0.30	15.26	190.94
	(0.13)	(0.08)	(0.11)	(0.06)	(0.62)	(0.53)	(0.52)	(0.36)	(11.66)	(155.77)
OE	21.88 ***	10.79 ***	4.94 ***	3.87 ***	109.4 ***	62.87 ***	22.85 ***	32.10 ***	-394.9***	-2427.7
	(0.80)	(0.47)	(0.47)	(0.40)	(3.72)	(2.67)	(2.31)	(2.00)	(58.86)	(1438.2)
CE	-1.37 ***	-0.78 ***	-0.18	-1.34 ***	5.29 ***	-1.69	0.67	-5.12 ***	380.4 ***	5818.2***
	(0.35)	(0.23)	(0.22)	(0.18)	(1.78)	(1.57)	(1.30)	(1.07)	(33.89)	(424.90)

Panel 2: Coefficient Estimates of Equation (2)

	TV									
	Dollar Spread				Percent Spread				Depth	
	QS	ES	RS	PI	QS	ES	RS	PI	ASD	ADD
Cons.	14.90 ***	16.18 ***	14.54 ***	18.52 ***	16.75 ***	22.03 ***	16.23 ***	29.15 ***	14.67 **	-3.56
	(1.69)	(1.85)	(1.68)	(2.82)	(1.86)	(2.78)	(2.01)	(5.17)	(3.57)	(8.00)
Lag	0.57 ***	0.58 ***	0.57 ***	0.59 ***	0.56 ***	0.58 ***	0.56 ***	0.61 ***	0.54 ***	0.54 ***
(TV)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.08)	(0.07)	(0.06)
#	-0.87 **	-2.64 ***	-3.45 **	-7.28 **	-0.14 **	-0.54 ***	-0.31 *	-2.55 ***	0.00	0.00 **
	(0.44)	(1.00)	(1.47)	(3.42)	(0.06)	(0.16)	(0.17)	(0.75)	(0.00)	(0.00)
PV	0.89	1.29	0.90	1.56	0.63	1.15	0.25	1.97 **	-0.36	0.44

	(0.69)	(0.80)	(0.69)	(1.11)	(0.62)	(0.75)	(0.62)	(0.94)	(0.49)	(0.65)
M	-0.51	-0.44	-0.39	-0.72	-0.59	-0.63	-0.69	-1.20	-0.91	-0.67
	(0.78)	(0.79)	(0.80)	(0.82)	(0.78)	(0.80)	(0.79)	(1.00)	(0.80)	(0.67)
Z	5.72 ***	5.71 ***	5.43 ***	6.13 ***	5.32 ***	4.46 **	4.74 **	5.74 **	5.33 ***	4.59 **
	(1.86)	(1.94)	(1.91)	(2.08)	(1.90)	(1.94)	(1.87)	(2.25)	(2.00)	(1.82)
OE	45.66 ***	53.94 ***	50.23 ***	55.54 ***	43.41 ***	61.41 ***	42.60 ***	109.2 ***	38.21 ***	34.08 ***
	(8.63)	(10.72)	(10.00)	(13.06)	(9.08)	(12.00)	(9.75)	(24.32)	(9.62)	(9.36)
CE	66.29 ***	66.02 ***	68.76 ***	61.51 ***	67.95 ***	68.19 ***	69.96 ***	59.82 ***	70.48 ***	59.07 ***
	(2.50)	(2.16)	(1.68)	(4.06)	(1.79)	(1.72)	(1.61)	(3.50)	(2.46)	(4.67)

Panel 3: Coefficient Estimates of Equation (3)

	PV									
	Dollar Spread				Percent Spread				Depth	
	QS	ES	RS	PI	QS	ES	RS	PI	ASD	ADD
Cons.	1.31 ***	1.30 ***	1.69 ***	0.87 *	0.84 **	0.71	0.89 *	1.08 *	4.39 ***	7.64 ***
	(0.28)	(0.32)	(0.30)	(0.45)	(0.34)	(0.52)	(0.48)	(0.64)	(0.50)	(0.71)
Lag	0.21 ***	0.22 ***	0.23 ***	0.21 ***	0.23 ***	0.24 ***	0.25 ***	0.26 ***	0.29 ***	0.24 ***
(PV)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
#	0.25 ***	0.52 ***	0.75 ***	1.33 ***	0.04 ***	0.08 ***	0.12 ***	0.18 **	-0.00 ***	-0.00 ***
	(0.04)	(0.10)	(0.19)	(0.31)	(0.01)	(0.02)	(0.03)	(0.07)	(0.00)	(0.00)
TV	0.00	0.01	0.01 *	0.00	0.01 **	0.01 *	0.01 *	0.01 **	0.02 ***	0.03 ***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
M	-0.28 **	-0.26 **	-0.29 **	-0.20	-0.27 **	-0.24 *	-0.27 *	-0.19	-0.28 **	-0.25 *
	(0.13)	(0.13)	(0.14)	(0.12)	(0.13)	(0.13)	(0.14)	(0.14)	(0.13)	(0.14)
Z	-0.83 ***	-0.83 ***	-0.86 ***	-0.86 ***	-0.82 ***	-0.72 ***	-0.67 ***	-0.97 ***	-0.96 ***	-0.68 ***
	(0.15)	(0.15)	(0.17)	(0.14)	(0.15)	(0.16)	(0.18)	(0.15)	(0.16)	(0.16)
OE	2.38 **	1.66 ***	2.37 *	1.47	3.23 ***	1.63	3.48 ***	0.46	6.26 ***	5.84 ***
	(1.04)	(1.27)	(1.37)	(1.44)	(0.98)	(1.54)	(1.14)	(2.65)	(0.75)	(0.77)
CE	0.99 **	0.61 ***	-0.17	1.56 **	0.17	-0.07	-0.54	0.18	-0.09	2.26 ***
	(0.49)	(0.48)	(0.53)	(0.68)	(0.44)	(0.46)	(0.51)	(0.64)	(0.59)	(0.65)

The abbreviation under each category represent different liquidity measures.
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

5.3 Retail Order Flows

In this section, I explore whether retail order flows contribute to the differing effect of zero-commission trading on market liquidity (positive) and market volatility (negative). I isolate the retail order flows from the entire market to see whether there is a significant change before and after the implementation of zero commission trading. As stated in Chapter 3, I follow the methodology proposed by Boehmer, et al. (2017) to identify retail order flows.

This study investigates four characteristics: Trading Volume, Number of Trades, Trade Size, Number of Odd-Lots Trades of the identified retail orders and of the entire market, respectively. Among 38,357,156 raw transactional data, 2,061,819 trading records (5.38%) are identified as retail order flows. I first calculate daily average of these characteristics for each firm and then find the cross-sectional average of the 100 stocks for each day.

Figure 11 shows the results of retail order flows over time. The first row presents the Trading Volume of the market on the left and the Number of Trades of the market on the right over the sample period. They show that trading activities are more active in September and November than in October. The left graph in the second row plots the proportion of retail orders in the market measured by Trading Volume. It shows that before the implementation of zero-commission, about 11.5% of the trading volume of the market comes from retail investors. After the implementation of zero-commission trading, this proportion increased to 12.3%. This is consistent with Citadel’s estimation that, induced by the implementation of zero-commission trading, the proportion of retail trading activities increased from historically 10% to ultimately 15% of the stock market at the end of 2019. And the right graph in the second row plots the proportion of retail orders in the market measured by Number of Trades. It shows that before the implementation of zero-trading, 6.5% of Number of Trades submitted to the market are retail orders. After the implementation of zero-commission trading, this proportion increased to 7.3%. Both graphs reveal that retail order flows are becoming a larger component of the stock market. I also conduct the Welch's t-test, reported in Table 7. It shows that the difference of proportion of retail orders in the market before and after the implementation of zero-commission trading measured by Trading Volume and Number of Trades are both significant at the 1% significance level. It confirms the third hypothesis that after the implementation of zero-commission trading, the proportion of retail orders increased significantly.

The left graph in the third row is the Trade Size of the stock market and of the retail orders. It seems there is no significant change before and after the implementation of zero-commission trading. The Welch's T-test result in Table 7 also confirms the visual finding. It is counterintuitive that the implementation of zero-commission trading did not result in a further fragmentation of trade size. It is posited that the overall trade size in the market has been reduced in the past such that the increased retail order flows does not further the trend. Therefore, the fourth hypothesis that "after the implementation of zero-commission trading, average trade size per trade decreased" is rejected. Another interesting fact is that the average Trade Size of retail orders, 239 shares, is higher than the average Trade Size of the entire market, 133 shares. Normally, it is believed that retail investors tend to trade smaller size compared to institutional investors, but the Trade Size comparison shows that this may not be true. To investigate the potential reduction of trade size in the stock market, I also calculated the proportion of Odd-Lots Trades measured by Trading Volume and Number of Trades. The right graph in the third row shows that above 50% of Number of Trades in the stock market are Odd-Lots Trades, which means more than 50% of trades in the stock market having trade size less than 100 shares. These Odd-Lots Trades account for about 17% of Trading Volume in the stock market.

Overall, the implementation of zero-commission trading increased the proportion of retail trading activities in the stock market, but it did not lead to a reduction of trade size.

Figure 11: Trading Activities & Proportion of Retail Orders & Market Fragmentation

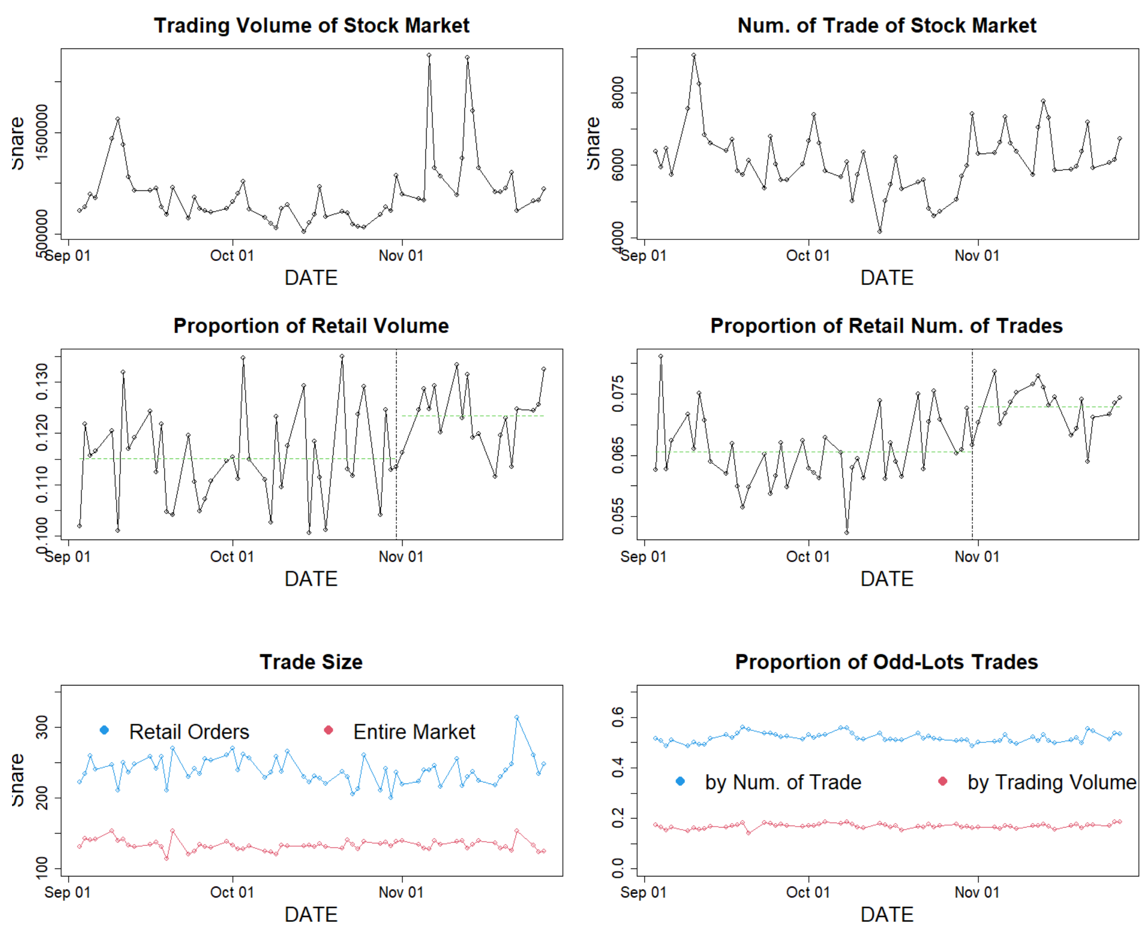


Table 7: Welch's T-test of Proportion of Retail & Market Fragmentation

Variables	Measurements	$\bar{X}_0$	$\bar{X}_1$	SE	T-statistic	
Proportion of Retail	Trading Volume	11.51%	12.35%	0.20%	-4.24	***
	Num. of Trades	6.56%	7.29%	0.12%	-6.14	***
Trade Size	Stock Market	133.49	133.85	1.99	-0.18	
	Retail Orders	239.38	239.15	5.87	0.04	
Proportion of Odd-Lots	Trading Volume	16.90%	16.99%	0.24%	-0.36	
	Num. of Trades	52.01%	51.73%	0.49%	0.56	

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

CHAPTER 6 CONCLUSION

This thesis first investigates the change of market liquidity before and after the implementation of zero-commission trading. The study considers 10 measures of indirect trading costs, including Dollar Quoted Spread, Dollar Effective Spread, Dollar Realized Spread, Dollar Price Impact, Percent Quoted Spread, Percent Effective Spread, Percent Realized Spread, Percent Price Impact, Average Share Depth, Average Dollar Depth. Higher Spreads and lower Depths indicate a less liquid market, and vice versa. Then this study quantifies the effect of zero-commission trading on market liquidity while controlling for related factors such as trading volume, price volatility and market performance. Finally, this study explores the possible reason underlying the effect of zero-commission trading on market liquidity by identifying retail orders in the stock market.

This thesis finds that Spreads decreased after the implementation of zero-commission trading. This means higher market liquidity and the reduced liquidity costs for investors. And this effect of zero-commission trading on Spreads holds significantly after controlling for other related factors as stated above. In addition, this study finds that the implementation of zero-commission trading also has a significant negative effect on price volatility after controlling for trading volume and various market liquidity measures. This further contributes to the decrease in spreads as price volatility positively correlates with spreads. Finally, this study finds that zero commission motivates more retail trading activities, dealers may have the motivation to decrease their spread to acquire the increased retail trading volume. The increased retail trading and decreased spreads implies that retail investors are more likely to be noise traders, which decreases the adverse selection risk of market makers and contributes to the decrease of spreads. But this needs to be further investigated. Overall, our study indicates the implementation of zero-commission trading improves the market liquidity and it is beneficial to retail investors from both commission costs and liquidity costs perspectives.

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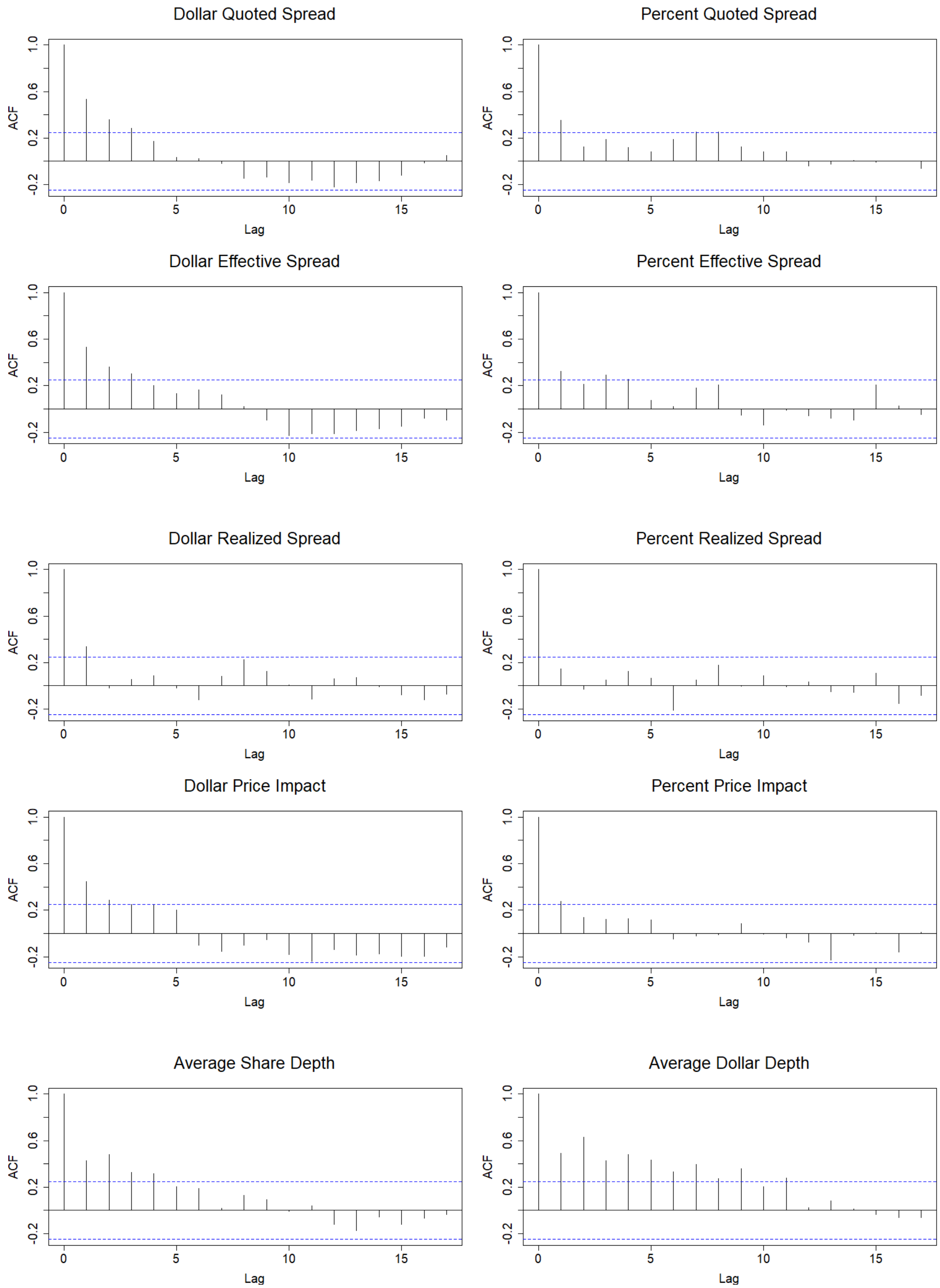
APPENDIX: AUTOCORRELATION PLOTS

Figure 12: Autocorrelation Plots of Liquidity Measures in Daily Data



Notes: blue dashed lines are 95% confidence interval. Exceeding the blue dashed lines indicating significant autocorrelation.

Figure 13: Autocorrelation Plots of Liquidity Measures in 15-Min Interval Data