

# The Intraday Market Liquidity of Japanese Government Bond Futures

Naoshi Tsuchida, Toshiaki Watanabe,  
and Toshinao Yoshiba

*We investigate the intraday market liquidity of the Japanese government bond (JGB) futures. First, we overview the movement of various market liquidity indicators during the past decade, classifying them into four categories: tightness, depth, resiliency, and volume. Second, using the data under the current trade time, we extract their intraday pattern and the autocorrelation. Third, we find that the announcement of economic indicator has a negative effect on these liquidity indicators while the monetary policy announcement and the surprise of economic indicator have a positive effect on volume indicators. Fourth, we show that the shock persistence in liquidity indicators rises around April 2013, and the increased persistence remains in some liquidity indicators even several months after April 2013.*

**Keywords:** Japanese government bond (JGB); Market liquidity; Liquidity indicator; Transaction data

**JEL Classification:** C32, G12, G14

Naoshi Tsuchida: Deputy Director and Economist, Institute for Monetary and Economic Studies (currently Financial System and Bank Examination Department), Bank of Japan (E-mail: naoshi.tsuchida@boj.or.jp)

Toshiaki Watanabe: Professor, Institute of Economic Research, Hitotsubashi University; Institute for Monetary and Economic Studies, Bank of Japan (E-mail: watanabe@ier.hit-u.ac.jp)

Toshinao Yoshiba: Director and Senior Economist, Institute for Monetary and Economic Studies, Bank of Japan (E-mail: toshinao.yoshiba@boj.or.jp)

.....  
The authors would like to thank Wataru Ohta (Osaka University), Yasuhiko Tanigawa (Waseda University), Ernst Schaumburg (Federal Reserve Bank of New York), participants at the Finance Workshop of the Institute for Monetary and Economic Studies in March 2016, the 24th Annual Meeting of the Nippon Finance Association, and the 9th World Congress of the Bachelier Finance Society, and the staff of the Bank of Japan for their useful comments and discussions. The views expressed in this paper are those of the authors and do not necessarily reflect the official views of the Bank of Japan.

## I. Introduction

Market liquidity is one of the key issues in the monitoring of the government bond market by central banks. Miyanoya, Inoue, and Higo (1999) comprehensively analyze the market microstructure and liquidity of Japanese government bonds (hereafter abbreviated JGB). Tanemura *et al.* (2004) analyze the market liquidity of JGB using its intraday bid-ask spread. With more recent data, Nishizaki, Tsuchikawa, and Yagi (2013) have studied the JGB market liquidity up to September 2013, and Kurosaki *et al.* (2015) have analyzed in detail JGB market liquidity until February 2015. The data of these analyses include the period of the introduction of the new monetary policy of quantitative and qualitative monetary easing, which involves large-scaled JGB purchases by the Bank of Japan and can therefore be a factor affecting JGB liquidity.

Regarding the U.S. Treasury bond market, Fleming (2003) provides a comprehensive liquidity analysis using both the daily and intraday data. More recently, the U.S. Department of the Treasury *et al.* (2015) published a staff report discussing the Treasury market on October 15, 2014, on which day a sudden price spike of as much as six times the standard deviation occurred within fifteen minutes, possibly related to the intraday market liquidity depletion. Although it quickly rolled back to the original price level, this unprecedented movement prompted market participants including the authorities to look at the intraday liquidity behind it. From the global perspective, BIS (2016) shows that jumps become more frequent in tightness and depth indicators in the sovereign bond markets worldwide, which may be associated with high-frequency trades or the regulation on arbitrage trades. These global observations suggest the importance of intraday monitoring of liquidity.

The studies mentioned above quantify the market liquidity by what is referred to as liquidity indicators. These indicators are often classified into four categories (Kyle, 1985; Fleming, 2003; Nishizaki, Tsuchikawa, and Yagi, 2013): (1) “tightness” (the spread between the selling quote price and the buying quote price), (2) “depth” (the amount of quotes), (3) “resiliency” or the market impact (the response of the market by unit transaction), and (4) “volume” (the turnover and the trade size of each transaction). Many of these indicators have been proposed and examined with the empirical data, especially for stock, foreign exchange (FX), and corporate bond markets. Amihud (2002) proposes the stock market illiquidity indicator referred to as Amihud ILLIQ by averaging the ratio of absolute return and trade volume, frequently cited as one of the major resiliency indicators. Pástor and Stambaugh (2003) define a measure of market impact by regression, applying it to stock markets. Liu (2006) notices that a no- or few-trading time-period can be used as an illiquidity indicator. Goyenko, Holden, and Trzcinka (2009) provide a comprehensive study of liquidity measures widely used, among which three are new proxies for effective or realized spreads and nine are those for price impact on stock markets. Karnaukh, Ranaldo, and Söderlind (2015) note the importance of effective cost in order to measure illiquidity of foreign exchange markets, showing that the effective cost defined intraday is strongly correlated with that defined daily. Most liquidity indicators can be extended into an intraday basis. Volatility can be extended into an intraday indicator by, for example, using the absolute return. The Amihud ILLIQ can be defined as the absolute return over the intraday volume.

In the context of the intraday volume and the absolute return, the preceding studies point to the importance of the intraday pattern and autocorrelation structure. In the line of the studies of volatility, it has been pointed out since the early 1990s, for example by Andersen and Bollerslev (1998), that the intraday pattern obscures the effect of economic indicator announcements. Harvey and Huang (1991) discovered the intraday U-shaped pattern of the volatility in hourly FX returns, in addition to the importance of macroeconomic announcements as the volatility source. Such intraday patterns are also noted in other studies such as that by Engle, Ito, and Lin (1990), although they are described differently. Andersen and Bollerslev (1997) show that in the FX and stock markets, the intraday periodicity has such a persuasive effect that the dynamics of volatility cannot be uncovered without incorporating the interference by the effect. Utilizing five-minutely spanned USD/DEM currency returns, Andersen and Bollerslev (1998) find that the intraday pattern obscures the macroeconomic announcement or the ARCH effects by controlling the intraday pattern, they find the ARCH effect and also the macroeconomic announcement effect. D'Souza and Gaa (2004) show a non-parametric intraday analysis which circumvents the intraday pattern by comparing the intraday liquidity indicator around the event time on the event days with that at the same time on the non-event days.

Once quantified, intraday liquidity indicators can be applied to measure the market impact or “shock” on liquidity invoked by macroeconomic indicators and monetary policy announcements, in the same way that price and volatility can. Regarding the effect of monetary policy on asset prices, Wright (2012) analyzes the intraday effect of the Federal Reserve policy changes on the U.S. Treasury futures and other assets, in addition to the daily analysis based on the structural vector autoregressive model. Rogers, Scotti, and Wright (2014) examine the effects of unconventional monetary policies by four major central banks on bond yields, stock prices and exchange rates using the daily and intraday price data. Regarding the response of market liquidity indicators to the macroeconomic announcements, Fleming and Remolona (1999) investigate the behavior of the volatility, trade volume, and spread of the U.S. treasury after the release of major economic announcements. Rühl and Stein (2015) focus on the impact of economic indicators and ECB announcements on the market liquidity of the European blue-chip stocks measured in the bid-ask spread.

We investigate the movement of intraday market liquidity of JGB futures. First, we give the overview of the JGB futures market liquidity. We introduce the liquidity indicators of the other markets into JGB futures and extend them into intraday ones, classifying them into the four categories: tightness, depth, resiliency and volume. Second, we reveal the intraday characteristics of the JGB futures market, not only extracting its intraday pattern and intraday correlation but also finding what brings liquidity shock by event analysis under intraday pattern and autocorrelation control. Our results show a temporary liquidity decline due to major events in addition to the importance of autocorrelation. Third, we consider how persistent the liquidity shocks in recent years are, and if structural changes occurred in the recent JGB futures market. We show that the elevated persistence following recent monetary policy changes is only temporal, but also that the persistence has increased gradually in recent years.

The remainder of this paper is organized as follows. Section II gives an overview

of the JGB futures market, the daily movements of several liquidity indicators in this decade, and the intraday movements for the past four years. Section III analyzes the intraday movement of the liquidity indicators. The analyses include the effects of economic indicators and monetary policy announcements. They also include the structural change of the shock persistence in intraday liquidity indicators. Section IV concludes the paper.

## II. Overview of the JGB Futures Liquidity Indicators

### A. Overview of the JGB Futures Market

Here we briefly explain the futures market of JGB. The most active JGB futures contract is that listed on the Osaka Exchange market.<sup>1,2</sup> Corresponding to the various maturities of cash bonds, contracts of three different maturities are listed: mid-term, long-term, and super long-term. Among these three, the long-term is traded most actively, and the maturity of its cheapest-to-delivery is approximately seven years. Contract months are quarterly and are at the end of March, June, September, and December. The most active contract is usually the nearest contract month, and shifts from the nearest month to the second-nearest month on the day a few days before trade for the nearest month ends. Hereafter we denote the most active long-term JGB futures contract simply as “JGB futures.” The trade unit amounts to 100 million Japanese yen in face value. The standard coupon rate of JGB futures is 6%; that is, JGB futures are priced as an imaginary cash bond whose coupon rate is 6%. The par value is assumed as 100 yen, and the unit price (pip) is one *sen* (0.01 yen).

One unique feature of the market is that it has a lunch break; the regular (intraday) time for trading has two sessions, the morning session from 8:45 to 11:00 and the afternoon session from 12:30 to 15:00.<sup>3</sup> Additionally, the evening session is open from 15:30 to 23:30.<sup>4</sup> The system of circuit breakers was also introduced in January 2008, and the system has been triggered 12 times since then. Four of these occurred in 2008 due to the global financial turmoil, and the other eight were in April and May 2013 reflecting the volatile movement of the JGB cash market. The duration of trading suspension was 15 minutes in 2008 and 10 minutes in 2013.<sup>5</sup> Figure 1 plots the price of the JGB futures, the yield of ten-year cash JGB, and the Nikkei 225 Average Stock Price in the last decade. It is observed that the cash bond yield has gradually declined from around 2% to approximately 0% during this decade. Consequently, the price of JGB futures has been far beyond par.

.....  
1. Prior to March 24, 2014, the JGB futures contract was listed on the Tokyo Stock Exchange (TSE). The TSE and the Osaka Exchange, formally named the Osaka Stock Exchange (OSE), were merged and became subsidiaries of the Japan Exchange Group (JPX) in 2013.

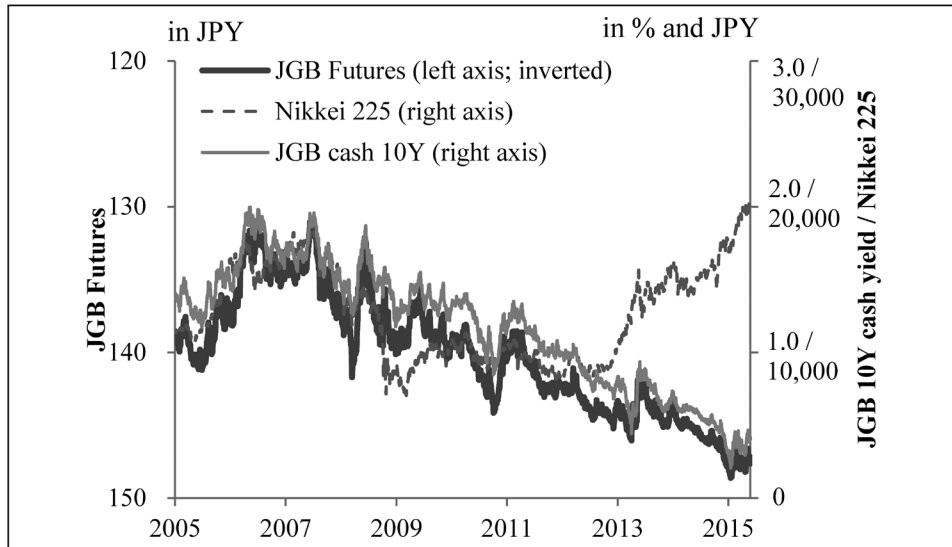
2. JGB futures contracts are also listed on the Singapore Exchange. In addition, until 2014, they were also listed on the NYSE Liffe. Contracts on the NYSE Liffe were automatically transferred to the TSE and vice versa, complementing overseas trading before the TSE and the Osaka Exchange started covering overseas time.

3. Prior to November 21, 2011, the morning session was from 9:00 to 11:00.

4. Prior to November 21, 2011, the trading time was until 18:00. The trades in the evening session are classified as trades of the next business day.

5. The conditions and duration for suspension have been modified several times; for details see the website of the Japan Exchange Group webpage (<http://www.jpx.co.jp/english/>).

**Figure 1 Price of the JGB Futures, 10-year JGB Yield, and the Nikkei 225 from 2005 to 2015**



Note: The data for Nikkei 225 and the JGB cash 10 year are downloaded from the Nihon Keizai Shimbun (Nikkei) and the Ministry of Finance of Japan, respectively.

## B. Data

We use a database named Nikkei NEEDS, which is collected and provided by the Nihon Keizai Shimbunsha (Nikkei). The database contains the price and volume of trades, bids and asks tick-by-tick. We use the data from January 4, 2005 to May 29, 2015 for daily charts. For intraday analysis, we use the data from November 21, 2011 to May 29, 2015; that is, the current trading time has been effective. In addition, we exclude the data during the system trouble of the trading platform (from 9:22 to 10:55 on August 7, 2012).

## C. Definitions of Liquidity Indicators and Daily Charts

In this section we define the liquidity indicators, describe their daily charts during the recent decade, and discuss their features. Following the preceding studies, we classify these indicators into (1) tightness, (2) depth, (3) resiliency, and (4) volume; we also consider (5) the absolute return. Table 1 describes each indicator considered in this paper.

The indicators classified into “tightness” in this paper, plotted in Figure 2, include the bid-ask spread and the effective cost. The bid-ask spread is defined as the difference between the highest quoted bid price by buyers (best-bid price) and the lowest quoted offer price by sellers (best-ask price). The daily average of the five-minutely-obtained bid-ask spreads is shown as “Bid-ask spread” in Figure 2, seemingly reacting to the market turmoil around 2008. As can be seen, however, with the exception of the time around 2008 the range of the bid-ask spread is so tight that it is difficult to detect changes. To avoid this, Kurosaki *et al.* (2015) also show the daily decile; that is, the average of the widest 10 percent of the minutely-obtained bid-ask spreads. This

**Table 1 List of Liquidity Indicators Considered**

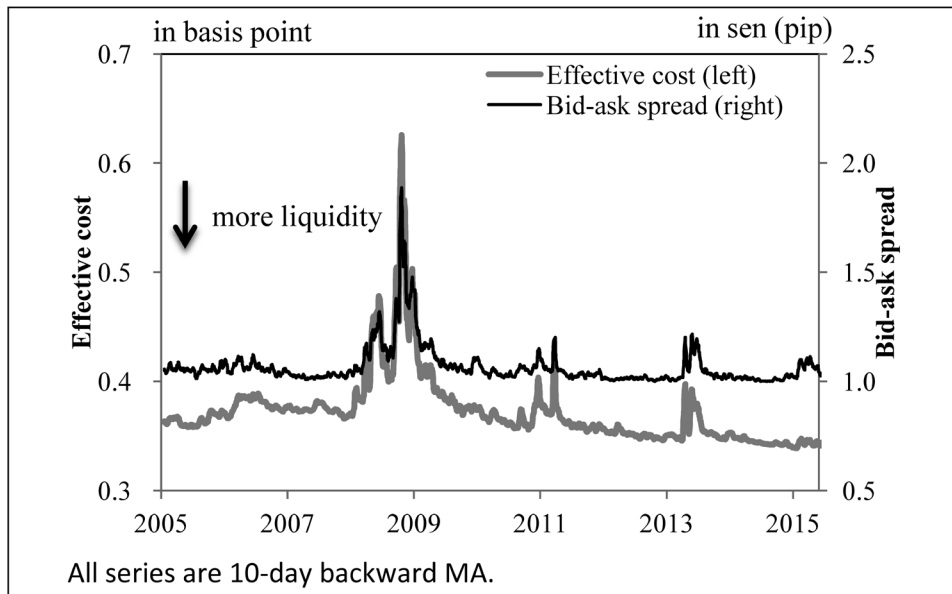
#	Name	Explanation	Type	Unit
1	Bid-ask spread	Difference between the best-bid and the best-ask prices	Tightness	<i>Sen</i> (pip)
2	Effective cost	Cost (difference between the trade and the best-bid/ask prices) divided by the trade price	Tightness	Basis point
3	Ask volume	Volume of best ask	Depth	Trade unit
4	Bid volume	Volume of best bid	Depth	Trade unit
5	Low quote seconds	Length of the seconds in which the best bid volume is less than ten trade units	Depth	Seconds
6	Amihud ILLIQ	Absolute return divided by the trade volume (in real value)	Resiliency	Basis point per JPY billion
7	Liquidity index	Bid-ask spread divided by the quote volume (sum of bid and ask volumes)	Resiliency	<i>Sen</i> (pip) per trade unit
8	Number of trades	Number of trades	Volume	Trade unit
9	Trade volume	Trade volume	Volume	Count
10	Volume per trade	Average trade volume in a single trade	Volume	Trade unit
11	Absolute return	Absolute value of log return of mid-price	—	Basis point

indicator is more sensitive to market conditions than the bid-ask spread itself, but is not available in real time.

As a tightness indicator, Karnaukh, Ranaldo, and Söderlind (2015) investigate the effective cost as the illiquidity measure of foreign exchange markets, and show that the effective cost obtained with high-frequency data well approximates the other indicators obtained by low-frequency data. To define the effective cost, let us suppose that a trade occurs at time  $t$ . Let  $P_t^T$  denote the trade price at time  $t$  and  $P_t^M$  denote the mid-price defined as the mean of the best-bid and the best-ask prices at the latest time before  $t$ . If the trade is initiated by a buyer compromising the best price, then the buyer is considered to pay the cost  $(P_t^T - P_t^M)$ ; this is a buyer-initiated case, and the effective cost at time  $t$  is then defined as  $(P_t^T - P_t^M)/P_t^M$ . Likewise, if the trade is seller-initiated, the effective cost is defined as  $(P_t^M - P_t^T)/P_t^M$ . The daily averaged value of the effective cost is also displayed in Figure 2.<sup>6</sup> The effective cost is more sensitive to market conditions than the bid-ask spreads, and is available in real time.

The indicators classified into “depth” in this paper, plotted in Figure 3, include the ask volume, bid volume, and low quote seconds. The ask volume in this paper is

.....  
6. The daily averaged value is the simple average of the effective cost, not the volume-weighted average.

**Figure 2 Tightness Indicators from 2005 to 2015**

Note: All series are five-minutely obtained; for this chart they are averaged for each day, then converted into a 10-day backward moving average.

defined as the quoted volume of the best ask (measured in trade unit), as is the bid volume. We plot the daily average of the ask and bid volumes in Figure 3. The ask and bid volumes show similar movements: they hit their lowest levels around 2008 and 2011, but have had a tendency to increase over the past few years. The low quote seconds is defined as the number of seconds in five minutes during which the ask volume is equal to or lower than 10 trade units. Figure 3 also plots the daily average (inverted logarithm) of the low quote seconds along with the ask and bid volumes. These series have peaks in similar points.

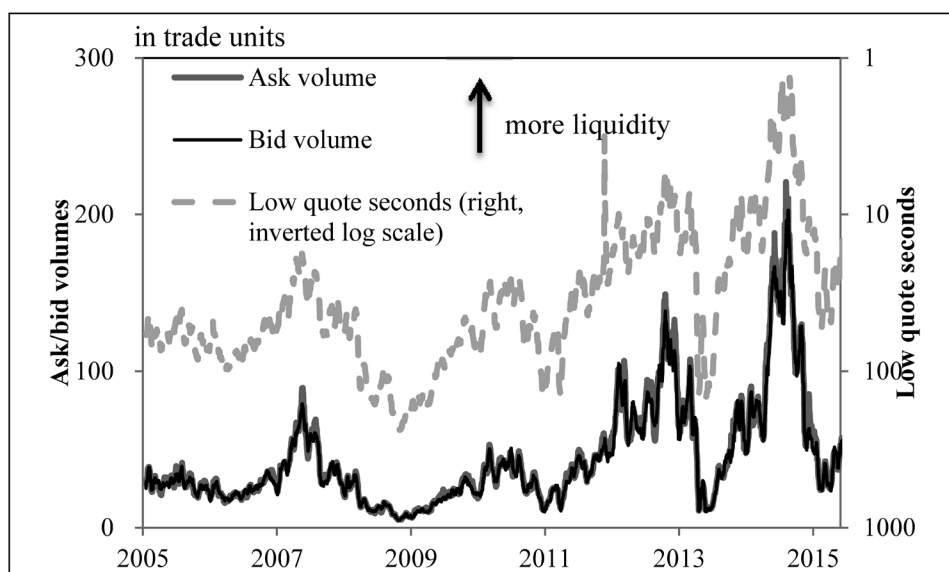
The indicators classified into “resiliency” in this paper include what we refer to as the Amihud ILLIQ measure and the liquidity index.<sup>7</sup> We consider the absolute mid-price return over the trade volume during a five minute period in order to incorporate a real-time indicator.<sup>8</sup> The daily average of these values can be regarded as the Amihud ILLIQ measure (Amihud, 2002) for the case that each five minute is considered as

7. One of the important resiliency indicators not covered in this paper is the price impact, usually defined as the price change followed by a trade of unit size. For example, Kurosaki *et al.* (2015) model that as the latent variable obeying random walk.

8. The mid-price is defined as the average of the best-bid and best-ask prices. We show the case of the mid-price in order to reduce the market microstructure noise. We also tried using the trade price, in which the intraday standard deviation becomes so large that the intraday pattern also becomes different from the mid-price case. For example, the R2 values in Tables 3 and 6 become less than 1% for the Amihud ILLIQ based on the trade price, suggesting that the microstructure noises are dominant in this case. The similar behavior is also observed in the case of the absolute return. In addition, while the movement of the daily averaged Amihud ILLIQ using the mid-price is similar to that of other “resiliency” indicators, the daily ratio of the price range over the trade volume and liquidity index, as mentioned below, the recent movement of the daily averaged Amihud ILLIQ using the trade price is somewhat different from that of the other “resiliency” indicators.



**Figure 3 Depth Indicators from 2005 to 2015**



Note: All series are five-minutely obtained; for this chart they are averaged for each day, then converted into a 10-day backward moving average.

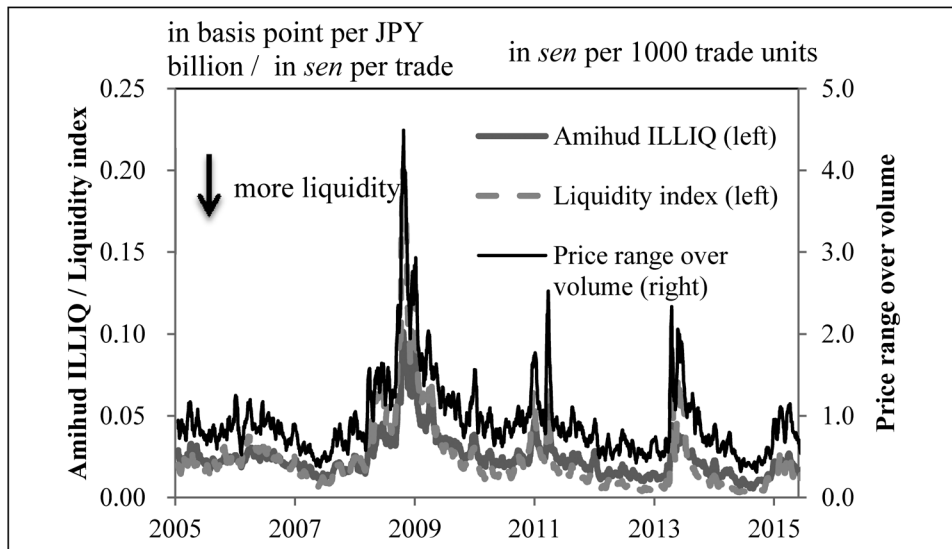
a single business day and the number of assets is one. Accordingly, we refer this indicator as the Amihud ILLIQ indicator. The liquidity index is defined as the quoted depth (bid-ask spread) divided by the quoted volume (the sum of ask and bid volumes), which is introduced by Bollen and Whaley (1998). The daily averages of the Amihud ILLIQ and the liquidity index are plotted in Figure 4, along with the daily ratio of the price range over the trade volume. They resemble each other.

The indicators classified into volume include the trade volume (measured in trade units), the number of trades, and the volume per trade (measured in trade units per trade), plotted in Figure 5. These indicators decreased after the financial crisis in 2008, and then recovered, but not to the level before 2007 for the trade volume or the number of trades. As for the volume per trade, it has recovered to the level before 2007, but shows sharp drops at certain points, such as the earthquake in March 2011 and the introduction of a new monetary policy in April 2013. It should be noted that the indicators belonging to “volume” have two different aspects. Generally, the larger values of the volume indicators are considered to show more liquidity, because that shows there is plenty of room to settle the trades. The arrows in Figure 5 show this general direction. It is possible, however, that the large volume of trades in the past can deplete liquidity by diminishing the availability of more trades in future. Fleming (2003) points out the limited capability of these indicators in measuring liquidity.

Additionally, we also consider the absolute return as a proxy for the return volatility (standard deviation) although it is not a liquidity measure. Its square sum across a day is referred to as the realized volatility (variance) for the day. Figure 6 plots the realized volatility, showing that it hit its peaks around 2008, the beginning of 2011, and the middle of 2013. It has a long history of study in the connection with the trade volume

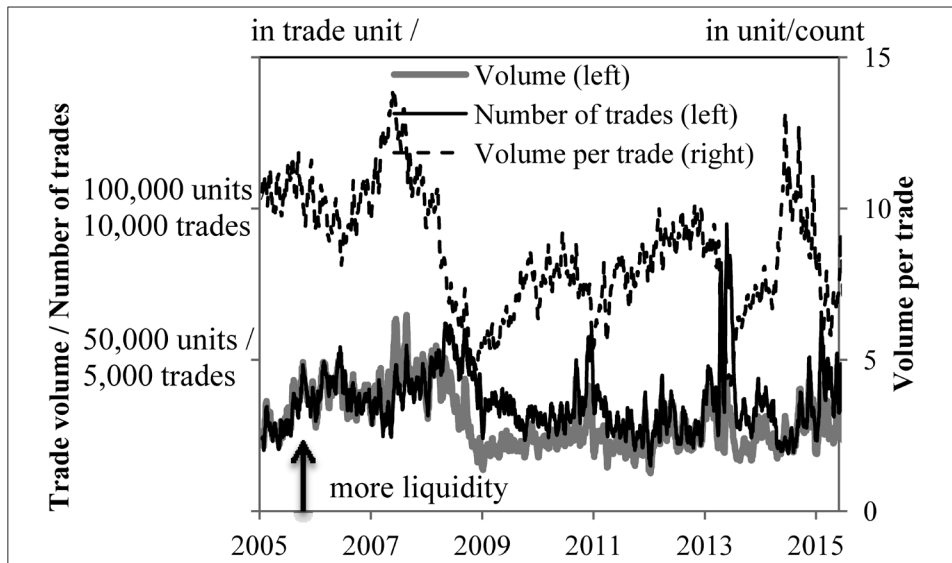


**Figure 4 Resiliency Indicators from 2005 to 2015**



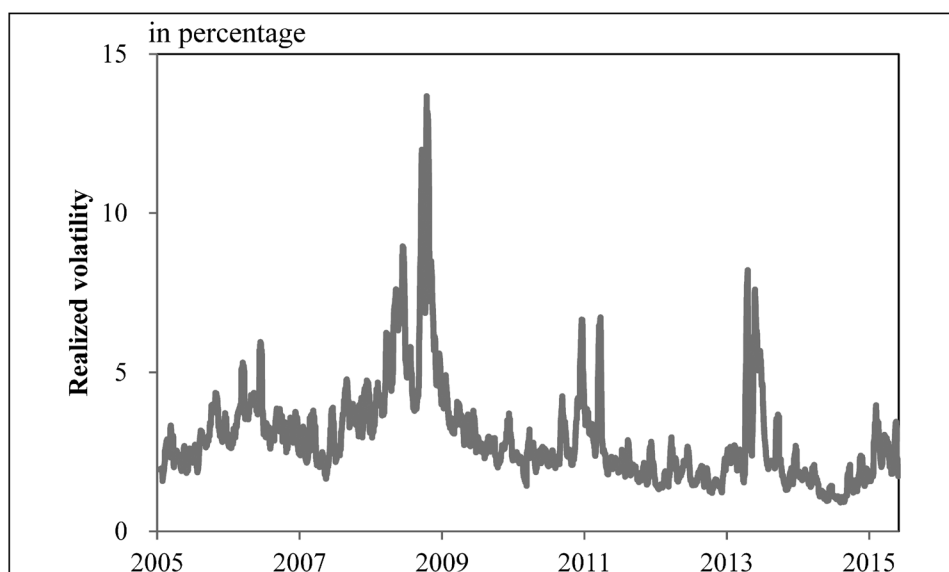
Note: The Amihud ILLIQ is five-minutely obtained; for this chart it is averaged for each day, and converted into a 10-day backward moving average. The Amihud ILLIQ is measured in basis point per JPY billion while the liquidity index is measured in *sen* per trade. The price range over volume is obtained daily; for this chart it is converted into a 10-day backward moving average.

**Figure 5 Volume Indicators from 2005 to 2015**



Note: All series are the daily sum; for this chart they are converted into a 10-day backward moving average.

**Figure 6 Realized Volatility from 2005 to 2015**



Note: For this chart, the realized volatility for each day is calculated as the square sum of the five-minutely returns and the squares of intersession returns. In addition, the realized volatility is converted into the 10-day backward moving average in this chart.

(for example, Andersen 1996; Admati and Pfleiderer 1998). In addition, the relation between volatility, trade volume and news announcements is predicted by the preceding studies (for example, Kim and Verrecchia 1994; Tetlock 2010).

Table 2 provides the descriptive statistics of the 11 liquidity indicators above; hereafter we focus on these 11 indicators.<sup>9</sup> Table 2 also shows the p-values of the Ljung–Box test (single lag) and the augmented Dickey–Fuller test applied to these indicators; accordingly they ought to have autocorrelation but no unit root.

#### **D. Intraday Movement of Liquidity Indicators**

Figure 7 draws the daily patterns of the liquidity indicators by averaging the values at each time point for days from November 21, 2011 to May 29, 2015, adjusted so that the upward direction represents more liquidity. Intraday patterns are easily observed in Figure 7. In the volume indicators (Nos. 8 to 10) and the absolute return (No. 11), we can see a W-shaped pattern for each day: for each session separated by a lunch break, we can see a U-shaped pattern, which was pointed out by Harvey and Huang (1991). The intraday patterns of the other indicators suggest lower liquidity in the opening of each session compared to closing. For the purpose of the intraday analysis, these

.....  
9. We assign the adjacent values for the Amihud ILLIQ or the liquidity indicator when the trade volume or the quoted volume is zero. As for the market suspension due to circuit breaker, we assign zero as the ask volume, the bid volume, the trade volume, the number of trades, and the absolute return, and we assign the adjacent values as the bid-ask spread, the effective cost, the low quote seconds, the Amihud ILLIQ, the liquidity index, and the volume per trade.

**Table 2 Descriptive Statistics of Liquidity Indicators**

	<b>1. Bid-ask spread</b>	<b>2. Effec. cost</b>	<b>3. Ask volume</b>	<b>4. Bid volume</b>	<b>5. Low quote sec.</b>		
Unit	<i>Sen</i> (pip)	Basis point	Trade unit	Trade unit	Seconds		
Mean	1.101	0.351	86	83	22		
Median	1.075	0.347	65	63	6		
Std. dev.	0.102	0.021	77	73	40		
Maximum	3.795	1.799	1,441	1,094	300		
Minimum	1.000	0.336	1	1	0		
Skewness	2.6	19.1	2.1	1.9	3.2		
Kurtosis	26.2	989.5	13.2	9.0	15.9		
p (Jarque-Bera)	0.00	0.00	0.00	0.00	0.00		
p (Ljung-Box)	0.00	0.00	0.00	0.00	0.00		
p (ADF)	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01		

	<b>6. Amihud ILLIQ</b>	<b>7. Liq. index</b>	<b>8. Number of trades</b>	<b>9. Trade volume</b>	<b>10. Vol. per trade</b>	<b>11. Abs. return</b>
Unit	BP, per JPY billion	<i>Sen</i> per trade unit	Count	Trade unit	Trade unit	Basis point
Mean	0.017	0.013	58	421	7.422	0.854
Median	0.012	0.007	45	321	6.910	0.690
Std.dev.	0.028	0.023	52	391	3.542	1.299
Maximum	2.012	0.926	960	8,590	85.000	70.290
Minimum	0.000	0.001	0	0	0.000	0.000
Skewness	23.4	10.6	3.5	3.3	2.3	10.7
Kurtosis	1339.3	199.0	28.4	27.6	20.7	339.6
p (Jarque-Bera)	0.00	0.00	0.00	0.00	0.00	0.00
p (Ljung-Box)	0.00	0.00	0.00	0.00	0.00	0.00
p (ADF)	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01

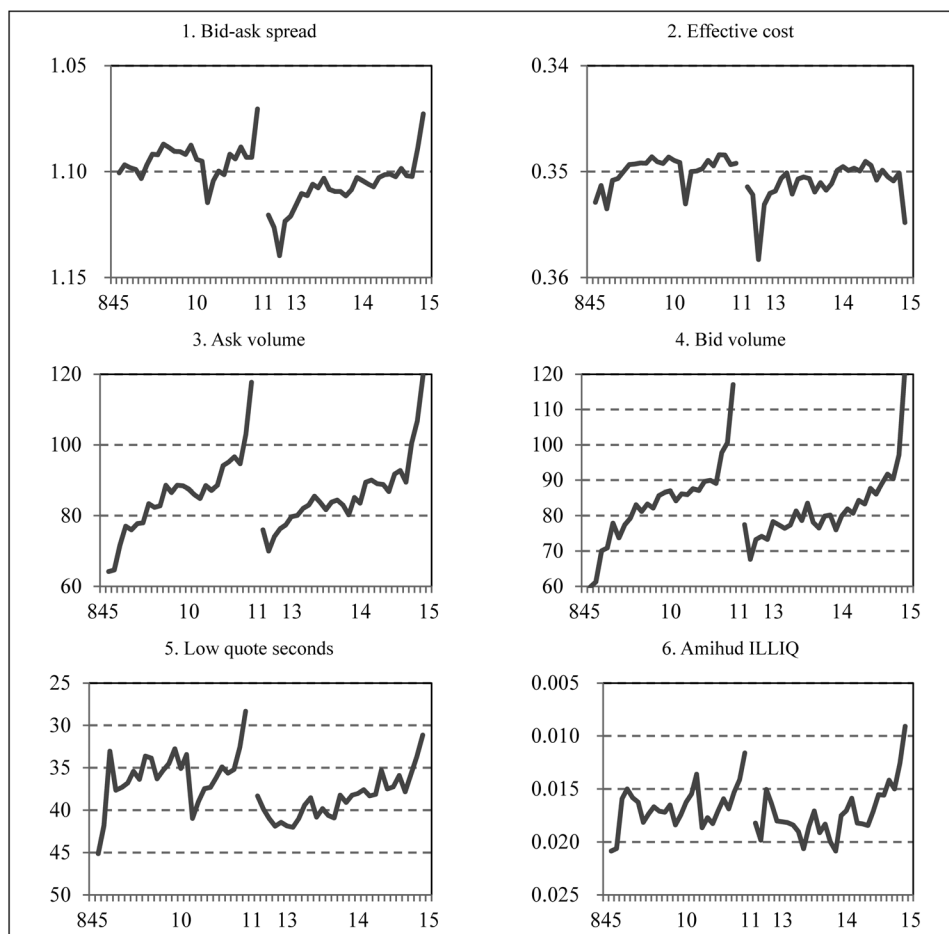
Note: The data are those five-minutely obtained from November 21, 2011 to May 29, 2015. There are 47,501 data points. The data of the evening session, the data at the session opening (8:45 and 12:30), the data at the session closing (11:00 and 15:00), and the data during the system trouble (from 9:22 to 10:55 on August 7, 2012) are excluded.

patterns should be considered in addition to the autocorrelation above.<sup>10</sup>

The pattern on a specific day is very different from the averaged pattern above. To give an example, we plot several market indicators of JGB Futures on April 4, 2013 in Figure 8. On that day, the Bank of Japan announced its new policy at 13:40 (the blue vertical line in the figures). We see that the number of trades and the trading volume rose immediately after the announcement and the other liquidity indicators tended to

10. Some specific peaks around 8:50, 10:10 and 12:45 are supposed to represent the macroeconomic indicator announcements, the offerings of the open market operations by the Bank of Japan, and the results of these operations and the JGB auctions by the Ministry of Finance. Among these events we deal with only the macroeconomic indicator announcements. Iwatsubo and Taishi (2016) provide a comprehensive study of the offerings of the open market operations.

**Figure 7 Intraday Pattern of the Liquidity Indicators**



(continued on next page)

decrease around the announcement.<sup>11</sup> In this paper, we first find the intraday pattern and autocorrelation shown in Figure 7, then investigate whether the monetary policy announcement invoked the liquidity indicator movements shown in Figure 8 with the intraday pattern and autocorrelation controlled.

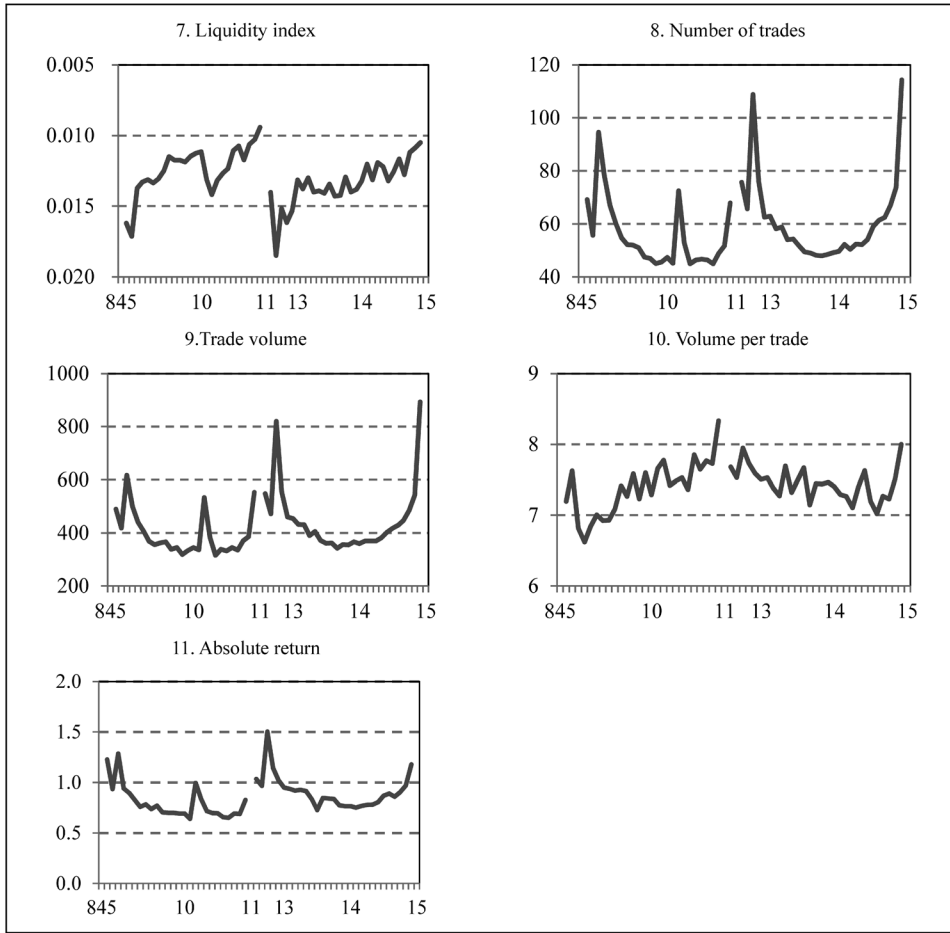
### III. Analysis

#### A. Methodology

Andersen and Bollerslev (1998) and Andersen *et al.* (2007) show that the intraday returns are affected by both the intraday lagged terms and the surprises of events, and the volatilities have the ARCH effect. Neely (2011) models the intraday absolute return as the sum of the intraday pattern terms, the daily GARCH term, the intraday lagged

.....  
11. Some indicators such as the bid volume increased after the announcement. This shows more buying of orders, supposedly invoked by the expectation of price increase under the new monetary policy.

Figure 7 (continued)



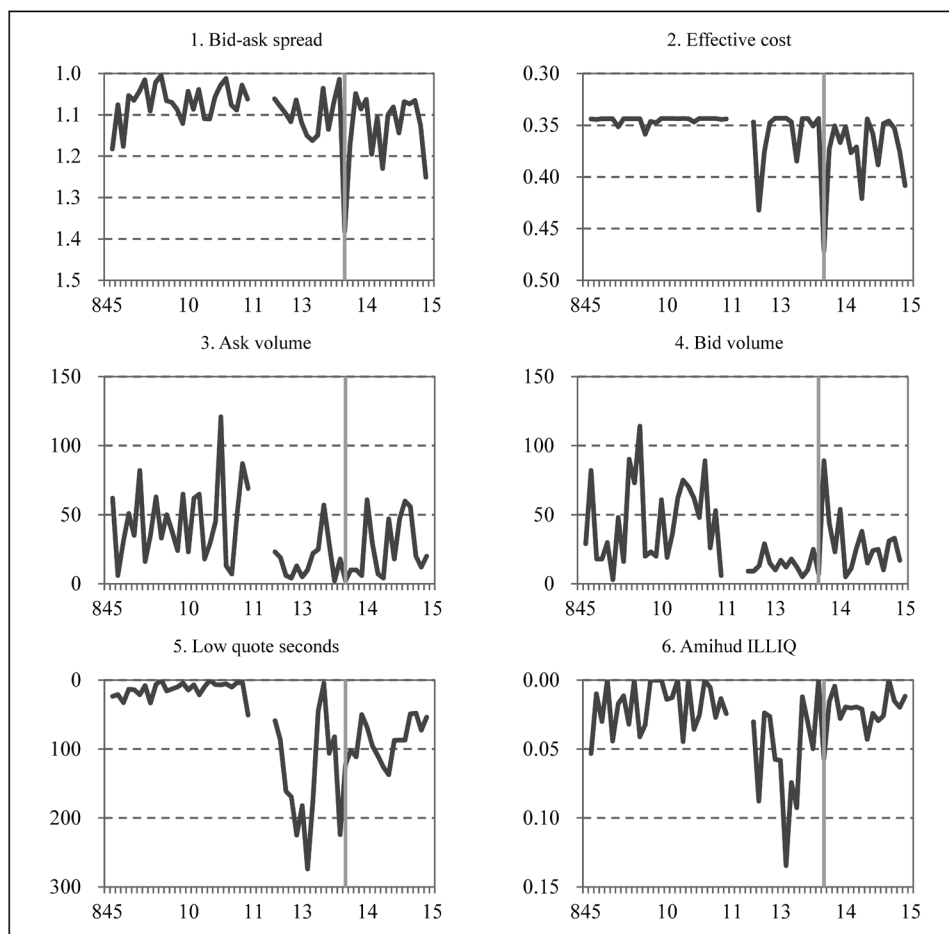
Note: The vertical axes of all indicators except the absolute return are adjusted so that the upward direction represents more liquidity; the vertical axis of the absolute return (not a liquidity indicator) is adjusted so that the upward direction represents more value.

variable terms, and event dummies. According to these studies, the absolute return has significant intraday pattern and autocorrelation.

The liquidity indicators are also expected to have the intraday pattern and the autocorrelation. In order to incorporate these effects, we extend the regression equation by Neely (2011) into the other liquidity indicators. We analyze the regression (1) in more detail to capture intraday movement of a liquidity indicator.

$$\begin{aligned}
 I_t = & \alpha + \beta_{\text{session}} \text{Dum}_{\text{session},t} + \sum_{q=1}^{q_M} (\beta_{\sin q} \sin q\theta_t + \beta_{\cos q} \cos q\theta_t) \\
 & + \beta_{\hat{I}_d} \hat{I}_{d(t)} + \sum_{i=1}^L \beta_{I,i} I_{t-i} + \beta_{\text{EI}} \text{Dum}_{\text{EI},t} + \beta_{\text{MP}} \text{Dum}_{\text{MP},t} + \sum_{j=1}^N \beta_{s,j} |s_{j,t}| + \varepsilon_t, \quad (1)
 \end{aligned}$$

**Figure 8 Liquidity Indicators on April 4, 2013**



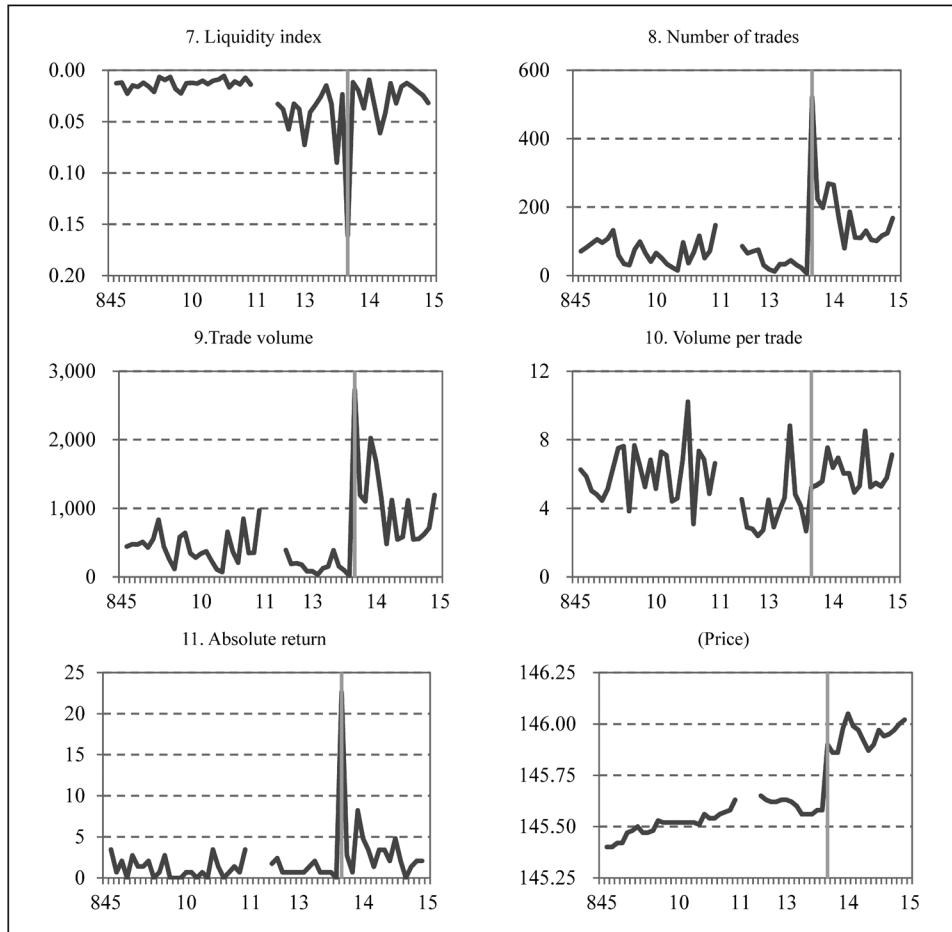
(continued on next page)

where  $I$  stands for a liquidity indicator (the effective cost, the Amihud ILLIQ indicator, the absolute return, etc.). Time  $t$  is an integer whose unit is five minutes. Constant  $\alpha$  is the intercept, and constants  $\beta$  are the regression coefficients of the following explanatory variables. The last term  $\varepsilon_t$  is the error term.

Variables  $Dum_{session,t}$  and  $\theta_t$  are introduced to represent intraday patterns. Variable  $Dum_{session,t}$  is the session dummy; it is zero if time  $t$  belongs to the morning session (8:50–10:55) and unity if to the afternoon session (12:35–14:55).<sup>12</sup> As noted in section II. A, the lunch break is an important, unique feature of the JGB futures market. For incorporating the effect entailed, we introduce the session dummy, which does not appear in Neely (2011). Meanwhile,  $\theta_t$  takes zero at the opening,  $\pi$  at the end of the morning session and the beginning of the afternoon session, and  $2\pi$  at the end of the afternoon session, for each trading day. The trigonometric terms containing  $\theta_t$  follow

12. We ignore the evening session (15:30–23:30) since it is off-hours. The first and last observations during a session are also removed, since the pattern during these periods is quite different from the others.

Figure 8 (continued)



Note: On this day the Bank of Japan introduced Quantitative and Qualitative Monetary Easing. The vertical line corresponds to 13:40 (1:40 PM), at which time the policy was announced. The vertical axes of liquidity indicators are adjusted so that the upward direction represents more liquidity; the vertical axes of the others (the absolute return and the price) are adjusted so that the upward direction represents more value.

the intraday pattern terms appearing in Neely (2011), while the value of  $\theta_t$  is defined differently due to the market close between sessions. We use  $q_M = 4$ .<sup>13</sup>

Variable  $\hat{f}_{d(t)}$  is the value of the daily prediction of the explained variable on the day to which time  $t$  belongs. This prediction is based on the GARCH(1,1) model for the absolute return, and on the AR(1) model for the other indicators; that is, the prediction is based on the information for up to the previous day.<sup>14</sup> This term controls the change

13. We follow Neely (2011), which also uses  $q_M = 4$ . In our case, this means that the trigonometric terms represent the periodic movements whose cycle is longer than approximately one hour (since the trade time is 4:45). In the case of Neely (2011), this means a cycle longer than six hours (since the trade time is 24 hours). These cycle hours are close to the length of  $L$ , which is one hour in our case (as discussed later) and five hours in the case of Neely (2011).

14. Table 3 shows the best order  $p$  of the daily AR model based on the BIC, the  $R^2$  values of AR(1) model, and



**Table 3 Autoregression of Daily Liquidity Indicators**

		Best order $p$ by BIC	R2 of daily pred. in eq. (1)	
			AR(1)	AR(p)
1	Bid-ask spread	14	43%	43%
2	Effective cost	18	31%	31%
3	Ask volume	9	40%	42%
4	Bid volume	11	41%	41%
5	Low quote seconds	5	62%	62%
6	Amihud ILLIQ	14	13%	14%
7	Liquidity index	18	46%	46%
8	Number of trades	5	43%	45%
9	Trade volume	10	26%	26%
10	Volume per trade	10	18%	19%
11	Absolute return	11	21%	21%

Note: The data are daily from November 21, 2011 to May 29, 2015, consisting of 864 days. The evening session data are excluded.

of levels in lower frequency such as daily or weekly. Variable  $I_{t-i}$  is the explained variable  $I_t$  lagged by  $i$  terms, i.e., the value of  $I_t$  at  $5i$  minutes ago, for introducing intraday autocorrelation.

Variable  $Dum_{EI,t}$  is the dummy variable representing the announcements of the economic indicators (EI) listed in Table 4. All the announcements are merged to a single series. If the announcement time belongs to the morning session, we set unity at that time. If it is before the morning session, we set unity at 8:50, the first time period considered during the day. We set zero otherwise. Variable  $Dum_{MP,t}$  is the dummy variable representing the announcements of the monetary policy (MP) meetings; it takes unity at the announcement time if it is during the session, and takes unity at 12:35 if it happens at the intersession time, and zero otherwise. The announcements considered are listed in Table 5.<sup>15</sup> Both  $Dum_{EI,t}$  and  $Dum_{MP,t}$  are the announcement dummies, but the difference is that the time is known prior to announcement in the case of  $Dum_{EI,t}$ , but not in the case of  $Dum_{MP,t}$ .<sup>16</sup>

Variable  $|s_{j,t}|$  is the absolute value of the surprise of the announcement of the  $j$ -th economic indicator  $EI_j$  ( $j = 1, \dots, N$ ) at time  $t$ . The  $EI_j$  considered are listed in Table 4, where eleven economic indicators are shown ( $N = 11$ ). We follow Balduzzi, Elton, and Green (2001) in the definition of  $s_{j,t}$ ; that is, the released “surprise” (difference between

the  $R^2$  values of  $AR(p)$ . Since the most of the explanatory power comes from the  $AR(1)$  term, we use the  $AR(1)$  model for simplicity.

15. The announcements listed in Table 5 include both those as for policy changes and those announcing no changes. It is possible to restrict these announcements to the former for the reason that no change conveys no information. However, in some meetings, there is an expectation of policy changes, and the announcement of no change conveys important information in such a case. For this reason we list all the regular monetary policy meetings here.

16. Although the MP result is announced in the afternoon on the scheduled day listed in Table 5, the exact time is unknown prior to the announcement.

**Table 4 Macroeconomic Indicator Announcements Considered**

Name	Time	Stats.		Surprises		Source	Note
		#obs.	Avg.	Avg.	S.D.		
Capacity investment	8:50	14	1.6%	0.7%	4.5%	Investment in plant and equipment in all industry in "Financial Statements Statistics of Corporations by Industry" issued by the MoF	Year-over-year
CPI ex. FF	8:30	43	1.0%	0.0%	0.1%	"Japan, all items, less fresh food" in "Consumer Price Index" issued by the MIC	Year-over-year
GDP deflator	8:50	28	0.0%	0.0%	0.2%	"Quarterly Estimates of GDP" issued by the CO	1st and 2nd estimates, seasonally adjusted
GDP growth	8:50	28	0.2%	-0.1%	0.3%	Real quarterly growth in "Quarterly Estimates of GDP" issued by the CO	1st and 2nd estimates, seasonally adjusted
IIP	8:50	43	0.0%	-0.6%	1.4%	Index of industrial production in "Indices of industrial production" issued by the METI	Seasonally adjusted, month-over-month
Job offering	8:30	43	0.94	0.01	0.01	"Active job openings-to-applicants ratio" in "Employment Referrals for General Workers" issued by the MHLW	Original series
Machinery order	8:50	42	0.8%	0.2%	6.6%	Private sectors excluding volatile orders in "Machinery order" issued by the CO	Seasonally adjusted, month-over-month
PPI	8:50	42	1.1%	0.0%	0.2%	Producer price index in "Corporate Goods Price Index" issued by the BoJ	Year-over-year
Tankan	8:50	14	4.71	-0.14	2.42	Business condition index for large manufacturers in "Tankan" issued by the BoJ	Original series
Unemployment	8:30	43	4.0%	0.0%	0.1%	Unemployment rate in "Labour Force Survey" issued by the MIC	Seasonally adjusted
Wage	10:30	33	0.2%	0.1%	0.7%	Total cash earnings in "Monthly Labour Survey" issued by the MHLW	Year-over-year

Note: The actual data are downloaded from the institution listed in "Source" column. The forecasts are downloaded from Bloomberg. Columns in "Stats." are the number of observations and the average of the original series. Columns in "Surprises" are the average of the difference between the actual value and the forecast value and the standard deviation. The surprise defined in this paper is the difference between the actual value and the forecast value divided by its standard deviation.

the released value and the forecast value) is scaled to unit variance. Similar to  $Dum_{EI,t}$ ,  $s_{j,t}$  can take the surprise value at the announcement time of  $EI_j$  if it is during the session or at 8:50 if it is before the morning session, and zero otherwise; however, in contrast to  $Dum_{EI,t}$ , the actual value of surprise  $|s_{j,t}|$  is unknown prior to its announcement, while its time is known. We downloaded the forecast values from Bloomberg and the actual values from the sources listed in Table 4.

## B. Intraday Pattern Analysis

Prior to event analysis, we analyze the intraday patterns and the autocorrelation in the liquidity indicators considered, utilizing regression equation (1). For that purpose we first set the coefficients of EI announcements, MP announcements and EI surprises to zero ( $\beta_{EI} = \beta_{MP} = \beta_{s,j} = 0$ ). Table 6 shows the p-value of the Ljung–Box test for the errors for the cases the order of lagged terms  $L = 12$  (up to one hour ago) and

**Table 5 Monetary Policy Announcements Considered**

Date	Time	Date	Time	Date	Time
Dec. 21, 2011	12:16	Mar. 07, 2013	12:24	May 21, 2014	11:41
Jan. 24, 2012	12:31	Apr. 04, 2013	13:40	Jun. 13, 2014	11:41
Feb. 14, 2012	12:43	Apr. 26, 2013	13:35	Jul. 15, 2014	11:58
Mar. 13, 2012	14:07	May 22, 2013	12:07	Aug. 08, 2014	12:08
Apr. 10, 2012	12:09	Jun. 11, 2013	11:48	Sep. 04, 2014	12:07
Apr. 27, 2012	12:46	Jul. 11, 2013	11:47	Oct. 07, 2014	13:54
May 23, 2012	11:37	Aug. 08, 2013	11:59	Oct. 31, 2014	13:44
Jun. 15, 2012	11:52	Sep. 05, 2013	11:42	Nov. 19, 2014	12:24
Jul. 12, 2012	12:51	Oct. 04, 2013	11:49	Dec. 19, 2014	12:28
Aug. 09, 2012	12:19	Oct. 31, 2013	13:14	Jan. 21, 2015	12:29
Sep. 19, 2012	12:44	Nov. 21, 2013	12:15	Feb. 18, 2015	11:49
Oct. 05, 2012	12:14	Dec. 20, 2013	11:57	Mar. 17, 2015	12:04
Oct. 30, 2012	14:46	Jan. 22, 2014	12:20	Apr. 08, 2015	12:36
Nov. 20, 2012	12:14	Feb. 18, 2014	12:28	Apr. 30, 2015	13:04
Dec. 20, 2012	13:01	Mar. 11, 2014	12:00	May 22, 2015	11:49
Jan. 22, 2013	12:47	Apr. 08, 2014	11:50		
Feb. 14, 2013	12:39	Apr. 30, 2014	12:51		

Note: Regular meetings. Times are taken from Bank of Japan website.

$L = 24$  (two hours ago).<sup>17</sup> In the five indicators (the effective cost, the ask volume, the bid volume, the liquidity index, and the trade volume), the null hypothesis of no autocorrelation cannot be rejected at the 5% significance level for 12 lags, while in the remaining six (the bid-ask spread, the low quote seconds, the Amihud ILLIQ, the number of trades, the volume per trade, and the absolute return) the null is rejected even for 24 lags.<sup>18</sup> Table 6 also shows the values of the model's  $R^2$  (the coefficient of determination), the Akaike and Bayesian information criteria (AIC and BIC); according to the AIC or the BIC,  $L = 24$  seems desirable. However, since the length of each session is 27 lags (in morning session, corresponding to 2:15) or 30 lags (afternoon session, 2:30), models with higher lags include the more effect of the previous session, which we want to separate from the effects of the session dummy  $Dum_{session,t}$  and the daily prediction  $\hat{I}_{d(t)}$ . Therefore, we adopt  $L = 12$  hereafter for simplification, in which the  $R^2$  values are about the same as those for  $L = 24$ .

The values of  $\alpha$  and  $\beta$  for the case  $L = 12$  are shown in Table 7. It is observed that  $\beta_{\hat{I}_d}$  (the coefficient of daily prediction) and  $\beta_{I,1}$  (the coefficient of first-order lag term) are significant for all the cases, suggesting that the liquidity terms have strong autocorrelation. The lagged terms of higher orders are also significant, reinforcing the existence of autocorrelation. Regarding the trigonometric terms ( $\beta_{\sin q}$  and  $\beta_{\cos q}$ ), many of them are significant, showing that the intraday pattern exists. The coefficient

17. We also tested the cases  $L = 0, 1$ , and 6, although we omitted the values for these cases since 12 or more lags seem necessary from the following discussion.

18. As for these indicators, it is observed that the autocorrelation of the error terms does not decrease as rapidly as the exponential function; in the case of the absolute return this is consistent with the long memory effect (Andersen *et al.*, 2001, 2003), which needs to be investigated further in future work.

**Table 6 Model Selection ( $L=12$  and 24)**(a)  $L=12$ 

Explained variable	1. Bid-ask spread	2. Effective cost	3. Ask volume	4. Bid volume	5. Low quote seconds	
<b>Model fitness</b>						
R2	0.43	0.31	0.40	0.41	0.62	
AIC	-108,823	-250,181	523,241	518,017	440,653	
BIC	-108,613	-249,971	523,451	518,227	440,863	
<b>P-values for error terms</b>						
Ljung-Box	0.00	0.29	0.00	0.15	0.00	
Jarque-Bera	0.00	0.00	0.00	0.00	0.00	
ADF	<0.01	<0.01	<0.01	<0.01	<0.01	

Explained variable	6. Amihud ILLIQ	7. Liquidity index	8. Number of trades	9. Trade volume	10. Volume per trade	11. Absolute return
<b>Model fitness</b>						
R2	0.13	0.46	0.43	0.26	0.18	0.20
AIC	-211,632	-253,246	483,665	687,450	245,425	148,871
BIC	-211,421	-253,036	483,875	687,661	245,635	149,081
<b>P-values for error terms</b>						
Ljung-Box	0.00	0.43	0.00	0.69	0.00	0.00
Jarque-Bera	0.00	0.00	0.00	0.00	0.00	0.00
ADF	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

(b)  $L=24$ 

Explained variable	1. Bid-ask spread	2. Effective cost	3. Ask volume	4. Bid volume	5. Low quote seconds	
<b>Model fitness</b>						
R2	0.43	0.31	0.40	0.41	0.62	
AIC	-108,982	-250,548	523,218	517,908	440,361	
BIC	-108,667	-250,232	523,534	518,223	440,677	
<b>P-values for error terms</b>						
Ljung-Box	0.00	0.43	0.00	0.18	0.00	
Jarque-Bera	0.00	0.00	0.00	0.00	0.00	
ADF	<0.01	<0.01	<0.01	<0.01	<0.01	

Explained variable	6. Amihud ILLIQ	7. Liquidity index	8. Number of trades	9. Trade volume	10. Volume per trade	11. Absolute return
<b>Model fitness</b>						
R2	0.13	0.46	0.43	0.26	0.18	0.20
AIC	-211,669	-253,449	483,054	687,306	245,403	148,857
BIC	-211,353	-253,133	483,369	687,621	245,719	149,172
<b>P-values for error terms</b>						
Ljung-Box	0.00	0.56	0.00	0.79	0.00	0.00
Jarque-Bera	0.00	0.00	0.00	0.00	0.00	0.00
ADF	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

of determination for each component in equation (1) is tabulated in Table 8, including those based on the event analysis described below. The lagged explained variables, followed by the daily predictions, have the largest explanatory powers for most of the liquidity indicators. We need to remove these dominant effects in order to consider the following event analysis.

**Table 7 Regression Coefficients (for Pattern and Autocorrelation Terms)**

	1. Bid-ask spread		2. Effective cost		3. Ask volume		4. Bid volume		5. Low quote seconds		6. Amihud ILLIQ	
	Coef.	p	Coef.	p	Coef.	p	Coef.	p	Coef.	p	Coef.	p
$\alpha$	-0.0215	(0.01)	0.0095	(0.00)	-6.62	(0.04)	26.44	(0.00)	1.46	(0.27)	0.0074	(0.00)
$\beta$ representing intraday pattern												
$\beta_{\text{session}}$	0.0213	(0.00)	0.0038	(0.00)	7.47	(0.00)	-14.47	(0.00)	-0.94	(0.28)	-0.0051	(0.00)
$\beta_{\text{sin } 1}$	0.0124	(0.00)	0.0020	(0.00)	5.18	(0.00)	-5.56	(0.00)	-1.47	(0.01)	-0.0035	(0.00)
$\beta_{\text{sin } 2}$	0.0261	(0.00)	-0.0001	(0.28)	-1.78	(0.00)	0.79	(0.04)	0.82	(0.00)	0.0008	(0.00)
$\beta_{\text{sin } 3}$	0.0003	(0.65)	0.0002	(0.14)	0.68	(0.24)	-0.15	(0.78)	-1.01	(0.00)	-0.0006	(0.01)
$\beta_{\text{sin } 4}$	0.0156	(0.00)	0.0004	(0.00)	-4.02	(0.00)	-1.45	(0.00)	1.63	(0.00)	0.0005	(0.00)
$\beta_{\text{cos } 1}$	-0.0057	(0.00)	-0.0004	(0.00)	-0.69	(0.08)	5.27	(0.00)	-1.08	(0.00)	0.0000	(0.80)
$\beta_{\text{cos } 2}$	0.0103	(0.00)	0.0006	(0.00)	1.04	(0.01)	5.13	(0.00)	1.60	(0.00)	-0.0007	(0.00)
$\beta_{\text{cos } 3}$	-0.0027	(0.00)	0.0004	(0.00)	-0.97	(0.01)	1.29	(0.00)	0.64	(0.00)	0.0004	(0.04)
$\beta_{\text{cos } 4}$	-0.0096	(0.00)	0.0007	(0.00)	0.52	(0.20)	2.00	(0.00)	0.94	(0.00)	-0.0003	(0.11)
$\beta$ representing daily predicted values and autocorrelation												
$\beta_{I,d}$	0.34	(0.00)	0.28	(0.00)	0.11	(0.00)	0.35	(0.00)	0.26	(0.00)	0.53	(0.00)
$\beta_{I,1}$	0.26	(0.00)	0.16	(0.00)	0.30	(0.00)	0.24	(0.00)	0.24	(0.00)	0.22	(0.00)
$\beta_{I,2}$	0.03	(0.00)	0.08	(0.00)	0.16	(0.00)	0.12	(0.00)	0.10	(0.00)	0.09	(0.00)
$\beta_{I,3}$	0.04	(0.00)	0.08	(0.00)	0.10	(0.00)	0.08	(0.00)	0.07	(0.00)	0.00	(0.45)
$\beta_{I,4}$	0.03	(0.00)	0.17	(0.00)	0.06	(0.00)	0.05	(0.00)	0.06	(0.00)	0.02	(0.00)
$\beta_{I,5}$	0.05	(0.00)	0.03	(0.00)	0.04	(0.00)	0.05	(0.00)	0.05	(0.00)	0.02	(0.00)
$\beta_{I,6}$	0.05	(0.00)	0.06	(0.00)	0.04	(0.00)	0.03	(0.00)	0.05	(0.00)	0.00	(0.57)
$\beta_{I,7}$	0.05	(0.00)	0.03	(0.00)	0.03	(0.00)	0.04	(0.00)	0.04	(0.00)	0.02	(0.00)
$\beta_{I,8}$	0.05	(0.00)	-0.02	(0.00)	0.03	(0.00)	0.02	(0.00)	0.03	(0.00)	0.03	(0.00)
$\beta_{I,9}$	0.04	(0.00)	0.01	(0.08)	0.02	(0.00)	0.03	(0.00)	0.02	(0.00)	0.02	(0.00)
$\beta_{I,10}$	0.04	(0.00)	0.04	(0.00)	0.03	(0.00)	0.02	(0.00)	0.04	(0.00)	0.01	(0.13)
$\beta_{I,11}$	0.02	(0.00)	0.01	(0.00)	0.01	(0.00)	0.02	(0.00)	0.03	(0.00)	0.00	(0.43)
$\beta_{I,12}$	0.02	(0.00)	0.03	(0.00)	0.01	(0.20)	0.02	(0.00)	0.03	(0.00)	0.02	(0.00)

(continued on next page)

### C. Event Analysis

Next we consider  $\beta_{\text{EI}}$ ,  $\beta_{\text{MP}}$ , and  $\beta_{s,j}$ ; that is, the effect of economic indicator (EI) monetary policy (MP) announcements and EI surprises. Table 9 shows the values of  $\beta_{\text{EI}}$  and  $\beta_{\text{MP}}$  and Table 10  $\beta_{s,j}$ , omitting  $\alpha$  and the other  $\beta$ . For cases for which the regression coefficient is significant at the 10% level except the case for the absolute return, the direction of the effect on the liquidity is shown by the plus (+) or minus (−) signs inside the parentheses; for the case of absolute return, the significance is shown by an asterisk (\*). No sign in parentheses or asterisk means that the coefficient is insignificant.

As for  $\beta_{\text{EI}}$ , six out of 11 coefficients are significant, and the five signs (that is, five significant cases except absolute return) are all negative, showing the lowered liquidity after EI announcements. Among the five, three are classified as volume (number of trades, trade volume, and volume per trade). The other two are the ask volume and the liquidity index, which are depth and resiliency indicators but are also defined by the volumes in quotes. As for the absolute return, its coefficient is significant, and its negative value indicates less volatility after EI announcements. Meanwhile, the other indicators are not significant in relation to EI announcements.

As for  $\beta_{\text{MP}}$ , seven out of 11 coefficients are significant. The signs of the tightness (bid-ask volume and effective cost), depth (low quote seconds), and resiliency (liquidity index) are negative, as with the case of  $\beta_{\text{EI}}$ . In contrast, the signs of the volume indicators (number of trades and trade volume) are positive, showing more liquidity after MP announcements. In addition, the positive value of absolute returns for  $\beta_{\text{MP}}$  shows more volatility after MP announcements, in contrast to  $\beta_{\text{EI}}$ . The signs of the

Table 7 (continued)

	7. Liquidity index		8. Number of trades		9. Trade volume		10. Volume per trade		11. Absolute return	
	Coef.	p	Coef.	p	Coef.	p	Coef.	p	Coef.	p
$\alpha$	-0.0021	(0.02)	-27.858	(0.00)	-183.466	(0.00)	0.485	(0.01)	-0.50807	(0.00)
$\beta$ representing intraday pattern										
$\beta_{\text{session}}$	0.0012	(0.04)	19.223	(0.00)	137.387	(0.00)	-0.053	(0.64)	0.29600	(0.00)
$\beta_{\text{sin } 1}$	0.0004	(0.30)	10.352	(0.00)	83.176	(0.00)	-0.070	(0.36)	0.14135	(0.00)
$\beta_{\text{sin } 2}$	0.0003	(0.00)	-1.285	(0.00)	-9.925	(0.00)	-0.212	(0.00)	0.10374	(0.01)
$\beta_{\text{sin } 3}$	0.0000	(1.00)	1.148	(0.01)	14.733	(0.00)	-0.061	(0.06)	0.01818	(0.11)
$\beta_{\text{sin } 4}$	0.0010	(0.00)	0.778	(0.01)	22.200	(0.00)	-0.055	(0.03)	0.08086	(0.00)
$\beta_{\text{cos } 1}$	-0.0005	(0.00)	1.290	(0.00)	22.899	(0.00)	-0.224	(0.00)	0.00485	(0.53)
$\beta_{\text{cos } 2}$	0.0004	(0.00)	6.542	(0.00)	77.553	(0.00)	0.043	(0.11)	0.11963	(0.00)
$\beta_{\text{cos } 3}$	0.0003	(0.02)	1.669	(0.00)	12.627	(0.00)	0.024	(0.28)	0.01824	(0.03)
$\beta_{\text{cos } 4}$	0.0003	(0.01)	4.454	(0.00)	42.824	(0.00)	0.181	(0.00)	0.00734	(0.69)
$\beta$ representing daily predicted values and autocorrelation										
$\beta_{i,t}$	0.25	(0.00)	0.0066	(0.00)	0.0044	(0.00)	0.6610	(0.00)	5.760532	(0.00)
$\beta_{i,1}$	0.16	(0.00)	0.4064	(0.00)	0.2700	(0.00)	0.2010	(0.00)	0.207758	(0.00)
$\beta_{i,2}$	0.12	(0.00)	0.1813	(0.00)	0.0857	(0.00)	0.0003	(0.14)	-0.000005	(0.00)
$\beta_{i,3}$	0.07	(0.00)	0.0044	(0.00)	0.1114	(0.00)	0.0006	(0.00)	-0.000002	(0.00)
$\beta_{i,4}$	0.06	(0.00)	-0.0168	(0.00)	0.0330	(0.00)	-0.0001	(0.59)	0.000003	(0.00)
$\beta_{i,5}$	0.06	(0.00)	0.0072	(0.00)	0.0321	(0.00)	0.0002	(0.24)	-0.000002	(0.03)
$\beta_{i,6}$	0.03	(0.00)	0.0036	(0.00)	0.0442	(0.00)	0.0003	(0.03)	-0.000002	(0.06)
$\beta_{i,7}$	0.03	(0.00)	-0.0008	(0.09)	0.0118	(0.01)	0.0007	(0.00)	-0.000002	(0.05)
$\beta_{i,8}$	0.06	(0.00)	-0.0006	(0.25)	0.0317	(0.00)	0.0004	(0.01)	-0.000001	(0.09)
$\beta_{i,9}$	0.00	(0.62)	-0.0004	(0.36)	0.0150	(0.00)	0.0004	(0.01)	-0.000001	(0.37)
$\beta_{i,10}$	0.06	(0.00)	-0.0006	(0.19)	0.0304	(0.00)	0.0004	(0.02)	0.000000	(0.63)
$\beta_{i,11}$	0.04	(0.00)	0.0002	(0.64)	0.0105	(0.03)	0.0008	(0.00)	0.000000	(0.52)
$\beta_{i,12}$	0.02	(0.00)	0.0013	(0.00)	0.0150	(0.00)	0.0001	(0.42)	0.000000	(0.82)

Note: The regression model is specified by equation (1). Event variables ( $Dum_{EI,t}$ ,  $Dum_{MP,t}$ , and  $|s_{j,t}|$ ) are not considered here.

tightness, depth, and resiliency indicators in both cases are consistent with the notion that the event announcements generally decrease the liquidity. On the other hand, the opposite signs of the volume indicators and the absolute return suggest the necessity of further consideration.

According to the discussion by Kim and Verrecchia (1994), the trade volume is expected to decrease immediately after the announcement since traders need time to interpret the information in the announcement, then to increase due to the traders starting trades under the new information. They also predict that following these traders' reactions to new information, the volatility decreases immediately after the announcement, then increases. Comparing their predictions with our analysis, the reaction immediately after the announcement seems to correspond to the case of  $\beta_{EI}$ , and the reaction after information processing seems to correspond to the case of  $\beta_{MP}$ . In the case of EI announcements, the new information entailed by the announcement is separated into the surprise ( $\beta_{s,j}$  or  $s_{j,t}$ ). Bringing no information, an EI announcement is not followed by the reaction due to information processing, entailing the reaction right after announcement only, which is as observed. On the other hand, in the case of MP announcements,  $\beta_{MP}$  ( $Dum_{MP,t}$ ) mainly indicates the reaction after information processing because the surprise is not separated in the regression.<sup>19</sup> Bringing new information, an MP announcement is followed by the opposite reactions proposed by Kim and Ver-

19. We cannot quantify the surprise because recent monetary policy changes include expansions of policy tools.

**Table 8 Coefficients of Determination of Model Components**

	# of vars.	1. Bid-ask spread	2. Effective cost	3. Ask volume	4. Bid volume	5. Low quote sec.
All variables	35	42.9%	30.8%	39.9%	41.0%	61.8%
Intraday pattern	9	0.9%	0.4%	1.0%	1.1%	0.3%
Daily prediction	1	31.3%	15.8%	13.0%	28.2%	51.6%
Lagged variables	12	36.0%	29.6%	39.5%	38.0%	60.6%
Econ. Announcements	1	0.1%	0.1%	0.0%	0.0%	0.0%
MP Announcements	1	0.0%	0.0%	0.0%	0.0%	0.0%
Econ. surprises	11	0.1%	0.2%	0.1%	0.1%	0.1%

	# of vars.	6. Amihud ILLIQ	7. Liquidity index	8. Number of trades	9. Trade volume	10. Volume per trade	11. Abs. return
All variables	35	13.3%	46.1%	42.9%	26.3%	18.3%	20.7%
Intraday pattern	9	0.2%	0.3%	5.5%	5.1%	0.5%	1.2%
Daily prediction	1	5.2%	34.7%	14.0%	3.8%	14.2%	12.9%
Lagged variables	12	11.9%	45.1%	39.6%	23.2%	10.3%	13.1%
Econ. Announcements	1	0.0%	0.0%	0.3%	0.2%	0.0%	0.2%
MP Announcements	1	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Econ. surprises	11	0.0%	0.0%	0.4%	0.3%	0.0%	0.3%

Note: The values in the table show the values of the coefficients of determination ( $R^2$ , except Column “# of vars.”; this column shows the numbers of explanatory variables). The values in the “All variables” row show the coefficient of determination in the case that all explanatory variables in equation (1) are considered. The values below show the coefficient of determination in the case that only the leftmost explanatory variables are considered.

**Table 9 Regression Coefficients ( $\beta_{EI}$  and  $\beta_{MP}$  for Announcement Dummies)**

	$\beta_{EI}$ (all econ-indicators)			$\beta_{MP}$ (monetary policy)		
	Coef.		p-value	Coef.		p-value
1 Bid-ask spread	0.008		(0.30)	0.088	(-)	(0.00)
2 Effective cost	0.000		(0.95)	0.024	(-)	(0.00)
3 Ask volume	-11.766	(-)	(0.06)	-3.242		(0.75)
4 Bid volume	1.105		(0.85)	-2.748		(0.77)
5 Low quote seconds	2.147		(0.41)	20.235	(-)	(0.00)
6 Amihud ILLIQ	0.001		(0.84)	-0.002		(0.60)
7 Liquidity index	0.004	(-)	(0.04)	0.009	(-)	(0.00)
8 Number of trades	-13	(-)	(0.00)	98	(+)	(0.00)
9 Trade volume	-114	(-)	(0.00)	557	(+)	(0.00)
10 Volume per trade	-0.899	(-)	(0.01)	-0.785		(0.14)
11 Absolute return	-0.416	(*)	(0.00)	1.880	(*)	(0.00)

Note: For the indicators except the absolute return, the sign in parentheses shows that the coefficient is significant with 10% level, and that the direction is positive (+) or negative (-) for the liquidity. For an absolute return, the (\*) signs show the coefficient is significant with 10% level.

recchia (1994). Since the time resolution is five-minutely, however, a combination of these opposite reactions can be observed in our analysis. With more frequent resolutions, it is possible that the reaction immediately after the announcement predicted by Kim and Verrecchia (1994) is also observed in the case of  $\beta_{MP}$ .

As for  $\beta_{s,j}$ , it is easily observed that the signs in the volume indicators are all positive and that the coefficients of the absolute return are mostly positive (5 out of 7 significant cases), showing more volume and volatility after surprise. These reactions are the same as the case after traders' information processing proposed by Kim and



**Table 10 Regression Coefficients ( $\beta_{s,j}$  for Macroeconomic Indicator Surprises)**

	Coef.	p	Coef.	p	Coef.	p	Coef.	p
	Capacity investments		CPI ex. FF		GDP deflator		GDP growth	
1 Bid-ask spread	0.000	(0.99)	0.011	(0.41)	0.038	(-)	0.008	(0.68)
2 Effective cost	0.003	(0.57)	-0.003	(0.32)	0.009	(-)	-0.001	(0.82)
3 Ask volume	-12.934	(0.43)	-20.449	(-)	-6.193	(0.69)	-8.466	(0.58)
4 Bid volume	5.116	(0.74)	0.724	(0.94)	-16.880	(0.25)	8.810	(0.54)
5 Low quote sec.	0.293	(0.97)	6.425	(0.14)	10.556	(-)	22.775	(-)
6 Amihud ILLIQ	0.002	(0.76)	0.002	(0.71)	0.005	(0.44)	0.003	(0.64)
7 Liquidity index	-0.001	(0.80)	0.003	(0.36)	0.000	(0.97)	0.000	(0.93)
8 # of trades	9	(0.38)	-6	(0.40)	11	(0.26)	32	(+)
9 Trade volume	155	(+)	-42	(0.47)	-13	(0.88)	240	(+)
10 Vol. per trade	1.757	(+)	0.057	(0.92)	0.110	(0.90)	0.211	(0.80)
11 Absolute return	0.576	(*)	0.173	(0.39)	-1.789	(*)	2.419	(*)

	IIP		Job offering		Machinery order		PPI	
1 Bid-ask spread	0.021	(0.12)	0.004	(0.80)	-0.002	(0.87)	0.021	(0.11)
2 Effective cost	0.004	(0.21)	-0.001	(0.71)	0.003	(0.36)	0.001	(0.78)
3 Ask volume	-0.546	(0.96)	30.856	(+)	-1.665	(0.87)	2.133	(0.83)
4 Bid volume	-7.520	(0.45)	0.323	(0.98)	3.788	(0.70)	-1.413	(0.88)
5 Low quote sec.	1.874	(0.67)	7.815	(-)	-3.378	(0.43)	6.792	(-)
6 Amihud ILLIQ	0.001	(0.77)	0.006	(0.23)	0.002	(0.72)	0.006	(0.18)
7 Liquidity index	-0.004	(0.17)	-0.002	(0.45)	-0.001	(0.61)	-0.001	(0.83)
8 # of trades	13	(+)	6	(0.42)	4	(0.60)	1	(0.85)
9 Trade volume	87	(0.14)	72	(0.26)	77	(0.18)	21	(0.70)
10 Vol. per trade	0.210	(0.71)	0.360	(0.55)	1.259	(+)	0.115	(0.83)
11 Absolute return	0.240	(0.24)	0.687	(*)	0.212	(0.29)	0.445	(*)

	Tankan		Unemployment		Wage	
1 Bid-ask spread	0.022	(0.32)	-0.009	(0.56)	-0.004	(0.81)
2 Effective cost	-0.001	(0.86)	0.004	(0.24)	0.001	(0.87)
3 Ask volume	-26.287	(0.13)	-5.923	(0.60)	-2.716	(0.81)
4 Bid volume	0.473	(0.98)	-11.636	(0.28)	21.363	(+)
5 Low quote sec.	2.737	(0.71)	-3.396	(0.48)	-0.281	(0.95)
6 Amihud ILLIQ	0.004	(0.57)	-0.005	(0.32)	-0.005	(0.31)
7 Liquidity index	0.006	(0.23)	0.000	(0.88)	-0.003	(0.30)
8 # of trades	58	(+)	0	(0.95)	14	(+)
9 Trade volume	391	(+)	-13	(0.84)	165	(+)
10 Vol. per trade	0.127	(0.89)	0.298	(0.62)	1.321	(+)
11 Absolute return	1.621	(*)	-0.429	(*)	0.256	(0.25)

Note: For the indicators except the absolute return, the sign in parentheses shows that the coefficient is significant with 10% level, and that the direction is positive (+) or negative (-) for the liquidity. For an absolute return, the (\*) signs show the coefficient is significant with 10% level.

Verrecchia (1994), consistent with the fact that surprises convey new information. As for the other seven liquidity indicators classified into tightness, depth and resiliency categories, the number of the significantly non-zero  $\beta_{s,j}$  is 9, about 12% of all cases. Among these, 7 coefficients are in the direction of lowering liquidity. Therefore, while weaker than its announcement, an EI surprise has the effect of lowering liquidity.

Combined with the significance of  $\beta_{EI}$ ,  $\beta_{MP}$ , and  $\beta_{s,j}$ , it seems fair to conclude that the tightness, depth, and resiliency indicators decrease after an EI announcement, a MP announcement, and an EI surprise. The volume indicators decrease after an EI

**Table 11 Correlation Coefficients between Error Terms**

	1	2	3	4	5	6	7	8	9	10
1 Bid-ask spread	1									
2 Effective cost	0.28	1								
3 Ask volume	0.08	0.04	1							
4 Bid volume	0.07	0.02	-0.26	1						
5 Low quote seconds	0.31	0.12	0.01	0.11	1					
6 Amihud ILLIQ	0.00	0.00	-0.02	-0.03	0.00	1				
7 Liquidity index	0.19	0.19	0.14	0.13	0.22	-0.01	1			
8 Number of trades	-0.21	-0.23	-0.05	-0.04	-0.09	0.10	-0.11	1		
9 Trade volume	-0.13	-0.18	-0.05	-0.04	-0.04	0.11	-0.05	0.83	1	
10 Volume per trade	0.04	-0.03	-0.02	-0.02	0.05	0.07	0.01	0.09	0.41	1
11 Absolute return	0.13	0.28	0.01	0.01	0.05	0.33	0.14	-0.43	-0.37	-0.11

Note: The correlation coefficients are shown for the case that all the explanatory variables in equation (1) are included in the regression. The signs are adjusted so that positive correlation indicates the same direction of liquidity except those regarding an absolute return.

announcement, but increase if the EI announcement is surprising, and always increase after an MP announcement. Table 11 shows the correlation coefficients of the error terms in equation (1), in which the signs are adjusted so that the positive value means the same direction of the liquidity. The table shows that the correlations are generally weak, indicating the multitude of determinants of liquidity indicators. Some exceptions are those between the absolute return and the number of trades, between the absolute return and the trade volume, and between the number of trades and the trade volume. The first two can be explained by the relation between the volatility (the daily version of the absolute return) and the trade volume documented in the previous studies such as Kim and Verrecchia (1994), and the last one is the expected relation.

#### D. Persistence of Market Liquidity

Kurosaki *et al.* (2015) point out that, by utilizing the vector autoregressive model incorporating the price changes and the volumes of trades and limit orders, the recovery speed of the JGB futures order book has been declining since 2012.<sup>20</sup> Through this slowdown of recovery speed, the more frequent jumps in the tightness and depth indicators indicated by BIS (2016) may have a considerable impact on liquidity. In this paper, we statistically detect and confirm whether the speed has declined, and in which indicator we can observe the decline.

First, we applied the statistical detection method of breakpoints. Assuming that coefficient parameters in equation (1) change a finite number of times at breakpoints, we detect the breakpoints minimizing the residuals square sum. Following Yao (1988) and Bai and Perron (2003), we determine the number of the breakpoints on the basis of the BIC.<sup>21</sup> If there are  $m$  breakpoints, then there are  $(m + 1)$  subperiods. Utilizing the method of partial optimization by Bai and Perron (2003), we allow structural changes

20. This speed is usually referred to as the *resiliency* in the studies of limit order book (Large, 2007), while Kyle (1985) use the word for the price recovery speed. In this paper we follow Kyle (1985) for the definition of the word, and represent the order book recovery speed by the concept of *persistence* in the following discussion, for distinction purpose.

21. We also tried to determine  $m$  by the sup  $F$  type test proposed by Bai and Perron (1998), and obtained more breakpoints in addition to those by the BIC. In order to avoid detecting too many breakpoints, we use the BIC.

**Table 12 Breakpoints of Intraday Patterns**

		Detected subperiods (Half-life in minutes)			
<b>1.Bid-ask spread</b>	2011/11 – 2013/03 (13.01)	2013/04 – 2013/06 (17.34)	2013/07 – 2015/5 (15.11)		
<b>2.Effective cost</b>	2011/11 – 2013/03 (11.59)	2013/04 (17.27)	2013/05 – 2013/06 (14.93)	2013/07 – 2015/5 (13.55)	
<b>3.Ask volume</b>	2011/11 – 2013/3 (14.42)	2013/04 – 2013/8 (15.99)	2013/09 – 2014/4 (15.79)	2014/05 – 2014/10 (18.17)	2014/11 – 2015/5 (17.73)
<b>4.Bid volume</b>	2011/11 – 2013/3 (14.59)	2013/04 – 2015/5 (17.63)			
<b>5.Low quote seconds</b>	2011/11 – 2013/3 (13.43)	2013/04 – 2013/6 (19.09)	2013/07 – 2015/5 (16.79)		
<b>6.Amihud ILLIQ</b>	2011/11 – 2013/3 (9.50)	2013/04 (8.26)	2013/05 – 2015/5 (11.17)		
<b>7.Liquidity index</b>	2011/11 – 2013/4 (18.44)	2013/05 (14.61)	2013/06 (15.78)	2013/07 – 2015/5 (16.15)	
<b>8.Number of trades</b>	2011/11 – 2015/5 (8.47)				
<b>9.Trade volume</b>	2011/11 – 2015/5 (15.98)				
<b>10.Volume per trade</b>	2011/11 – 2013/3 (4.94)	2013/04 – 2015/5 (4.38)			
<b>11.Absolute return</b>	2011/11 – 2013/3 (2.39)	2013/04 (4.60)	2013/05 – 2013/6 (2.75)	2013/07 – 2014/10 (2.33)	2014/11 – 2015/5 (2.57)

Note: The regression model is specified by equation (1) except that event variables ( $Dum_{EI,t}$ ,  $Dum_{MP,t}$ , and  $|s_{j,t}|$ ) are excluded. The coefficient of intraday lag terms ( $\beta_{I,-i}$ ) are assumed to change at the breakpoints, and the other coefficients are fixed. We follow Yao (1988) and Bai and Perron (2003) to find breakpoints, restricting the candidates of the breakpoints to the beginning of the month.

only in the coefficients of the intraday lag effect ( $\beta_{I,i}$ ) and the intercept  $\alpha$  in equation (1); the other pattern coefficients ( $\beta_{\text{session}}$ ,  $\beta_{\sin q}$ ,  $\beta_{\cos q}$ , and  $\beta_{I_d}$ ) are assumed to be fixed across the whole period and the coefficient of event analysis ( $\beta_{EI}$ ,  $\beta_{MP}$ , and  $\beta_{s,j}$ ) to be zero. In addition, to reduce the number of breakpoints, we limit the candidates of breakpoints only to the beginning of the month. Consequently, we obtained the subperiods tabulated in Table 12.<sup>22</sup>

22. In addition, we tried the case allowing other pattern coefficients ( $\beta_{\text{session}}$ ,  $\beta_{\sin q}$ ,  $\beta_{\cos q}$ , and  $\beta_{I_d}$ ) to change at the breakpoints, and obtained subperiods similar to those in Table 12. Furthermore, fixing the breakpoints shown in Table 12, we applied the F-test to compare the model where the other pattern coefficients can also

Next, we measure the persistence of shock. Supposing a unit shock occurs at time  $t = 0$ , we compute the shock remaining at time  $t$  based on equation (1). Using this remaining shock, we measure the half-life, the time elapsed until a unit shock decays to half, also tabulated in and Bai and Perron (2003).<sup>23</sup> The values of the half-lives range from 2.33 minutes (in the absolute return from 2013/7 to 2014/10) to 19.09 minutes (in the low quote seconds from 2013/4 to 2013/6). If the half-life is 18 minutes, then it takes about an hour for a unit shock to decay to 0.1, suggesting that an intraday shock remains within the session (about two hours) in which the shock occurs. These values seem short, but are much longer than the length from 9:33 to 9:45 a.m. EDT on October 15, 2014, during which a sudden price surge and liquidity depletion were observed in the U.S. Treasury market (U.S. Department of the Treasury *et al.*, 2015), suggesting that a similar event in the JGB market would have a considerable impact on the liquidity.

We also plot the chart of the half-lives in Figure 9. In the tightness and depth indicators and the absolute return, the half-life increased around April 2013, on which day the Bank of Japan introduced quantitative and qualitative monetary easing. In the absolute return, the half-life decreased in one month to the level before April 2013, showing that increased persistence in the month is only temporary. In the tightness indicators and the low quote seconds, the half-lives also decreased in two or three months, and then stayed higher than before 2013, showing not only the temporary effect but also the long-term tendency of increasing persistence. In the ask volume and bid volume, the half-lives increased not only in April 2013 but also in later months, showing that the increasing persistence is not specific to April 2013 but is a general tendency during the period. These results show the slower recovery from the shock of liquidity measured in these liquidity indicators, suggesting more vulnerability of the market against a shock even if no change of liquidity level is supposed.<sup>24</sup>

## IV. Conclusion

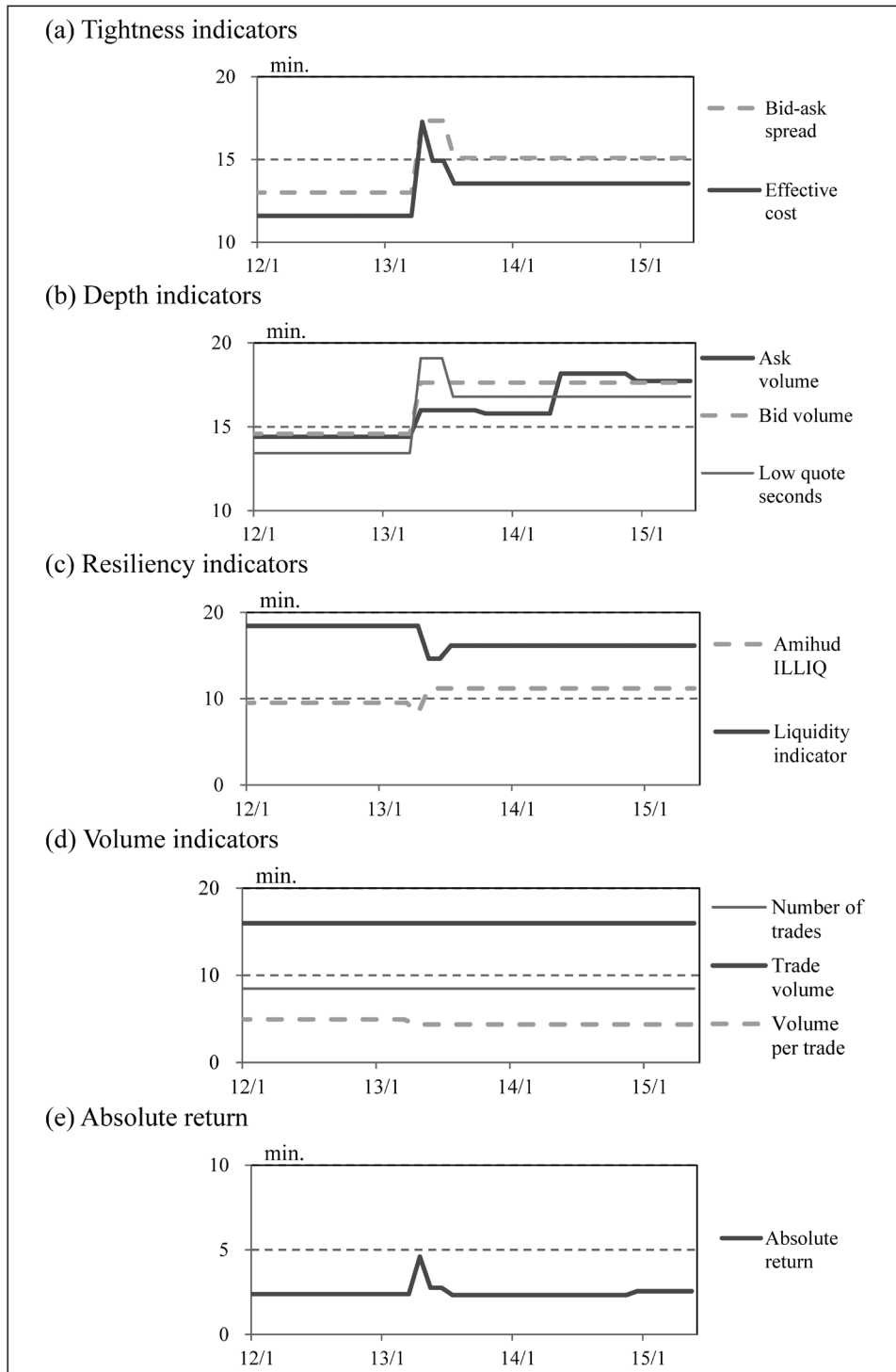
This paper contributes to providing a basis for the discussion about intraday market liquidity movement of the JGB futures. First, we compare various kinds of liquidity indicators within the four categories: tightness, depth, resiliency, and volume, extending these indicators into an intraday basis. Second, confirming the significance of the intraday pattern and autocorrelation within these liquidity indicators, we estimate the effect on the liquidity evoked by the economic indicator announcements, economic indicator surprises, and monetary policy announcements. As for the tightness, depth and

---

change and the model where only  $\beta_{I,i}$  can change, and obtained the result that the other pattern coefficients can also change. Therefore, it is expected that the intraday pattern has also changed during the observation period. Since we focus on the change of persistence in the following discussion, however, we show only the model where only  $\beta_{I,i}$  can change.

23. To compute the half-life, we use the linear regression in which the variable explained is the log of the remaining shock and the explanatory variable is the time elapsed from  $t = 1$  (5 min.) to 12 (60 min.). To capture the non-exponential element of the remaining shock, we also analyze the details of the remaining shock around one hour. The results are almost the same as those of the half-lives.
24. Note that the volume indicators show no evident changes of half-lives. As for the resiliency indicators, two indicators show mixed directions around April 2013, suggesting no clear tendency of persistence change in the resiliency indicators as a whole.

**Figure 9 Half-life of Unit Shock**



Note: The remaining shocks are computed by equation (1) under the assumption of a unit shock at time 0. The breakpoints are detected by the method by Yao (1988) and Bai and Perron (2003).

resiliency indicators, these events always lower liquidity. The effect on the volume indicators and the absolute return depends on the new information. Finally, we detect the structural changes of the model by statistical means, suggesting not a temporary increase of the liquidity shock persistence around April 2013 but also a tendency of the persistence to increase over the long term.

What brings the breakpoints detected during the analysis period is not fully investigated in this paper; whereas that around April 2013 can be related to the monetary policy. The expanding algo-trades and developing post-crisis financial regulation on arbitrage trading may cause the other breakpoints, which need to be investigated. The relation of the liquidity of the futures with that of the underlying assets, that is, the JGB cash bonds, is also an important issue not covered in this paper. The liquidity indicators such as price impact remain to be investigated further. Studying other types of announcements including open market operation would also be interesting.

## References

- Admati, Anat R., and Paul Pfleiderer, "A Theory of Intraday Patterns: Volume and Price Variability," *Review of Financial Studies*, 1(1), 1988, pp. 3–40.
- Amihud, Yakov, "Illiquidity and Stock Returns: Cross-section and Time-series Effects," *Journal of Financial Markets*, 5(1), 2002, pp. 31–56.
- Andersen, Torben G., "Return Volatility and Trading Volume: An Information Flow Interpretation of Stochastic Volatility," *Journal of Finance*, 51(1), 1996, pp. 169–204.
- , and Tim Bollerslev, "Intraday Periodicity and Volatility Persistence in Financial Markets," *Journal of Empirical Finance*, 4, 1997, pp. 115–158.
- , and ———, "Deutsche Mark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies," *Journal of Finance*, 53(1), 1998, pp. 219–265.
- , ———, Francis X. Diebold, and Heiko Ebens, "The Distribution of Realized Stock Return Volatility," *Journal of Financial Economics*, 61(1), 2001, pp. 43–76.
- , ———, and Paul Labys, "Modeling and Forecasting Realized Volatility," *Econometrica*, 71(2), 2003, pp. 579–625.
- , ———, ———, and Clara Vega, "Real-time Price Discovery in Global Stock, Bond and Foreign Exchange Markets," *Journal of International Economics*, 73(2), 2007, pp. 251–277.
- Bai, Jushan, and Pierre Perron, "Estimating and Testing Linear Models with Multiple Structural Changes," *Econometrica*, 66(1), 1998, pp. 47–78.
- and ———, "Computation and Analysis of Multiple Structural Change Models," *Journal of Applied Econometrics*, 18(1), 2003, pp. 1–22.
- Balduzzi, Pieluigi, Edwin J. Elton, and T. Clifton Green, "Economic News and Bond Prices: Evidence from the U.S. Treasury Market," *Journal of Financial and Quantitative Analysis*, 36(4), 2001, pp. 523–543.
- Bank for International Settlements (BIS), "Fixed Income Market Liquidity," CGFS Papers No. 55, January 2016.
- Bollen, Nicolas P. B., and Robert E. Whaley, "Are 'Teenies' Better?" *Journal of Portfolio Management*, 25(1), 1998, pp. 10–24.
- D'Souza, Chris, and Charles Gaa, "The Effect of Economic News on Bond Market Liquidity," Working Paper No. 2004-16, Bank of Canada, 2004.
- Engle, Robert F., Takatoshi Ito, and Wen-Ling Lin, "Meteor Showers or Heat Waves? Heteroskedastic Intra-Daily Volatility in the Foreign Exchange Market," *Econometrica*, 58(3), 1990, pp. 525–542.
- Fleming, Michael J., "Measuring Treasury Market Liquidity," *Economic Policy Review*, 9(3), 2003, pp. 83–108.
- Fleming, Michael J., and Eli M. Remolona, "Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information," *Journal of Finance*, 54(5), 1999, pp. 1901–1915.
- Goyenko, Ruslan Y., Craig W. Holden, and Charles A. Trzcinka, "Do Liquidity Measures Measure Liquidity?" *Journal of Financial Economics*, 92(2), 2009, pp. 153–181.
- Harvey, Campbell R. and Roger D. Huang, "Volatility in the Foreign Currency Futures Market," *Review of Financial Studies*, 4(3), 1991, pp. 543–569.
- Iwatsubo, Kentaro, and Tomoki Taishi, "Quantitative Easing and Liquidity in the Japanese Government Bond Market," IMES Discussion Paper No. 2016-E-12, Institute for Monetary and Economic Studies, Bank of Japan, 2016.
- Karnaukh, Nina, Angelo Ranaldo, and Paul Söderlind, "Understanding FX Liquidity," *Review of Financial Studies*, 28(11), 2015, pp. 3073–3108.
- Kim, Oliver, and Robert E. Verrecchia, "Market Liquidity and Volume around Earnings Announcements," *Journal of Accounting and Economics*, 17(1–2), 1994, pp. 41–67.
- Kurosaki, Tetsuo, Yusuke Kumano, Kota Okabe, and Teppei Nagano, "Liquidity in JGB Markets: An Evaluation from Transaction Data," Bank of Japan Working Paper No. 15-E-2, 2015.



- Kyle, Albert S., "Continuous Auctions and Insider Trading," *Econometrica*, 53(6), 1985, pp. 1315–1335.
- Large, Jeremy, "Measuring the Resiliency of an Electronic Limit Order Book," *Journal of Financial Markets*, 10(1), 2007, pp. 1–25.
- Liu, Weimin, "A Liquidity-augmented Capital Asset Pricing Model," *Journal of Financial Economics*, 82(3), 2006, pp. 631–671.
- Miyanoya, Atsushi, Hirotaka Inoue, and Hideaki Higo, "Nihon no Kokusai Shijou no Microstructure to Shijouryuudousei (Microstructure and Liquidity in JGB Markets)," Working Paper No. 99-J-1, Financial Markets Department, Bank of Japan, 1999 (in Japanese).
- Neely, Christopher J., "A Survey of Announcement Effects on Foreign Exchange Volatility and Jumps," *Review*, 93(5), Federal Reserve Bank of St. Louis, 2011, pp. 361–385.
- Nishizaki, Kenji, Akira Tsuchikawa, and Tomoyuki Yagi, "Indicators Related to Liquidity in JGB Markets," *Bank of Japan Review*, No. 2013-E-3, Bank of Japan, 2013.
- Pástor, Ľuboš, and Robert F. Stambaugh, "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy*, 111(3), 2003, pp. 642–685.
- Rogers, John H., Chiara Scotti, and Jonathan H. Wright, "Evaluating Asset-market Effects of Unconventional Monetary Policy: A Multi-country Review," *Economic Policy*, 29(80), 2014, pp. 749–799.
- Rühl, Tobias R., and Michael Stein, "The Impact of ECB Macro-announcements on Bid-ask Spreads of European Blue Chips," *Journal of Empirical Finance*, 31, 2015, pp. 54–71.
- U.S. Department of the Treasury, Board of Governors of the Federal Reserve System, Federal Reserve Bank of New York, U.S. Securities and Exchange Commission, and U.S. Commodity Futures Trading Commission, "Joint Staff Report: The U.S. Treasury Market on October 15, 2014," July 2015.
- Tanemura, Tomoki, Yasunari Inamura, Shinichi Nishioka, Hideaki Hirata, and Tokiko Shimizu, "Liquidity in JGB Markets—Analysis on the Intraday Bid-Ask Spreads—," *Market Review* No. 2004-E-1, Financial Markets Department, Bank of Japan, 2004.
- Tetlock, Paul C., "Does Public Financial News Resolve Asymmetric Information?" *Review of Financial Studies*, 23(9), 2010, pp. 3520–3557.
- Wright, Jonathan H., "What does Monetary Policy do to Long-term Interest Rates at the Zero Lower Bound?" *Economic Journal*, 122(564), 2012, pp. F447–F466.
- Yao, Yi-Ching, "Estimating the Number of Change-points via Schwarz' Criterion," *Statistics and Probability Letters*, 6(3), 1988, pp. 181–189.