Monetary Policy Announcements and Algorithmic News Trading in the Foreign Exchange Market

Keiichi Goshima and Yusuke Kumano

We analyze the effects of Algorithmic News Trading (ANT) in the foreign exchange market around the time that the Bank of Japan makes public announcements of its policy decisions. To observe the activity level of ANT, we propose a novel measure based on a web access record to a central bank's webpage. We find that our proposed measure appropriately captures the activity level of ANT. Employing an event study analysis and a VAR analysis, we find that ANT increases market volatility immediately after the monetary policy announcements, and that ANT activity indirectly decreases market liquidity through increasing volatility. In addition, we suggest that ANT trades based on changes in texts on the monetary policy announcements.

Keywords: Algorithmic trading; Monetary policy; Foreign exchange market; News trading; Market microstructure
JEL Classification: E58, F31, G14

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I. Introduction

The Algorithmic Trading (AT) is now widely employed in the financial business, with widespread use of electronic trading platforms and advancement of information technology. AT is commonly defined as the use of computer algorithms to automatically make certain trading decisions, submit orders, and manage those orders after submission (Hendershott, Jones, and Menkveld [2011]). Recently, AT is expanding both in quantity and quality, i.e., transaction volume as well as trading strategies, due to the increased availability of big data, increase in computational resources, and development of computer science technology.

Many parties, including market participants, securities exchanges and financial authorities, have a great interest in how the growth of AT influences financial markets. For market participants, AT enables them to seek alpha, save trading costs, and reduce capital costs. For securities exchanges and financial authorities, AT needs to be examined whether to ensure the stability and sustainability of financial systems through enhancing market efficiency and price discovery function.

Many empirical studies show that AT and the High-Frequency Trading (HFT) generally contributes to improving market efficiency and price discovery function, suggesting that AT is beneficial to financial markets on the whole (Hendershott, Jones, and Menkveld [2011], Hasbrouck and Saar [2013], Brogaard, Hendershott, and Riordan [2014], Chaboud *et al.* [2014]).[1] However, when the market condition is different from normal, it is not obvious that AT improves market quality in terms of factors like market volatility and liquidity. The Bank for International Settlements (2017) points out that "With fewer traders relying more heavily on algorithms, the market may tend to move in the same direction. In this setting, sudden FX moves might be amplified, increasing volatility." Some HFT kept trading and submitting orders during "Flash Crash," which was a period of large and temporary selling pressure, and this behavior was different from traditional market makers (Kirilenko *et al.* [2017]). Weller (2018) shows that AT has a large negative effect on information acquisition up to a month before scheduled disclosures.

What factors account for those differences in empirical findings? One factor could be that the effect of AT in financial markets varies depending on AT strategies and market conditions. As market participants have various transactions motives and operate different trading strategies, there are also various AT strategies in the financial business, such as "market-making," "arbitrage," and "directional." Each AT strategy is known to take a different trading and ordering behavior. Different types of AT are activated in different market states. To achieve a deeper understanding of the effect of AT on market quality, we need to examine closely the effect of a specific AT under a specific market condition.

In this paper, we study the effects of the Algorithmic News Trading (ANT) in the foreign exchange market around the time that the Bank of Japan (BOJ) makes public announcements of its policy decisions. ANT is one AT strategy. By making use of advanced computer science technology, ANT extracts new information directly from

1. HFT is a subset of AT, which automatically operates at the level of milliseconds or microseconds (U.S. Securities and Exchange Commission [2010] and Bank for International Settlements [2011]).

websites and information terminals and then automatically makes trading. For example, in the case of a monetary policy announcement by a central bank, computer programs try to obtain documents on monetary policy decisions from the central bank's website just after their release, and then immediately and automatically execute orders.

To examine the effects of ANT, we propose a novel measure of the activity level of ANT constructed from the access record of the BOJ's webpage. We focus on the fact that the BOJ makes an announcement of its policy decisions immediately after concluding the MPM. That is, the BOJ's publication times of its statement on monetary policy decisions varies at each MPM. Moreover, unlike in the case of the Federal Reserve System and the European Central Bank, the BOJ does not notify the times in advance. When ANT trades based on the BOJ's policy announcements, they tend to repeatedly visit the BOJ's website well before the expected policy announcement time, so as to obtain primary information of the monetary policy announcements immediately after its release.

Using this ANT measure, we conduct an event study analysis and a Vector Autoregression (VAR) analysis to examine the intraday effects of ANT on market volatility and market liquidity of the USD/JPY foreign exchange market by using high frequency datasets. We find that ANT significantly increases market volatility immediately after the monetary policy announcements and that ANT indirectly decreases market liquidity through increasing market volatility. Furthermore, we suggest that ANT trades based on changes in texts on the monetary policy announcements. To the best of our knowledge, we present the first trial to uncover ANT activity by focusing on its effects on the foreign exchange market around the monetary policy announcements.

The remainder of this paper is organized as follows. Section 2 briefly discusses the related literature on the effect of AT in financial markets and the analysis of macroeconomic news releases. Section 3 provides details of our analytical framework, such as the concept of ANT, our data, and our measures of ANT. Section 4 examines the effect of ANT on market quality using the event study methodology. Section 5 studies the integrated effect of ANT, compared with the effect of monetary policy surprises using the time-series methodology. Finally, Section 6 concludes the paper.

II. Related Literature

A. Empirical Studies on Algorithmic Trading

Most studies on AT discuss how the growth of AT influences market efficiency and price discovery function. Hendershott, Jones, and Menkveld (2011) compute a proxy for AT activity level in the New York Stock Exchange using electronic message traffic, and concludes that AT narrows spreads, reduces adverse selection costs, and improves market price discovery function. Hendershott and Riordan (2013) show that AT consumes market liquidity when it is cheap, and provides market liquidity when it is expensive, likely stabilizing market liquidity in the 30 Deutscher Aktienindex stocks on the Deutsche Boerse. Chaboud *et al*. (2014) describe that AT improves two measures of price efficiency in the foreign exchange market: the frequency of triangular arbitrage opportunity and the autocorrelation of high frequency returns. Boehmer, Fong, and Wu (2015) present that AT improves market liquidity and informational efficiency but increases market volatility. Most report that AT on the whole contributes to improving market quality, including market volatility and market liquidity.

Few previous studies identify AT strategies, because it is too difficult to identify AT strategies from publicly available data on orders and transactions. The data do not contain the identity of buyers and sellers, and do not reveal the AT activity level directly. Therefore, most empirical studies attempt to calculate proxies for the AT activity level indirectly from publicly available data, such as the volume of electronic message traffic, and the ratio of deal to quote. These indirect approaches in the previous empirical studies enable us to examine the effect of AT on the whole, but not the effect of a specific AT strategy. Only a few studies directly measure the AT activity level using a unique dataset, such as audit-trail data (Menkveld [2013], Chaboud *et al*. [2014], Brogaard, Hendershott, and Riordan [2014], and Kirilenko *et al*. [2017]). Even the rich information attached to publicly unavailable data does not record the identity of AT strategies. Hence, we need to take a different approach to understand the effect of a specific AT strategy.

We contributes to these empirical studies by examining the effect of ANT on foreign exchange markets using a novel measure to directly capture ANT activity level. By processing the access records of the BOJ's webpages around the time of the BOJ's monetary policy announcements, we specifically capture the activity level of the ANT strategy. By comparing with the transaction data of the foreign exchange market, we then examine the influence of ANT on the markets at the time of the monetary policy announcements.

B. Effect of Macroeconomic News on Financial Markets

This study is also related to the studies on the effect of macroeconomic news, such as the monetary policy announcements, and economic indicators releases on financial markets (Andersen *et al*. [2003], Bauwens, Omrane, and Giot [2005], Andersen *et al*. [2007], and Cheung, Fatum, and Yamamoto [2017]). Recently, due to increased availability of high frequency data, many studies attempt to analyze the intra-day effect of macroeconomic news (Conrad and Lamla [2010], and Demir [2014]). These studies focus on either how published information influences financial markets or how public information is reflected in asset prices from the view point of the informational efficiency of financial markets.[2] This study is classified as the former.

Several empirical studies show that macroeconomic news announcements influence market volatility and market liquidity through surprise components, which are defined as a deviation from market forecasts (Fatum and Scholnick [2008], Rosa [2011], Neely [2011], and Tsuchida, Watanabe, and Yoshiba [2016], etc.). However, according to these studies, surprise components only partly explain variations in asset prices. This is a puzzle in this field. Regarding this puzzle, Rigobon and Sack (2008) say that in measuring surprise components of the released macroeconomic statistical data, it is generally the case that errors in the market estimates (survey data) are ignored. They propose some improvement measures by using statistical procedures, including principal component analysis. Focusing on the monetary policy announcements, Rosa (2011)

2. In particular, since Fama (1970) has systematized the efficient market hypothesis, a great deal of empirical studies report, either supporting or disproving the hypothesis.

constructs two types of surprise indicators on monetary policy news stemming separately from policy decisions and balance of risk statements, and empirically analyze the effects of U.S. monetary policy surprises on level and volatility of foreign exchange rates. These approaches partly explain the puzzle, but do not explain it fully. Some important variables might be omitted.[3]

We show that fluctuations in ANT activity help explain this puzzle. In other words, ANT activity might provide a more elaborate analysis of asset price variation which is difficult to explain only with the monetary policy surprise component. Our study also implies that studies on macroeconomic news need to take the effect of ANT into consideration.

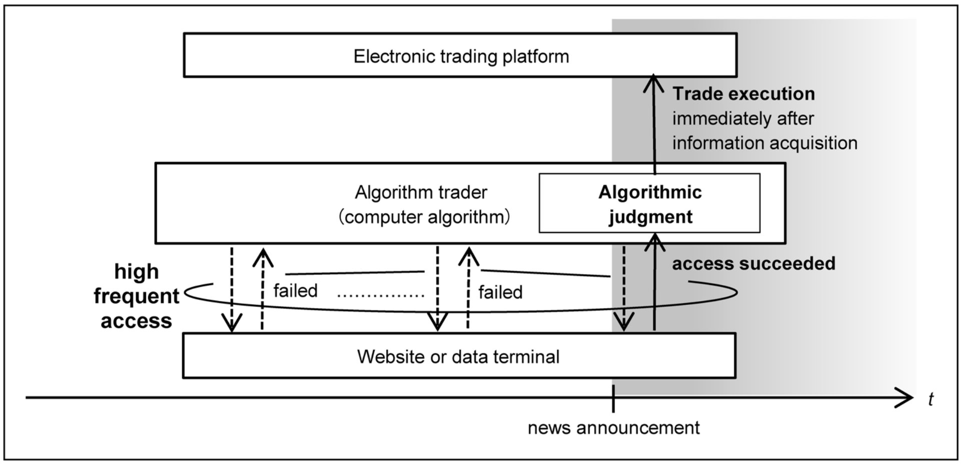
III. Concept and Measures of Algorithmic News Trading

A. Algorithmic News Trading

News plays an important role in financial markets, and thus many investors constantly use it for trading. News trading is one of the directional strategies, which detects and reacts to news announcements quickly, establishing positions based on past patterns between news announcements and price changes to profit. More recently, utilizing computer science technology for news analyses, such as computational linguistics and natural language processing, enables investors to process textual data and make trading decisions without human judgment. Investors who employ ANT are considered to be one type of "news trader," who tries to profit using new information that causes fundamental values to change (Harris [2003]). Figure 1 illustrates a work process of ANT.

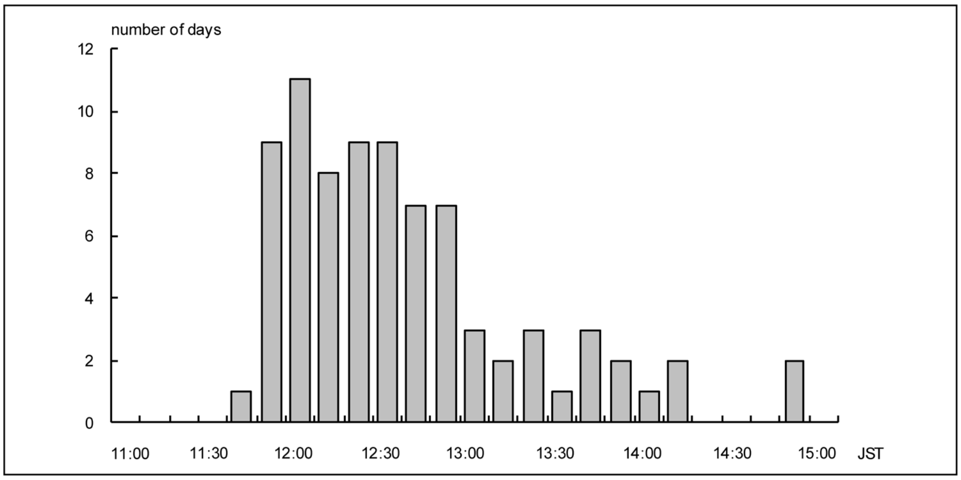
ANT repeatedly accesses websites and information terminals before a news re-

Figure 1 Work Process of Algorithmic News Trading



3. In addition, Andersen *et al*. (2003) and Swanson and Williams (2014) report that the sensitivity of asset price fluctuations to macroeconomics news announcements is time-varying. It may be thought that this time-varying is attributed in part to time-variation in market efficiency due to widespread use of AT. A natural progression of this work is to analyze this point.

Figure 2 Histogram of the Announcement Times on BOJ's Monetary Policy Statements



Note: The publication times of the BOJ's monetary policy statements on the MPM dates, from January 2011 to March 2017 (except for an unscheduled MPM on November 30, 2011).
Source: Bank of Japan

lease, and automatically extracts and analyzes information on news immediately after it release, thereby submitting orders.

In the case of the BOJ's monetary policy announcements, computer programs repeatedly access the BOJ websites to get documents immediately after the release of policy statements. Unlike in the case of the Federal Reserve System and the European Central Bank, the BOJ does not notify in advance the publication times of its statement on monetary policy decisions. Figure 2 shows the histogram of publication times on its monetary policy statements, and we can find that the time varied at each Monetary Policy Meeting (MPM).[4] Since ANT traders are assumed to repeatedly access the BOJ website until policy statements are released, we use the access record of BOJ's webpage to measure ANT activity level.

B. Measures of Algorithmic News Trading Activity

To trace the activity level of ANT, we use the access record of the BOJ's webpage to count only visitors who automatically access the documents on monetary policy decisions.[5] To be more specific, we extract visitors who may access the documents with machines, using four criteria: (1) access within two hours before the monetary policy statements are released; (2) access to the documents in English; (3) access through

4. Currently, the Federal Reserve System publishes its monetary policy decisions at 2:00 p.m. EST (Eastern Standard Time) or EDT (Eastern Daylight Time), and the European Central Bank publishes at 1:45 p.m. CET (Central European Time).
5. Web access records commonly contain information about "client IP address," "time stamp," "access request," "URL that referred (the URL of the previous webpage from which a link was followed)" and others. See the following websites which explain in detail "common log format" and "combined log format" originated at the National Center for Supercomputing Applications (NCSA).
http://publib.boulder.ibm.com/tividd/td/ITWSA/ITWSA_info45/en_US/HTML/guide/c-logs.html#common

the direct and automatic channel; (4) unique visitors (extracted by excluding duplicate visitors). Below, we explain the idea of each of the four criteria.

The first criterion is when a visitor accesses the BOJ's webpage. We sort visitors who access the monetary policy statement documents within two hours before the monetary policy statements are released. As mentioned above, if ANT is operating, we expect to observe someone continually accessing the BOJ website until policy statements are released. The publication times of monetary policy statements are recorded only at the minute level, with the number of seconds unavailable. We regard that documents were released exactly at the publication times.

The second criterion is whether a visitor accesses the monetary policy statement documents in English, rather than in Japanese. The BOJ releases monetary policy statements in both English and Japanese at the same time. Since there are more tools of computational linguistics and natural language processing for analyzing English text than for Japanese text, we consider visitors who access English documents as ANT investors.

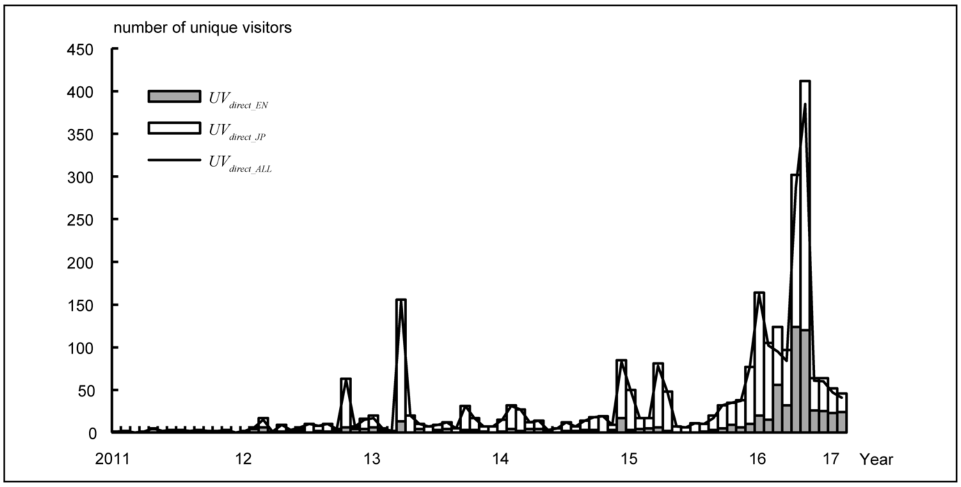
The third criterion is whether a visitor browses any other webpages before accessing the URL of the monetary policy statement documents. If visitors take advantage of web scraping, they are likely to predict in advance the URL of a webpage for the monetary policy statement. Thus, we regard visitors who directly access the URL of the monetary policy statement before the announcement time as ANT investors.[6] Finally, we count the number of unique visitors, not the number of times accessed, to the monetary policy statement document in order to observe how many ANT investors are active at that time. A unique visitor refers to a distinct individual requesting the specified website during a given period, regardless of how often they visit. We count the number of IP addresses excluding duplications from the access record of BOJ's webpage.

The mean number of times accessed per minute per person to the documents within two hours before it was released on the MPM dates from January 2011 to March 2017 for each language (English or Japanese) and each channel (direct or indirect) are (direct/English) : (direct/Japanese) : (indirect/English) : (indirect/Japanese) = 22 : 12 : 1 : 4. Direct visitors generally accessed the documents more frequently than indirect visitors. In particular, visitors who access English documents directly tend to access in the most frequent manner. Indeed, such visitors typically access the English documents repeatedly from 1 to 2 hours before publication, in an extremely high-frequent manner with a constant interval.[7] We thus use the number of unique visitors who directly access the URL of the English documents on the BOJ's monetary policy announcements on the MPM dates, UV_{direct_EN}, as a proxy variable for ANT activity level, the ANT indicator.

Figure 3 plots the number of unique visitors (UV_{direct_EN}) who directly access the

6. Depending on the content on the MPM, in some cases the BOJ published multiple documents at times, but we count only the number of unique visitors who accessed the first document.
7. Particularly during the period from 2015 to 2016, in the foreign exchange market, we can observe a remarkable widening of the USD/JPY bid-offer spread from 1 to 2 hours before monetary policy announcements. Such market movements are thought not to be directly related to ANT which affects the market not before but after the announcement. However, it indicated that the market on the whole prepares for monetary policy announcements from 1 to 2 hours before publication.

Figure 3 Number of Unique Visitors



Note: The horizontal axis indicates the monetary policy announcement dates (except for an unscheduled MPM on November 30, 2011), while the vertical axis indicates the total number of unique visitors for 2 hours before the monetary policy announcements. Since UV_{direct_EN} and UV_{direct_JP} may overlap, the sum of both is not equal to UV_{direct_ALL}. The latest date is March 19, 2017.
Source: Bank of Japan

URL of the English documents within two hours before they are released on the MPM dates. We also show the number of all unique visitors (UV_{direct_ALL}) and those who directly access Japanese documents (UV_{direct_JP}).

According to Figure 3, all three indicators, UV_{direct_EN}, UV_{direct_JP}, and UV_{direct_ALL} recently decreased somewhat, but generally follow an increasing trend in the long run. In the next section, comparing these three series (UV_{direct_EN}, UV_{direct_JP}, and UV_{direct}), we verify that UV_{direct_EN} especially captures the activity level of ANT appropriately.

C. Foreign Exchange Data

In order to observe intra-day market movements around the time of the monetary policy announcements, we focus on the foreign exchange market because of the market opening 24 hours a day, not bond futures and stock markets with a lunch break. We use the high-frequency USD/JPY dataset from Electronic Broking Services (EBS) as foreign exchange transaction data.[8] The EBS Market, which is an inter-dealer platform provided by EBS, is widely used for inter-bank transactions, and provides an interface available for AT.

Our data set records both deal prices and quote prices at 100-millisecond intervals. The trading volume sums up all transactions within 100-millisecond, and is not recorded when there is no transaction in each 100-millisecond. The quote information is not recorded when the quotation price is not updated in each 100-millisecond, and the bid side and the offer side are recorded separately.

8. Chaboud *et al*. [2014] also used EBS datasets to empirically examine the effect of AT in foreign exchange markets.

IV. Analysis of the Effect of ANT Using an Event Study Method

A. Estimation Model

Following the literature about empirical studies on macroeconomic news, we employ an event study analysis to examine the effect of ANT on the foreign exchange market around the monetary policy announcements (Cook and Hahn [1989], Andersen *et al.* [2003], Andersen *et al.* [2007], and Cheung, Fatum, and Yamamoto [2017], etc.).[9] The regression model is shown in equation (1).

$$MQ_i = \alpha + \beta ANT_i + \gamma S_i + \boldsymbol{\delta X}_i + \varepsilon_i, \tag{1}$$

where MQ_i denotes the market quality variables, including volatility, liquidity indicators and others, ANT_i denotes a proxy representing the activity level of ANT extracted from the access record data of BOJ's webpage. S_i denotes monetary policy surprise index, $\boldsymbol{X}_i$ denotes some control variables, ε_i denotes error terms at i-th MPM.[10] Our regression model is similar to the one considered in Andersen *et al.* [2007].

We use a monetary policy surprise index as a control variable. It is generally known that the macroeconomic news announcements will influence the foreign exchange market volatility and market liquidity through its surprise component—the gap between the published value and its market predictions (Fatum and Scholnick [2008], Rosa [2011], Neely [2011] and Tsuchida, Watanabe, and Yoshiba [2016], etc.). In particular, in the studies on the announcements of MPMs, the gap between the announced target policy interest rate and the prior market forecast value based on the survey data, or the forward rate, is often used as a measure of the surprise component. However, in Japan, in the period prior to the introduction of "Quantitative and Qualitative Monetary Easing (QQE) with a Negative Interest Rate" in January 2016, while interest rates have been subject to virtually zero and a minimum limit for a long period of time, monetary easing measures were taken by expanding the monetary base. Taking these facts into account, existing research methods cannot capture the monetary policy surprise component appropriately. Therefore, we use the survey data of professional forecasters concerning the following monetary policy decisions to construct a monetary policy surprise index S_i.

$$S_i = \left| Dummy_{change,i} - Forecast_i \right|, \tag{2}$$

where $Dummy_{change,i}$ represents a dummy variable that takes 1 when the policy is actually changed and 0 when it is unchanged at the i-th meeting. $Forecast_i$ represents the proportion of economists forecasting policy changes (monetary easing) at the following meeting, in advance (around the beginning of the month the MPM is held). It was

9. Cook and Hahn (1989), Andersen *et al.* (2003), Andersen *et al.* (2007), and Cheung, Fatum, and Yamamoto (2017) estimate both event study analysis and time series analysis as a robustness check. In Appendix 1, we also estimate an autoregression model, but the main result is not changed.

10. In this research, we assume that the ANT indicator, which is a proxy for the number of traders who work ANT, linearly influences foreign exchange market quality, such as the number of transactions and market volatility. For this reason, we do not take the logarithm of ANT indicator. It is confirmed that similar results are obtained using logarithmic or the 99% winsorized mean of the ANT indicator and that the coefficients of determination are higher when using the original sequence of ANT indicator.

calculated using JCER (Japan Center for Economic Research) ESP Forecast data.[11] In our sample period, no economist forecast monetary tightening at the next meeting, so we did not consider the direction of monetary policy changes (tightening or easing).

Since the reactions of foreign exchange markets to macroeconomic news depend on market conditions, we add control variables like equation (1) to adjust the effect of market conditions. Specifically, we introduce two types of control variables: $Control_{long,i}$ adjusts the long-term market condition and a variable $Control_{pre,i}$ controls the market condition immediately before the announcements. Moreover, when the policy announcement time is largely delayed in comparison with normal, there is a possibility that the delay itself has some information and influences the market. For this reason, we added a control variable $Dummy_{delay,i}$ that takes 1 if the policy announcement time is later than the 75 percentile of the previous 50 meetings and 0 otherwise.[12] In appendix 2, we list the definition of each market variable.

We use the OLS (Ordinary Least Squares) methods to estimate our models. The t-values reported are computed using heteroskedasticity-consistent standard errors (White [1980]).[13]

B. Validity of ANT Indicator

Before analyzing the effect of ANT on market quality, we examine whether our proposed indicator properly captures ANT activity level by analyzing the relationship between ANT indicator (UV_{direct_EN}) and market response speed immediately after the monetary policy announcements. As measures of market response speed, we use the number of quote update ($MQ_{quote,i}$), the number of contracts ($MQ_{deal,i}$), and the trading volume ($MQ_{volume,i}$) within 1 minute after the monetary policy announcements.[14] For comparison, we will also consider the number of unique visitors accessing the Japanese documents on monetary policy decisions (UV_{direct_JP}) and the total number of unique visitors accessing the documents regardless of language (UV_{direct_ALL}).

If ANT increases (decreases) immediately after the monetary policy announcements, it is conceivable that the response speed on the market is rising (falling). This is because if investors try to earn profit using ANT, they need to instantly execute their transactions before the information becomes stale, by a market order or a marketable limit order.[15] Foucault, Hombert, and Rosu (2016) show that, theoretically, speculators with fast trading speeds contribute to the increase in trading volume. Hence, we use equation (1) to examine whether ANT indicator considered as a proxy for ANT is capturing well the effect of ANT on $MQ_{quote,i}$, $MQ_{deal,i}$, and $MQ_{volume,i}$ at each MPM date. $Control_{long,i}$ is calculated as a mean of the number of quote update, the number of contracts, and the trading volume per minute at each of five trading days prior to the

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11. There is a correlation between the ANT indicator and $Forecast_i$. There is a possibility that if monetary policy change expectation increases, the number of traders who work ANT will increase.
12. It is confirmed that even if the $Dummy_{delay,i}$ is defined based on the period such as the mean of the previous four years, the main result does not change.
13. More precisely, we use the HC1 which adjusts for degrees of freedom.
14. As mentioned earlier, it is impossible to identify the times of publication of monetary policy statements at the second level. Thus, we use 1-minute interval data.
15. To be more specific, a marketable limit order is a buy order with a price at or above the lowest offer in the market or a sell order with a price at or below the highest bid in the market.

Table 1 Effect of ANT Indicator on the Total Number of Quote Updates

	MQ_{quote}			
$UV_{direct\_EN}(=ANT)$	2.64**			
	(2.82)			
UV_{direct_JP}		1.88**		
		(2.94)		
UV_{direct_ALL}			1.33**	
			(3.04)	
S	401.74**	368.86**	381.21**	390.09**
	(3.44)	(3.17)	(3.31)	(3.18)
$Control_{long,\ quote}$	1.71**	1.44*	1.49*	2.07**
	(2.84)	(2.29)	(2.39)	(3.42)
$Control_{pre,\ quote}$	1.13*	1.10*	1.11*	1.15*
	(2.25)	(2.33)	(2.33)	(2.10)
$Dummy_{delay}$	0.00	0.00	0.00	0.00
	(−0.35)	(−0.61)	(−0.61)	(0.07)
$Constant$	0.00	0.00	0.00	0.00
	(1.30)	(1.52)	(1.47)	(0.99)
Observations	80	80	80	80
Adjusted R^2	0.35	0.39	0.38	0.33

Note: This table summarizes the estimation results for the regression models with ordinary least squares method using the total number of USD/JPY quote updates during one minute just after the monetary policy announcements, ANT indicator, monetary policy surprise index, and control variables on the day of MPMs from January 2011 to March 2017 (except for an unscheduled MPM on November 30, 2011). Figures in parentheses show t-values in the regression analysis results, and **, * denotes two-tailed significance at the 1% and 5% levels, respectively. We compute variables in equations using data which is provided by the Bank of Japan, EBS Service Company Ltd., and the Japan Center for Economic Research. Hereafter, except for variables, the same applies to Tables 2 to 6.

MPM date, from 9:00 a.m. to 3:00 p.m. JST (Japan Standard Time), and calculates a mean of those means per trading day. $Control_{pre,i}$ is a mean value of the number of quote updates, the number of contracts, and the trading volume per minute in the 10 minutes immediately before the monetary policy announcements.

Tables 1 to 3 summarize estimation results with event study analysis using equation (1). Figures in parentheses show t-values in the regression analysis results, and **, * denote two-tailed significance at the 1% and 5% levels, respectively. Table 1 shows the results on the MQ_{quote}. UV_{direct_EN}, UV_{direct_JP}, and UV_{direct_ALL} are all significantly positive at the 1% level. Next, Table 2 shows the results on MQ_{deal}. UV_{direct_JP} and UV_{direct_ALL} are also significantly positive at the 1% level. Finally, Table 3 indicates the results on MQ_{volume}, and only UV_{direct_EN} is significantly positive at the 5% level.

Since UV_{direct_EN} shows the most significant effects on market response speed variables, we argue that ANT activity level is most appropriately captured by UV_{direct_EN}.[16]

16. We have also confirmed that $UV_{indirect\_EN}$ and $UV_{indirect\_JP}$, the number of unique visitors who indirectly access the URL of the English and Japanese documents within two hours before released on the MPM dates,

Table 2 Effect of ANT Indicator on the Total Number of Trades

	MQ_{deal}			
$UV_{direct\_EN}(=ANT)$	2.35**			
	(3.61)			
UV_{direct_JP}		1.35**		
		(2.89)		
UV_{direct_ALL}			0.99**	
			(2.95)	
S	201.24**	176.97**	185.33**	188.54**
	(3.50)	(3.67)	(3.78)	(2.96)
$Control_{long,\ deal}$	8.21*	8.03*	8.09*	7.44*
	(2.41)	(2.41)	(2.44)	(2.06)
$Control_{pre,\ deal}$	2.62	2.27	2.37	2.85
	(0.84)	(0.91)	(0.91)	(0.81)
$Dummy_{delay}$	−32.25	−42.31	−43.45	0.35
	(−0.74)	(−1.11)	(−1.10)	(0.01)
$Constant$	−12.86	−16.06	−16.62	7.16
	(−0.42)	(−0.56)	(−0.57)	(0.22)
Observations	80	80	80	80
Adjusted R^2	0.39	0.47	0.46	0.27

Table 3 Effect of ANT Indicator on the Total Volume of Trades

	MQ_{volume} (USD in millions)			
$UV_{direct\_EN}(=ANT)$	5.28*			
	(2.31)			
UV_{direct_JP}		3.43		
		(1.92)		
UV_{direct_ALL}			2.45	
			(1.94)	
S	634.00*	569.00**	592.00**	610.00*
	(2.60)	(2.75)	(2.74)	(2.41)
$Control_{long,\ volume}$	8.62	8.08	8.29	7.44
	(1.80)	(1.66)	(1.72)	(1.44)
$Control_{pre,\ volume}$	0.62	0.80	0.78	0.42
	(0.18)	(0.27)	(0.25)	(0.11)
$Dummy_{delay}$	−72.71	−114.00	−112.00	4.39
	(−0.42)	(−0.68)	(−0.65)	(0.03)
$Constant$	−7.20	−22.33	−22.26	46.69
	(−0.10)	(−0.29)	(−0.29)	(0.60)
Observations	80	80	80	80
Adjusted R^2	0.27	0.35	0.33	0.20

cannot capture ANT activity.

In the following sections, we will use UV_{direct_EN} as ANT indicator (ANT_i), and analyze the effect of ANT in the foreign exchange market.

C. Effect of ANT on Market Volatility

In this subsection, we examine how the ANT indicator influences market volatility immediately after the monetary policy announcements. The Bank for International Settlements (2017) points out that AT might exacerbate volatility. Moreover, Scholtus, Dijk, and Frijns (2014) uses the volume of message traffics as a proxy for AT activity level, and reports that volatility increases as the volume of message traffics increases around macroeconomic news releases. These empirical studies do not purely extract the effects of ANT. However, as in the case of previous studies, there is a possibility that ANT transactions assume a specific direction of price changes immediately after the monetary policy announcements, thereby amplifying foreign exchange fluctuation by simultaneously placing the market order.

As proxies of market volatility, we use two indicators: the absolute return (AR) and the high price minus low price (HML). AR is the absolute return for 5 minutes immediately after the monetary policy announcements as given in equation (3). HML is the difference of the high price and low price in the 5 minutes immediately after the monetary policy announcements as given in equation (4). Here, we compute these two indicators at 5-minute intervals to ease market microstructure noise.

$$MQ_{AR,i} = \left|\ln Mid\_Price_{i,t=5min} - \ln Mid\_Price_{i,t=0min}\right|, \tag{3}$$

$$MQ_{HML,i} = High\_Price_{i,0min:5min} - Low\_Price_{i,0min:5min}, \tag{4}$$

where $Mid\_Price_{i,t}$ represents mid-price between the best bid price and best offer price that were first updated in t-th 5-minute interval immediately after the monetary policy announcements at i-th MPM. $High\_Price_{i,t:t+h}$ and $Low\_Price_{i,t:t+h}$ represent the highest and lowest transaction prices between t to $t+h$ minutes just after the monetary policy announcements at i-th MPM, respectively. The publication time is t=0. $Control_{long,i}$ is calculated as a mean of 5-munite AR and 5-minute HML on each of five trading days prior to the MPM date, from 9:00 a.m. to 3:00 p.m. JST, and calculates a mean of those means per trading day. $Control_{pre,i}$ is a mean value of 5-minute AR and 5-minute HML in the 10 minutes immediately before the monetary policy announcements.

Table 4 summarizes estimation results. The coefficients of ANT indicator on both market volatility indicators are significantly positive, implying that ANT increases market volatility immediately after the monetary policy announcements. Moreover, the great increase in adjusted R^2 implies that our ANT indicator is an important variable to explain market volatility immediately after the announcements.

D. Effect of ANT on Market Liquidity

In this subsection, we analyze the effect of ANT on market liquidity. Many previous studies have reported that market liquidity improves when AT activity increases. In this case, specifically, AT employing market making strategies, which supply liquidity, is presumed to increase. On the other hand, if AT employing market taking (directional) strategies, which demands liquidity, increases, market liquidity does not

Table 4 Effect of ANT Indicator on Market Volatility

	MQ_{AR}		MQ_{HML}	
$UV_{direct\_EN}(=ANT)$	0.008*		0.013*	
	(2.05)		(2.36)	
S	0.444**	0.425*	0.610*	0.549*
	(2.84)	(2.46)	(2.43)	(2.21)
$Control_{long,\ deal}$	7.144*	14.317**	2.739	4.326
	(2.56)	(2.69)	(1.21)	(1.47)
$Control_{pre,\ deal}$	1.257	0.984	3.754	6.315**
	(0.46)	(0.30)	(1.64)	(3.35)
$Dummy_{delay}$	−0.112	−0.009	−0.205	−0.119
	(−0.88)	(−0.07)	(−1.04)	(−0.62)
$Constant$	−0.111	−0.201*	−0.115	−0.197*
	(−1.92)	(−2.23)	(−1.50)	(−2.31)
Observations	80	80	80	80
Adjusted R^2	0.40	0.21	0.61	0.48

necessarily improve. Scholtus, Dijk, and Frijns (2014) show that in the minute following a macroeconomic news arrival, algorithmic activity increases trading depth at the best quotes, but also leads to a drop in overall depth.

Our paper assumes ANT employ market taking strategies, as generally believed. If ANT demands liquidity using marketable limit orders or market order and other market participants cannot provide the same or exceeding liquidity by limit order, market liquidity on the whole may decrease. Thereby, utilizing the event study analysis of equation (1), we investigate how ANT indicator influences market liquidity just after the monetary policy announcements.

As proxies for market liquidity, we use the bid-offer spread (BOS) and the market depth which is computed by summing up the best bid and best offer quotes. Each variable is showed as following equations.

$$MQ_{BOS,i} = \frac{1}{5}\sum_{t=0min.}^{t=4min.}(Best\_Offer\_Price_{i,t} - Best\_Bid\_Price_{i,t}), \tag{5}$$

$$MQ_{depth,i} = \frac{1}{5}\sum_{t=0min.}^{t=4min.}(Depth_{Best\_Offer\_Price_{i,t}} + Depth_{Best\_Bid\_Price_{i,t}}), \tag{6}$$

where $Best\_Offer\_Price_{i,t}$ and $Best\_Bid\_Price_{i,t}$ represents the best offer and best bid price that were first updated in t-th 1-minute interval immediately after the monetary policy announcements at i-th MPM, respectively. Additionally, $Depth_{Best\_Offer\_Price_{i,t}}$ and $Depth_{Best\_Bid\_Price_{i,t}}$ denote the mean order amount of the best bid and offer quotes in t-th 1-minute interval after the announcements at i-th MPM, respectively. For example, if the best bid price is updated ten times in t-th 1-minute interval after the announcements at i-th MPM, $Depth_{Best\_Bid\_Price_{i,t}}$ is the mean value of the ten bid order amounts. $Control_{long,i}$ is calculated as a mean of 1-minute BOS and 1-minute depth

Table 5 Effect of ANT Indicator on Market Liquidity

	MQ_{BOS}		MQ_{depth} (USD in thousands)	
$UV_{direct\_EN}(= ANT)$	0.000		1.063	
	(1.82)		(0.09)	
S	0.012	0.014*	2798.772	2791.855
	(1.81)	(2.02)	(1.35)	(1.38)
$Control_{long}$	1.914**	2.214**	0.432**	0.432**
	(3.81)	(3.63)	(3.43)	(3.46)
$Control_{pre}$	0.109	0.291**	0.379*	0.378*
	(0.87)	(3.55)	(2.38)	(2.37)
$Dummy_{delay}$	−0.006	−0.005	−358.282	−343.924
	(−1.29)	(−1.17)	(−0.30)	(−0.32)
$Constant$	−0.009	−0.013*	609.781	625.033
	(−1.74)	(−2.22)	(1.00)	(1.02)
Observations	80	80	80	80
Adjusted R^2	0.64	0.57	0.38	0.39

at each of five trading days prior to the MPM date, from 9:00 a.m. to 3:00 p.m. JST, and calculates a mean of those means per trading day. $Control_{pre,i}$ is a mean value of 1-minute BOS and 1-minute depth in the 10 minutes immediately before the monetary policy announcements.

Table 5 summarizes the estimation results. The ANT indicator does not significantly influence market liquidity for the 5 minutes immediately after the monetary policy announcements.

V. A Dynamic Analysis of ANT

In this section, we investigate the dynamic and integrated effect of ANT using a VAR analysis with impulse response functions. The results in the previous section show that during the time period immediately after the monetary policy announcements ANT has influence on market speed and volatility, but not on market liquidity directly. However, there is a possibility that market liquidity is influenced after a certain period of time, in the case that ANT influences the other market participants' behavior through increasing trading volume and volatility.

For example, in response to the increasing volatility immediately after the policy announcements, risk-averse market makers avoid having inventory risks, and re-enter quoted prices away from mid prices, or make the order amount small. In these cases, ANT indirectly widens spread and decrease depth. In contrast, market liquidity may improve when the effects of an increase in trading activity (such as an increase in trading volume) is relatively strong, in the process that financial markets reflect the content of the announced MPM decisions.

A. Model

We estimate the following simple VAR model with four variables: trading volume, absolute return, bid-offer spread, and depth. In appendix 2, we list the definition of each market variable.

$$\boldsymbol{MQ}_t = \boldsymbol{\alpha} + \sum_{j=1}^{J} \boldsymbol{\beta}_j \boldsymbol{MQ}_{t-j} + \boldsymbol{\gamma} ANT_t + \boldsymbol{\delta} S_t + \boldsymbol{\rho} Dummy_{release,t} + \boldsymbol{\varepsilon}_t, \tag{7}$$

where $\boldsymbol{MQ}_t$ denotes the vector variables mentioned above, ANT_t denotes the ANT indicator, S_t denotes monetary policy surprise index, $Dummy_{release,t}$ denotes a control variable that takes 1 at the moment of the monetary policy announcements and 0 otherwise, and J denotes lag order. The coefficients $\boldsymbol{\alpha}, \boldsymbol{\beta}_j, \boldsymbol{\gamma}, \boldsymbol{\delta}, \boldsymbol{\rho}$ and the error term $\boldsymbol{\varepsilon}_t$ are given by vectors. t is the indicator at a 5-minute frequency. We set ANT_t and S_t variables as exogenous variables. Lag order J is set to 2 according to Schwarz Information Criteria (SIC) and it was assumed that the monetary policy surprise index and ANT indicator only influence the financial variables immediately after the announcements.

Time series data consist of only 100-minute windows surrounding the every monetary policy announcement, where every 100-minute window encompasses observations 10 minutes before and 90 minutes after the announcements. Our sample size is 1,600, which equals 80 meetings multiplied by 20 observations for each meeting.[17] ANT_t and S_t take $ANT_{t(i)} = ANT_i$ and $S_{t(i)} = S_i$ at the $t(i)$, the moment of the policy announcement at the meeting i, and $ANT_t = 0$ and $S_t = 0$ otherwise.

The interest here is to examine the dynamic effects of the ANT indicator on the foreign exchange market. Therefore, we measure the impulse response of each market quality variable when shock is given to ANT_t. Specifically, in the four-variable VAR model estimated by equation (7), we can calculate $\boldsymbol{IRF}(k)$ sequentially to the simultaneous ANT indicator shock vector, which has multiplied values of the estimated coefficient vector of ANT indicator and one standard deviation ($\boldsymbol{\gamma} \times \sqrt{\mathrm{Var}\left(ANT_{t(i)}\right)}$). The impulse response function here is expressed as follows.

$$\boldsymbol{IRF}(k) = \frac{\partial \boldsymbol{MQ}_{t+k}}{\partial ANT_t}, \qquad k = 0, 1, \ldots, 19. \tag{8}$$

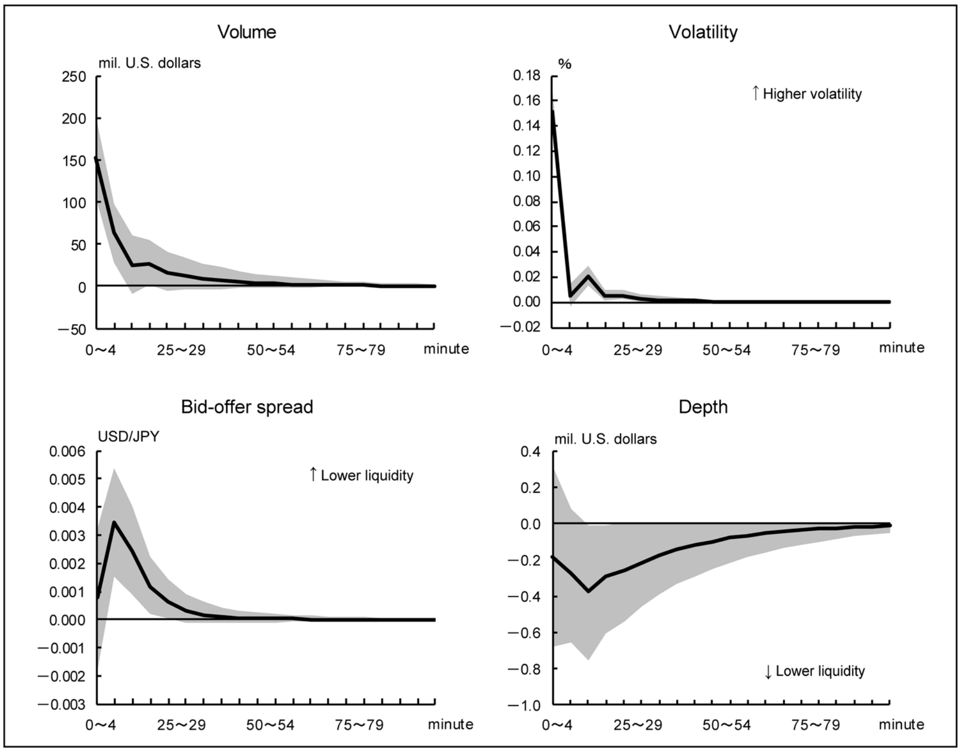
B. Dynamic Effect of ANT Indicator

Figure 4 shows the impulse responses of each market quality variable to an exogenous 1 standard deviation increase in ANT indicator. The solid lines and shaded areas indicate estimated responses and 90-percent confidence intervals, respectively. Confidence intervals are calculated by the Monte Carlo method.[18]

According to the top-left panel of Figure 4, the impulse response of the trading volume to a positive ANT indicator shock jumps rapidly right after the shock is generated,

17. With regard to such handling of sample data, Andersen *et al.* (2007) and Cheung, Fatum, and Yamamoto (2017) show that in the case of using the full-time sample and in the case where the sample size was reduced to 100 minutes before and after the macroeconomic news announcements, there is no substantial difference in the obtained results. As a robustness check, we also estimate the VAR model with 5-minute interval data of 240 minutes before and after each monetary policy announcement (120 minutes before and 120 minutes after the announcements). We then found the main results to be intact.
18. There are 2,000 iterations in the Monte Carlo simulation.

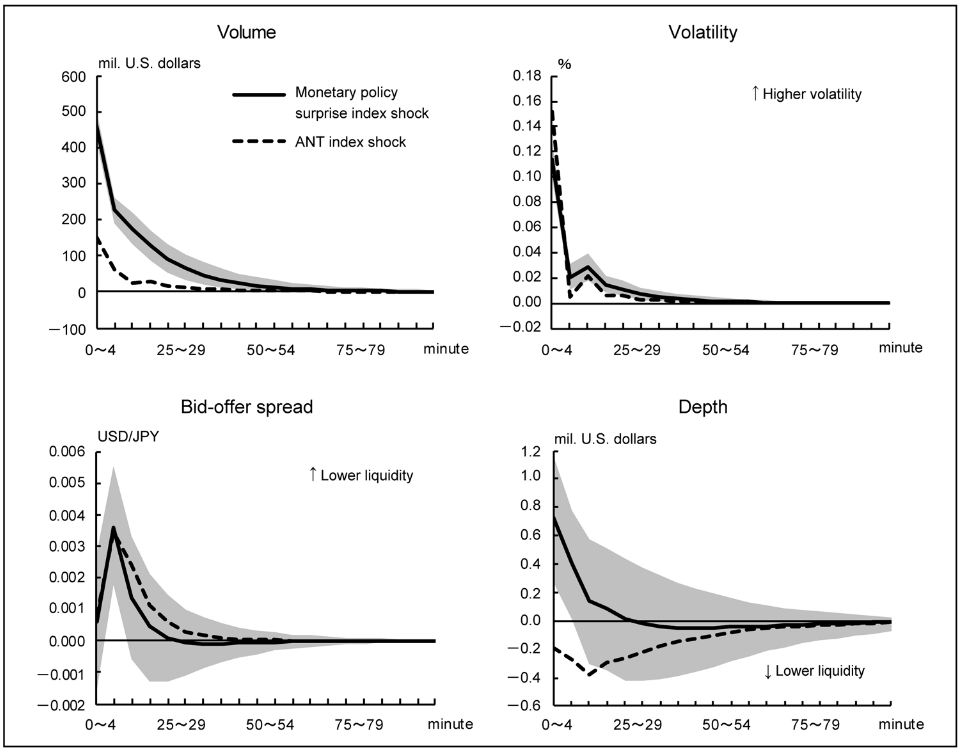
Figure 4 Integrated Impulse Response to ANT Indicator Shock



Note: Impulse responses to 1 standard deviation of ANT indicator shock vector in the estimated VAR model with 4 endogenous variables (trading volume, absolute return, bid-offer spread, depth) and 2 exogenous variables (ANT indicator, monetary policy surprise index) using 5-minute interval data of 100 minutes before and after each monetary policy announcement on the MPM dates from January 2011 to March 2017 (except for an unscheduled MPM on November 30, 2011). The shaded areas indicate 90-percent confidence intervals. We compute variables in equations using data which is provided by Bank of Japan, EBS Service Company Ltd., and Japan Center for Economic Research. Hereafter, except for variables, the same applies to Figures 5 to 7.

and declines to around zero thereafter. Next, looking at the effect on market volatility, as shown in the top-right panel, positive ANT indicator shock also generates a sharp rise in the absolute return for 5 minutes after the shock is generated. However, 10 minutes later, the impulse response converges to almost zero and the integrated effect of ANT indicator on volatility gets dissipated. Next, focusing on the effect on market liquidity, the bottom-left panel shows that the impulse response of bid-offer spread to positive ANT indicator shock rises and reaches the peak level with a lag of 5–9 minutes after the shock, and stays positive from 5 to 29 minutes later. It also leads to a persistent fall in the depth, not always statistically significant, as shown in the bottom-right panel. To sum up, from the viewpoint of market liquidity, the positive shock of ANT indicator contributes to decreasing market liquidity.

Figure 5 Integrated Impulse Response to Monetary Policy Surprise Index Shock



Note: Impulse responses to 1 standard deviation of monetary policy surprise index shock vector in estimated VAR model with 4 endogenous variables (trading volume, absolute return, bid-offer spread, depth) and 2 exogenous variables (ANT indicator, monetary policy surprise index) using 5-minute interval data of 100 minutes before and after each monetary policy announcement on the days of MPMs from January 2011 to March 2017 (except for an unscheduled MPM on November 30, 2011). The shaded areas indicate 90-percent confidence intervals.

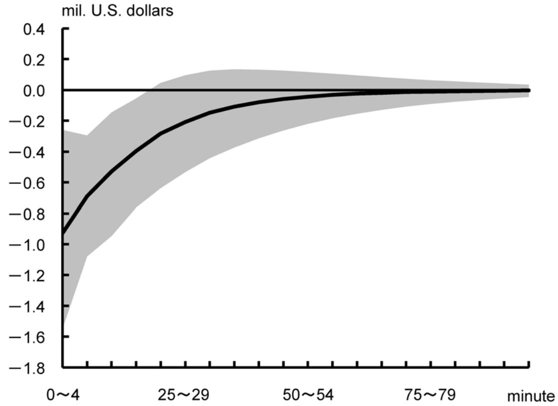
C. Dynamic Effect of Monetary Policy Surprise Index

Using the same framework explained above, we examine the impulse responses of market quality variables to an exogenous of 1 standard deviation increase ($\sqrt{\mathrm{Var}\,(S_{t(i)})}$) in the monetary policy surprise index.

According to the top-left and top-right panels of Figure 5, an increase in monetary policy surprise index leads to an increase in the trading volume and the absolute return, like an increase in ANT indicator. However, it can be pointed out that the impulse responses to ANT indicator shock and the monetary policy surprise index differ in the magnitude of the relative influence on the two variables. The rise shock of the ANT indicator has a relatively large influence on volatility over the trading volume.

We now examine the influence of monetary policy surprises on market liquidity. Looking at the effect on the bid-offer spread shown in the bottom-left panel, an increase in monetary policy surprise index contributes to widening the spread, like ANT indicator shock. In contrast, while ANT indicator shock contributed to the downward direction against the market depth, monetary policy surprise index shock contributed to

Figure 6 The Difference of Impulse Response within 5 Percent Error Band



Note: This figure shows the difference between the impulse response of depth to the ANT indicator shock and that to the monetary policy surprise index shock, and its 5 percent error band. Each impulse responses are estimated in the same way as Figures 4 and 5. The shaded areas indicate 90-percent confidence intervals.

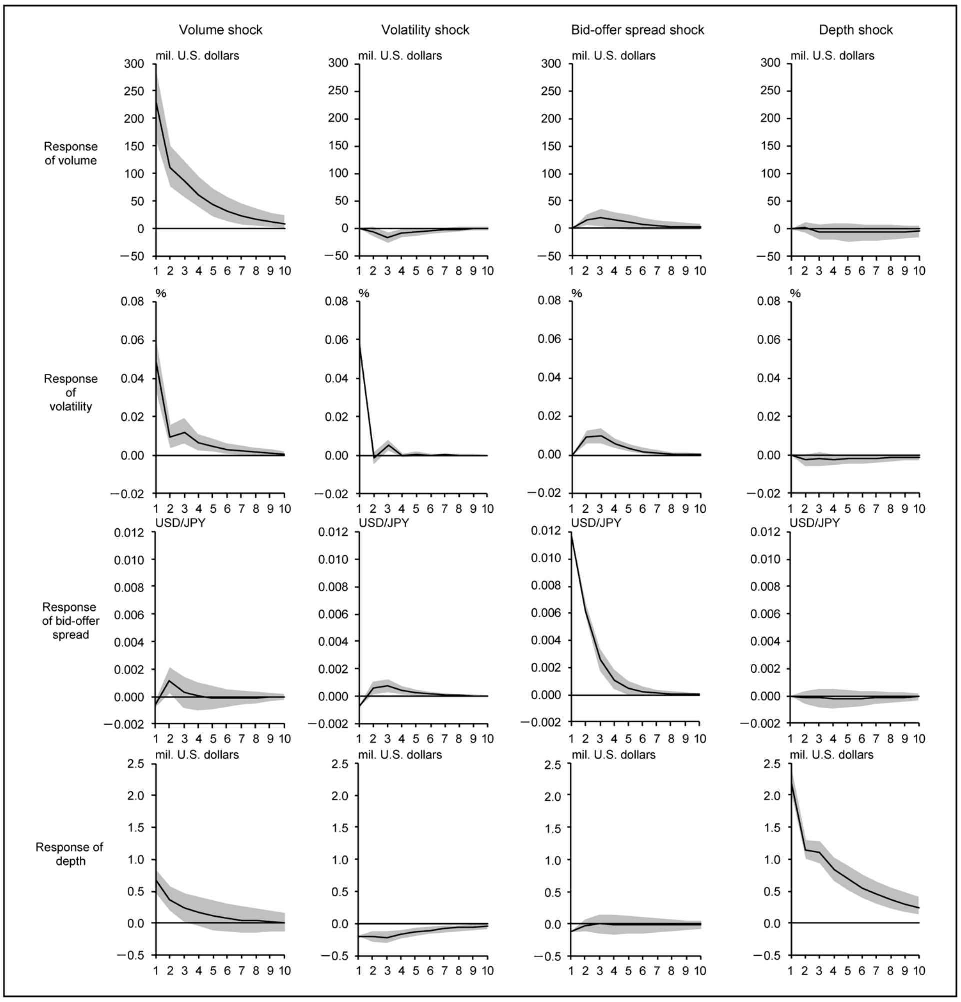
the upward direction, shown in the bottom-right panel. Figure 6 shows the difference between the impulse responses of depth to the ANT indicator shock and the monetary policy surprise index shock with 90-percent confidence intervals. According to this figure, the difference in the impulse response functions is statistically significant for up to 25 minutes.

D. The Differences in the Impulse Responses of Market Depth to ANT Shock and Monetary Policy Surprise Shock

What factors account for the difference in the impulse responses of market depth to ANT indicator shock and monetary policy surprise index shock? We examine the VAR model with four endogenous variables in order to investigate the dynamics between these variables. Specifically, we examine the 4-variable VAR model of the equation (7), and give a shock to orthogonalized disturbance term in that model. In this study, based on Chordia, Sarkar, and Subrahmanyan (2005), the structural shocks are identified by using the Cholesky decomposition in the following order: trading volume, absolute return, bid-offer spread, and depth.[19] The result of the impulse response based on the estimated 4-variable VAR is shown in Figure 7. Here, each column shows the dynamic effects on each variable to the trading volume shock, the absolute return shock, the bid-offer spread shock, and the market depth shock, respectively. The size

19. We determined the order based on Chordia, Sarkar, and Subrahmanyan (2005). In Chordia, Sarkar, and Subrahmanyan (2005), proxies for market activity (order imbalance or trading volume) are placed first in the VAR ordering as the most exogenous variable, as these are determined by the demand–supply conditions in the markets. Next, price variation (volatility or return) is placed as the second variable in the VAR ordering, as it could be regarded as a predetermined variable, which has a relatively immediate impact on market liquidity. Finally, market liquidity indicators are last variables. In this study, as a robustness check, we estimate by replacing the order of two market liquidity indicators, the bid-offer spread and depth, but the results were not greatly affected.

Figure 7 Impulse Response



Note: Impulse responses to 1 standard deviation of each endogenous variables shock in estimated VAR model with 4 endogenous variables (trading volume, absolute return, bid-offer spread, depth) and 2 exogenous variables (ANT indicator, monetary policy surprise index) using 5-minute interval data of 100 minutes before and after each monetary policy announcement on the day of MPMs from January 2011 to March 2017 (except for an unscheduled MPM on November 30, 2011). Shock identification is based on the Cholesky decomposition in the above order. The shaded areas indicate 90-percent confidence intervals.

of each shock is normalized to be one standard deviation. The solid lines and shaded areas indicate estimated responses and 90-percent confidence intervals, respectively. Confidence intervals are calculated with the Monte Carlo method.

Figure 7 shows that an increase in trading volume contributes to a statistically significant improvement in the depth, especially just after the shock occurred. On the other hand, an increase in absolute return leads to a persistent deterioration in the depth over the whole period.

Based on the dynamics between these variables, we attempt to interpret the difference of the response of market depth to ANT indicator shock and monetary policy surprise index shock. First, the positive shock of the ANT indicator influences the absolute return more strongly than on trading volume. For this reason, market depth may be influenced by the indirect channels through increase on absolute returns, more strongly. As a result, ANT indicator shock leads to the decrease in depth, affected through the indirect channels.

To summarize these results, it is consistent with the aforementioned hypothesis. That is, during the time period immediately after the monetary policy announcements, ANT has no direct influence on market liquidity. However, market liquidity is affected after a certain period of time, in the case that ANT influences the behavior of other market participants, for example market makers, through increasing volatility.

VI. Trading Strategies Adopted in ANT

Finally, we additionally examine under which conditions ANT is active. We conducted analyses on the presumption that the more the number of ANT ($=UV_{direct\_EN}$) increases, the more trading by ANT increases linearly. As a practical matter however, ANT, which focuses on the monetary policy announcements, may make certain trading decisions based on some changes, such as monetary policy decisions and texts on the documents. Jiang, Lo, and Valente (2014), which examine the effect of HFT around macroeconomic news announcements, assumes the HFT trading algorithm that would be executed depending on news surprises. They introduce the interaction of a proxy for monetary policy surprises and HFT activity. Hence, we expand equation (1) to equations (9), (10), and (11) for additional verification. For the market quality variables MQ_i, we use two indicators: the absolute return ($MQ_{AR,i}$) and the trading volume ($MQ_{volume,i}$).

$$MQ_i = \alpha + \beta ANT_i + \psi ANT_i \times S_i + \gamma S_i + \boldsymbol{\delta X}_i + \varepsilon_i, \tag{9}$$

$$MQ_i = \alpha + \beta ANT_i + \psi ANT_i \times Dummy_{change,i} + \gamma S_i + \boldsymbol{\delta X}_i + \varepsilon_i, \tag{10}$$

$$MQ_i = \alpha + \beta ANT_i + \psi ANT_i \times Tone_i + \gamma S_i + \boldsymbol{\delta X}_i + \varepsilon_i. \tag{11}$$

In equation (9), we add the interaction of the ANT indicator ($=UV_{direct\_EN}$) and monetary policy surprise index (S_i), assuming that ANT trades based on the market surprise on the BOJ's policy announcements. In equation (10), we add the interaction of the ANT indicator and the monetary policy change dummy ($Dummy_{change,i}$), assuming that ANT trades based on the changes in monetary policy decisions. In equation (11), we introduce the interaction of the ANT indicator and the tone of the statements on monetary policy decisions ($Tone_i$). We count positive and negative words in the documents on monetary policy decisions, based on Loughran and McDonald Sentiment Word Lists (Loughran and McDonald [2011]), and calculate $Tone_i$ by equation (12).

$$Tone_i = -\frac{P_i - N_i}{P_i + N_i}, \tag{12}$$

Table 6 Trading Strategies Adopted in ANT

	MQ_{Volume}			MQ_{AR}		
	eq.(9)	eq.(10)	eq.(11)	eq.(9)	eq.(10)	eq.(11)
$ANT \times S$	14.005			0.009		
	(0.586)			(0.343)		
$ANT \times Dummy_{change}$		−9.194			−0.014	
		(−1.695)			(−1.401)	
$ANT \times Tone$			23.185**			0.042**
			(3.844)			(4.473)
ANT	1.609	10.890**	7.321**	0.006	0.019*	0.013**
	(0.354)	(2.704)	(3.844)	(1.619)	(2.003)	(5.777)
S	556.337*	244.755	587.184*	0.402*	0.319*	0.328**
	(2.525)	(0.999)	(2.519)	(2.377)	(2.109)	(3.254)
$Dummy_{change}$		410.429			0.140	
		(2.182)			(1.534)	
$Tone$			26.945			−0.030
			(0.210)			(−0.343)
$Control_{long}$	8.720	7.837*	8.066	7.621**	6.388*	2.835
	(1.838)	(2.090)	(1.595)	(3.372)	(2.023)	(0.879)
$Control_{pre}$	0.580	0.202	0.099	1.015	1.394	1.890
	(0.176)	(0.058)	(0.031)	(0.398)	(0.484)	(0.823)
$Dummy_{delay}$	−61.890	−32.651	−12.200	−0.105	−0.044	−0.013
	(−0.385)	(−0.180)	(−0.075)	(−0.854)	(−0.406)	(−0.163)
$Constant$	8.679	−6.479	−15.557	−0.107	−0.151*	−0.071
	(0.114)	(−0.116)	(−0.193)	(−1.780)	(−2.020)	(−0.966)
Observations	80	80	80	80	80	80
Adjusted R^2	0.27	0.27	0.35	0.40	0.48	0.71

where P_i and N_i denote the number of positive and negative words on the documents at i-th MPM, respectively. From the assumption that the possibility of monetary policy changes (monetary easing) will increase as the tone becomes weaker, we multiply the negative sign. If the coefficient ψ for the interaction term of ANT and each status value, S_i or $Dummy_{change,i}$ or $Tone_i$, takes a statistically significant positive value, it indicates the possibility that ANT is active under the specific conditions.

Table 6 summarizes estimation results for equations (9), (10), and (11). On both market quality variables, the coefficient ψ is significantly positive in equation (11), but is insignificant in equation (9) or (10). These results indicate that the larger the tone become, the larger impact ANT has on the FX markets, whereas the impact of ANT is not amplified when the surprise or the policy change exists.[20] In other words, ANT could react to the tone rather than to the surprise or the policy change. In summary, these results imply that ANT trades based on changes in texts on documents of monetary policy decisions.

20. However, we need to pay attention to the estimated result, that the coefficient β of the ANT indicator becomes insignificant in equation (9) using each MQ_i. This is because that there was a high correlation between variables and the coefficient might not have been estimated accurately. Thus, we must be careful in interpreting this result.

VII. Conclusion

We propose a novel measure of the activity level of ANT based on the web access record of a central bank's webpage, thereby studying the effects of ANT on the foreign exchange markets around the time of the monetary policy announcements. Employing an event study analysis and a VAR analysis, we find that ANT increases market volatility immediately after the monetary policy announcements, and that ANT activity indirectly decreases market liquidity through increasing volatility. We also find that our proposed measure appropriately captures the activity level of ANT, suggesting our measure as an effective market monitoring tool for ANT activity. In addition we suggest that ANT trades based on changes in texts on the monetary policy announcements. To the best of our knowledge, we present the first trial to uncover ANT activity by focusing on its effects on the foreign exchange market around the monetary policy announcements.

Since AT techniques, including ANT, are likely to vary depending on technological advances and market circumstances, attention must be paid to changes in the trading methods and market structures. More research is required to make a sophisticated surprise index of the monetary policy announcements, and to understand which factors determine ANT activity. Future tasks include applying the analysis to central banks in other countries, other macroeconomic news announcements, and other asset markets.

APPENDIX 1: ROBUSTNESS CHECK OF ANT INDICATOR

As a robustness check, using an autoregression model, we examine whether ANT indicator has a significant positive effect on market response speed immediately after the monetary policy announcements. We use the number of best quote updates ($MQ_{quote,t}$), the number of contracts ($MQ_{deal,t}$), and the trading volume ($MQ_{volume,t}$) as proxies for market response speed.

$$MQ_t = \alpha + \sum_{j=1}^{J} \beta_j MQ_{t-j} + \gamma ANT_t + \delta S_t + \varepsilon_t. \tag{A-1}$$

Lag order J is set to 2 according to Schwarz Information Criterion (SIC) and it is assumed that the monetary policy surprise index and ANT indicator only affect the financial variables immediately after the announcements. Table A-1 summarizes the values estimated by equation (A-1). Estimated coefficients for ANT indicator are all significantly positive at the 1 to 5% level.

Table A-1 Effect of ANT Indicator on Quote, Deal, and Volume Using Autoregression Models

	MQ_{quote}	MQ_{deal}	MQ_{volume} (USD in millions)
$UV_{direct\_EN}(=ANT)$	31.17**	8.22**	12.85*
	(4.60)	(4.83)	(2.34)
MQ_{t-1}	0.67**	0.50**	0.49**
	(25.41)	(20.05)	(9.48)
MQ_{t-2}	0.12**	0.14**	0.14**
	(5.75)	(6.09)	(3.08)
S	3318.80**	481.66**	1987.21**
	(6.58)	(3.47)	(3.84)
$Constant$	147.52**	27.03**	44.87**
	(8.97)	(8.45)	(8.22)
Observations	1598	1598	1598
Adjusted R^2	0.70	0.49	0.56

Note: This table summarizes the values estimated by equation (A-1) autoregression models using MQ_{quote}, MQ_{deal}, MQ_{volume}, ANT indicator, monetary policy surprise index, and control variables on the day of MPMs from January 2011 to March 2017 (except for an unscheduled MPM on November 30, 2011). Figures in parentheses show t-values in the regression analysis results, and **, * denote two-tailed significance at the 1% and 5% levels, respectively. The t-values are computed using Newey-West standard errors. We calculate these variables using data which is provided by the Bank of Japan, EBS Service Company Ltd., and the Japan Center for Economic Research.

APPENDIX 2: MARKET VARIABLES LIST

A. Event Study Analysis

Variable name	Definition
$MQ_{quote,i}$	The total number of quote updates in the 1 minute after the monetary policy announcements.
$MQ_{deal,i}$	The total number of contracts in the 1 minute after the monetary policy announcements.
$MQ_{volume,i}$	The total trading volume in the 1 minute after the monetary policy announcements.
$MQ_{AR,i}$	The absolute return (AR) of mid-price for the 5 minutes immediately after the monetary policy announcements.
$MQ_{HML,i}$	The difference of high price and low price (HML) in the 5 minutes immediately after the monetary policy announcements.
$MQ_{BOS,i}$	The mean value of minute by minute bid offer spread (BOS) for the 5 minutes immediately after the monetary policy announcements.
$MQ_{depth,i}$	The mean value of minute by minute market depth which is computed by summing up the best bid and best offer quotes for the 5 minutes immediately after the monetary policy announcements. The best bid and best offer quotes denote the mean order amount of all the best bid and offer quotes updated in the 1-minute interval, respectively.

$Control_{long,quote,i}$	A mean of the number of quote update per minute at each of five trading days prior to the MPM date, from 9:00 a.m. to 3:00 p.m. JST (Japan Standard Time), and calculates a mean of those means per trading day.
$Control_{long,deal,i}$	A mean of the number of the number of contracts per minute at each of five trading days prior to the monetary policy meeting (MPM) date, from 9:00 a.m. to 3:00 p.m. JST, and calculates a mean of those means per trading day.
$Control_{long,volume,i}$	A mean of the number of the trading volume per minute on each of five trading days prior to the MPM date, from 9:00 a.m. to 3:00 p.m. JST, and calculates a mean of those means per trading day.
$Control_{long,AR,i}$	A mean of 5-minute AR at each of five trading days prior to the MPM date, from 9:00 a.m. to 3:00 p.m. JST, and calculates a mean of those means per trading day.
$Control_{long,HML,i}$	A mean of 5-minute HML at each of five trading days prior to the MPM date, from 9:00 a.m. to 3:00 p.m. JST, and calculates a mean of those means per trading day.
$Control_{long,BOS,i}$	A mean of 1-minute BOS at each of five trading days prior to the MPM date, from 9:00 a.m. to 3:00 p.m. JST, and calculates a mean of those means per trading day.
$Control_{long,depth,i}$	A mean of 1-minute market depth at each of five trading days prior to the MPM date, from 9:00 a.m. to 3:00 p.m. JST, and calculates a mean of those means per trading day.
$Control_{pre,quote,i}$	A mean value of the number of quote updates per minute in the 10 minutes immediately before the monetary policy announcements.
$Control_{pre,deal,i}$	A mean value of the number of contracts per minute in the 10 minutes immediately before the monetary policy announcements.
$Control_{pre,volume,i}$	A mean value of the trading volume per minute in the 10 minutes immediately before the monetary policy announcements.
$Control_{pre,AR,i}$	A mean value of 5-minute AR in the 10 minutes immediately before the monetary policy announcements.
$Control_{pre,HML,i}$	A mean value of 5-minute HML in the 10 minutes immediately before the monetary policy announcements.
$Control_{pre,BOS,i}$	A mean value of 1-minute BOS in the 10 minutes immediately before the monetary policy announcements.
$Control_{pre,depth,i}$	A mean value of 1-minute market depth in the 10 minutes immediately before the monetary policy announcements.

B. Time Series Analysis

Variable name	Definition
$MQ_{volume,t}$	The total trading volume at 5-minute intervals of 10 minutes before and 90 minutes after each monetary policy announcement.
$MQ_{AR,t}$	The absolute return of mid-price at 5-minute intervals of 10 minutes before and 90 minutes after each monetary policy announcement.
$MQ_{BOS,t}$	BOS observed at 5-minute intervals of 10 minutes before and 90 minutes after each monetary policy announcement.

$MQ_{depth,t}$	Market depth which is computed by summing up the best bid and best offer quotes observed at 5-minute intervals of 10 minutes before and 90 minutes after each monetary policy announcement. The best bid and best offer quotes denote the mean order amount of all the best bid and offer quotes updated in the 5-minute interval, respectively.
$MQ_{quote,t}$	The total number of quote updates at 5-minute intervals of 10 minutes before and 90 minutes after each monetary policy announcement.
$MQ_{deal,t}$	The total number of contracts at 5-minute intervals of 10 minutes before and 90 minutes after each monetary policy announcement.

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