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An Overview of Algorithmic Trading in Foreign Exchange Markets and Its Impacts on Market Liquidity

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In recent years, the foreign exchange market has seen a growing presence of algorithmic trading, that is, a process of automated transactions based on pre-determined programs. Concurrently, the need to better understand its characteristics has become more important. In this paper, we construct proxy indicators of algorithmic trading in the USD/JPY spot market by focusing on its general features - high-speed and high-frequency transactions. Based on the proxy indicators, algorithmic trading has been on an upward trend since around 2016 and is more active in European and U.S. time zones than in Japan. Our analysis shows that algorithmic trading on average helps improve market liquidity in normal times. Its liquidity-providing function was generally maintained under market stress triggered by the COVID-19 pandemic from late-February to end-March 2020, though it could have been dampened albeit temporarily in times of severe stress when the market experienced sudden and sharp price fluctuation.

Introduction

Looking back at the transition of transaction methods in the foreign exchange (FX) markets[1], the electronic trading, in which buy and sell orders and transactions are conducted on electronic platforms, has emerged since the early 1990s in the interbank market where banks and securities companies (dealers) transact. At the beginning of the 2000s, electronic trading has begun to prevail in the dealer-to-customer market where dealers trade with customers including institutional investors. At the early stage, human traders make final investment decisions in electronic trading. However, around the mid-2000s, algorithmic trading has started to prevail. In algorithmic trading, a series of transaction processes varying from an investment decision to execution are conducted automatically based on pre-determined programs. In recent years, algorithmic trading has been on an upward trend because it enables high-speed and high-frequency trading, which human traders cannot implement, and improves trade efficiency. For example, algorithmic trading share has went up to approximately 70-80% in 2019 in the FX spot market transacted on the EBS[2], one of the most commonly used electronic broking systems in the interbank market. These shifts in transaction methods have seemed to change the FX rate pricing mechanism and market functioning. Thus, understanding characteristics of algorithmic trading is becoming important.

In this paper, we outline FX markets' algorithmic trading and conduct quantitative analysis on its recent developments and impacts on market liquidity in the USD/JPY spot market.

Algorithmic Trading in FX Markets

Trading Algorithms

Algorithmic trading is categorized into two types: "trading algorithms" and "execution algorithms" (Chart 1).[3] Trading algorithms are transactions that automatically implement a series of investment decision-making processes ranging from price and volume order to timing, in pursuit of profits. Trading algorithms mainly comprise "market make,"

[Chart 1] Major types of algorithms

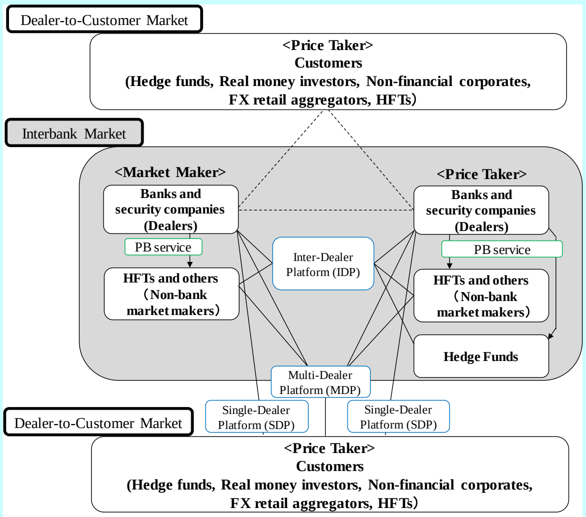
Strategy		Contents
Trading Algorithms		
	Market make	Providing the bid-ask quotes as market maker and generating the profit from the spread between sell price and buy price (bid-ask spread).
	Directional	Following a trend or momentum of price, or pursing the profit by digesting news and events in short time.
	Arbitrage	Generating profits by the arbitrage in the same financial products, in the gap between actual price and theoretical price, and in latency (difference in arrival time of information among markets).
Execution Algorithms		Executing pre-determined amounts of trade smoothly in order to mitigate market impacts (e.g., slicing original orders into small orders to execute gradually)

Note: The table is made by referring to Advanced Financial Engineering Center of NTT DATA Financial Solutions (2018), "Unmasking Algorithmic Trading," (*Kinzai*, available only in Japanese) and others.

"directional," and "arbitrage," and market make is said to be widely used in the FX spot market. Market make automatically offers a bid–ask quote and makes profits from the difference between executed buy and sell prices (the bid–ask spread), which automates dealers' traditional market making function (liquidity provision).

Dealers, particularly large European and U.S. banks, and non-banks including high frequency trading (HFT) entities, are said to actively use market make algorithms (Chart 2).[4] Market make algorithm controls the width of spread and volumes finely, offers new orders, and changes or cancels existing orders depending on overall market developments and market order changes. Particularly, non-banks repeat these transaction behaviors at high speed and frequency. These non-banks have rapidly grown in FX markets, making them comparable with large European and U.S. banks.[5] Meanwhile, price-takers, such as hedge funds, tend to use other types of trading algorithms, including directional. Directional can also be conducted at a high speed and frequency because taking buy and sell quotes quickly in response to news contents and market developments are essential to generate profits.

[Chart 2] Structure of FX markets



Note: The solid and dotted lines show electronic trading and voice trading, respectively. IDP, SDP, and MDP are electronic trading platforms. PB refers to the prime-brokerage service (refer to Note 4).

Execution Algorithms

While trading algorithms automate a series of decision-making process of transactions, execution algorithms aim to automatically and smoothly execute a pre-determined amount of buy and sell contract. For example, when a dealer seeks to execute a customer's large amount of USD buying/JPY selling order, the order execution itself puts upward price pressure on the USD/JPY, resulting in a poor execution result that the USD was bought against the JPY at higher prices than expected when the trading decision was made. In order to mitigate this unwanted price impact (called "market impact"), in general, a dealer slice a customers' large order into small orders and execute them gradually. Execution algorithms automate this type of execution method, and have been widely used in recent years along with trading algorithms.[6]

Real money (i.e., pension funds and life insurance companies) is said to be dominant execution algorithm users, and dealers including banks are both providers and users of the execution algorithm.[7] Additionally, details of execution results are recorded electronically, enabling users to analyze the results and enhance stakeholder accountability of the execution.[8]

Quantitative Analysis of Algorithmic Trading

In this section, we introduce proxy indicators of algorithmic trading in the USD/JPY spot markets, and analyze impacts of algorithmic trading on market liquidity in normal times and market stress times.

Proxy indicators of algorithmic trading

Data in the FX market that can identify individual traders and analyze their trading behaviors in detail are limited.[9] This situation reflects the FX market's unique characteristics, that is, no specific regulatory authorities exist, and various participants trade over-the-counter (OTC) at various venues all over the world. Hence, specifying "algorithmic traders" and analyzing their transactions in detail is difficult. Under such circumstances, certain previous studies focus on algorithmic trading's general features, that is, high-speed and high-frequency transactions relative to human traders. They measure individual contracts' transaction speed and regard it as an algorithmic trading if transacted faster than a certain threshold.[10] This paper refers to these studies, and tick data of EBS[11], which is a kind of granular transaction data, are used to construct the following two proxy indicators of algorithmic trading.[12]

First, we construct an indicator referred to as "fast-paced orders," which captures a market maker behavior that cancels a quote below 100 milliseconds (0.1 second) after it was newly provided.[13] This indicator is assumed to mainly capture market make algorithm developments, which typically provide new quotes and cancel them at a high speed and frequency. From the liquidity provider or consumer's perspective, this indicator focuses on liquidity providers' (i.e., market makers) behavior.

Second, we calculate another indicator called "fast executions," which captures an investor behavior that takes a quote below 100 milliseconds (0.1 second) after it was newly provided by market makers. This indicator is assumed to capture liquidity consumers' (i.e., price-takers) behaviors, who use trading algorithms including "directional." However, this indicator would also by and large capture cover deals[14] accompanied with market making activities, implying that this is a comprehensive indicator that involves activities of liquidity providers (market makers) as well.[15]

Based on the concept above, we construct time-series data of these two indicators, focusing on developments within 10 minutes after release of the U.S. employment report (from 8:30 A.M. to 8:39 A.M. Eastern Standard Time). As a result, the two indicators have been are on an upward trend since around 2016, implying that algorithmic trading has prevailed in the USD/JPY spot market as well (Chart 3).[16] In addition, a calculation of the hourly average of these indicators from November 2019 to January 2020 shows that indicator levels are higher in European and U.S. time zone than in Japan (Chart 4). In general, the use of algorithmic trading is said be limited by Japanese non-financial corporations, although total USD/JPY trading volumes in Japanese time zone are large due to their transactions. Conversely, large European and U.S. banks as well as non-banks, which utilize algorithmic trading actively, are said to have strong presence in European and U.S. time zones. The two indicators we calculated are consistent with these general characteristics of algorithmic trading in the USD/JPY spot market.

Impacts on market liquidity in normal times

While the widespread use of algorithmic trading is assumed to have various impacts ranging from FX rate's pricing mechanism to overall market functioning, most previous studies focus on the impacts on market liquidity. Empirical study results often highlight that the increased presence of algorithmic trading positively contributes to market liquidity improvement, at least in normal times.[17]

The regression analysis below is conducted based on previous literature methods, using algorithmic trading's two proxy indicators to verify whether the above observations are consistent with the USD/JPY spot market.[18]

$$|Spread_t| = \alpha + \beta_A lnAlgo_t + \beta_L|L\_Shock_t| + \beta_C Control_t + \varepsilon_t$$

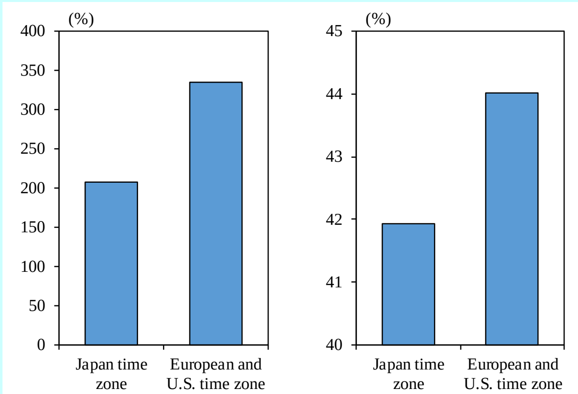
[Chart 3] Algorithm trading indicators (time series)

Note: These indicators are calculated in the USD/JPY spot market. The time-series data are shown as yearly average of indicators within 10 min after release of the U.S. employment report each month. The data in 2020 comprise the average from January to March. The value of fast-paced orders and fast executions are divided by total trading volumes to control the impact of the increase in total trading volumes. The values of fast-paced orders capture behaviors of cancelling quotes; therefore, the values can exceed 100%.

Source: EBS

[Chart 4] Algorithm trading indicators (hourly-average)

<Fast-paced Orders> <Fast Executions>



Note: The data comprise the hourly average of the algorithm trading indicators in the USD/JPY spot market from November 2019 to January 2020, excluding Christmas holidays, year-end, and new year holidays. "Japan time zone" and "European and U.S. time zone" show the hourly average from 7 a.m. to 3 p.m. and from 3 p.m. to 7 a.m. the next day in Tokyo time, respectively.

Source: EBS

Data within 10 minutes after the release of the U.S. employment report from January 2014 to March 2020 (each variable is a mean value of tick data recorded within the 10 minutes) are used to estimate the above regression analysis. We adopt effective spread for the dependent variable ($Spread_t$) as a liquidity indicator, that is, the spread between traded price and mid-quote price (best bid and best ask average price) at the same time.[19] The following independent variables are used: logarithmic form of either of the two algorithmic trading proxy indicators ($Algo_t$) and degree of surprise in the U.S. employment report (L_Shock_t; calculated by dividing the gap between the actual number of nonfarm payrolls and its market expectation by the standard deviation of the gap during the estimation period). Control variables ($Control_t$) comprise the lagged value of $Spread_t$ and logarithmic form of the amount of best quotes (so-called "depth,"[20] another liquidity indicator).

Estimation results are as follows. First, estimation results using fast-paced orders as a proxy indicator of algorithmic trading show a negative and statistically significant coefficient, whereas other coefficients satisfy the expected signs (Chart 5). In other words, the more algorithmic trading by liquidity providers (fast-paced orders) are used, the tighter is the spread (better market liquidity). The higher the absolute degree of surprise in the U.S. employment report, the wider the effective spread in the previous month, and a deterioration in another liquidity indicator (lower depth level) tends to lead to wider spread (worse market liquidity).[21] Next, estimation results using fast executions as the proxy indicator of algorithmic trading show a negative but not statistically significant coefficient on the indicator. As discussed in the previous section, this proxy indicator contains both liquidity consumers and providers' behavior. This may be the reason of statistically insignificant impact on market liquidity. In sum, it can be concluded that algorithmic trading, particularly market make (liquidity provision), contributes to improving market liquidity in the USD/JPY spot market in normal times. This finding is supported by the fact that regression coefficient is interpreted as the average value throughout the estimation period.

[Chart 5] Estimation results

	Dependent variables	Effective Spread	
	Explanatory variables		
Algorithm trading indicators	Fast-paced orders	-0.075*** (0.018)	
	Fast executions		-0.253 (0.172)
	Degree of surprise in the U.S. employment report	0.025 (0.019)	0.040* (0.021)
	Effective spread in previous month (lag-term)	0.538*** (0.086)	0.730*** (0.076)
	Depth	-0.232*** (0.059)	-0.154** (0.068)
	Constant	0.953*** (0.197)	1.369* (0.766)
	Adjusted-R^2	0.67	0.61
	Sample size	75	75

Note: ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. Standard Error has been provided in parenthesis.

Source: EBS, Bloomberg

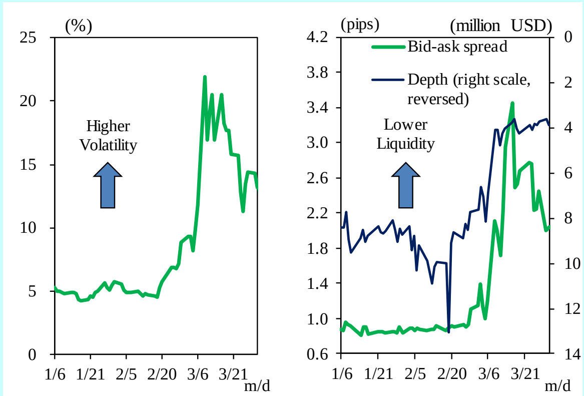
Impacts on market liquidity: in market stress times

This section examines whether the results above are consistent even in times of market stress when volatility is high. Previous literature finds that algorithmic trading can deteriorate market liquidity by stopping the liquidity-providing function in times of market stress not well assumed in the algorithm program.[22] For example, in times of market stress where JPY appreciates sharply, the following risks increase for market makers: inventory risk (i.e., holding considerable inventories due to market makers' biased position toward JPY short) and FX risk (i.e., valuation losses of inventories <JPY short position> caused by additional JPY appreciation). In times of such stress, market makers are said to (1) keep providing buy and sell quotes with wider bid–ask spread and then (2) stop providing liquidity when market fluctuation degree exceeds a certain maximum threshold.[23] By contrast, other previous literature claims that algorithmic trading's liquidity-providing function was maintained in times of market stress.[24] These findings show that a firm consensus on algorithmic trading's functions in times of market stress has not been reached. Stress events do not emerge frequently, and their degree, duration, and impact on FX rates including USD/JPY, diverge across events. Under such circumstances, algorithmic program and operation have been gradually advanced in response to stress events, making it difficult to perform an objective evaluation.

Based on the above understanding, we here try to capture algorithmic trading developments from late

[Chart 6] Market environment in the USD/JPY market (from January to March, 2020)

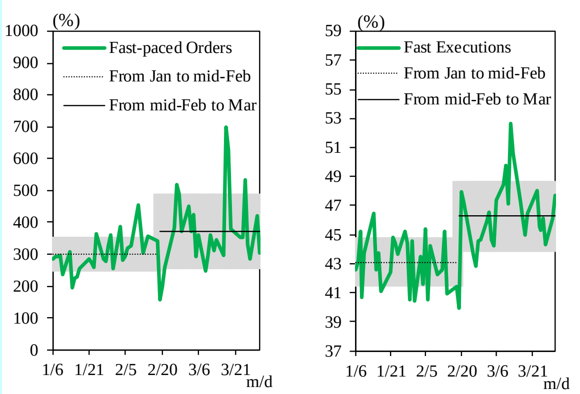
<Implied volatility> <Liquidity indicators>



Note: The left panel shows the one-month implied volatility in the USD/JPY market. On the right panel, the bid-ask spread is shown as daily average of the spread in each minute (from 5 p.m. to 5 p.m. next day in NY time). Depth indicates daily averages of the total volumes in best bid and best ask. The latest data are as of March 31, 2020.

Source: EBS, Bloomberg

[Chart 7] Algorithm trading indicators (from January to March, 2020)



Note: "From Jan to mid-Feb" and "From mid-Feb to Mar" represent the average from the beginning of January to February 18, 2020 and from February 19, 2020 to the end of March, respectively. The shadow area shows the range of two standard deviations in each period. The latest data are as of March 31, 2020.

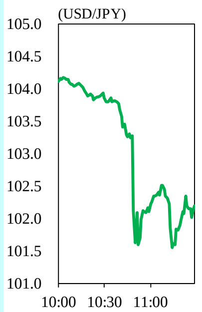
Source: EBS, Bloomberg

February 2020 to end of March 2020 as an example of stress time, when global market volatility surged due to the COVID-19 pandemic. The USD/JPY volatility moved up sharply in March, whereas liquidity indicators, such as the bid–ask spread and amount of best quotes (depth) deteriorated dramatically (Chart 6).[25] Algorithmic trading's proxy indicators during this period generally remained unchanged, albeit with fluctuations, from previous months when the market volatility was not high (Chart 7). This finding implies that algorithmic trading's liquidity-providing function has not ceased. In addition, market intelligence suggests that algorithmic trading's liquidity provision during this period approximately remained the same on average, though the algorithm's bid–ask spread widened.

Next, we focus on severe stress time within the above period such that the market dramatically fluctuates in a short time and analyze algorithmic trading developments. Particularly, we focus on the timeframe from 10:00 A.M. to 11:30 A.M., Tokyo Time, on March 9, 2020, when market environments extremely deteriorated. The USD/JPY dropped from approximately 104.0 to 101.5 levels (Chart 8, left-panel). During that time, fast-paced orders, which is assumed to better reflect market maker's behavior, is significantly lower than the 5-business-day average before and after the event (Chart 8, right-panel).[26] Another example of severe stress time of the USD/JPY market is the flash crash observed in the early morning on January 3, 2019, Tokyo Time. Fast-paced orders on the event day is also significantly lower than the average (Chart 9).

[Chart 8] From 10 a.m. to 11:30 a.m. Tokyo time on March 9, 2020

<USD/JPY> <Algorithm trading indicators>



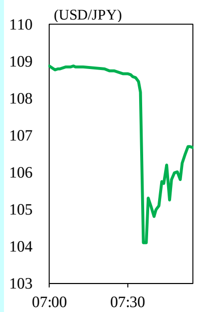
	Fast-paced Orders	Fast Executions
1.Event day (%)	221	49
2. The average before and after five business days from the event day	347	47
t-statistics (null hypothesis: 1 = 2)	-3.02***	1.25

Note: The left panel shows the lowest values in each minute. The t-statistics in the right panel are results of the one-sided t-test in which null hypothesis is the equality between 1. (event day) and 2. (the average before and after five business days from the event day). The negative (positive) value shows that the algorithm trading indicators on 1. is significantly lower (higher) than 2. The same applied to Chart 9. *** indicates the statistical significance at the 1% level.

Source: EBS, Bloomberg

[Chart 9] From 7 a.m. to 8 a.m. Tokyo time on January 3, 2019

<USD/JPY> <Algorithm trading indicators>



	Fast-paced Orders	Fast Executions
1.Event day (%)	16	57
2. The average before and after five business days from the event day	202	44
t-statistics (null hypothesis: 1 = 2)	-2.17**	1.85**

Note: ** indicates the statistical significance at the 5% level.

Source: EBS, Bloomberg

These results imply that algorithmic trading, particularly market make, can maintain its liquidity-providing function despite in times of market stress, but can lower such function in times of severe stress, albeit temporarily.

Conclusion

This paper examines FX markets' algorithmic trading, constructs its proxy indicators by focusing on its general characteristics (i.e., high-speed and high-frequency compared with human trading), highlights its stylized facts, and analyzes its impact on market liquidity. Based on the proxy indicators, algorithmic trading in the USD/JPY spot market has been on an upward trend since around 2016 and has more presence in European and U.S. time zones when large European and U.S. banks and non-banks transact actively. Our analysis of the algorithmic trading on market liquidity shows that it on average has a positive contribution on market liquidity in normal times. Its liquidity-providing function was generally maintained under market stress (during the COVID-19 pandemic from late-February to end-March 2020), though it could have been dampened albeit temporarily in times of severe stress when the market experienced sudden and sharp price fluctuation (from 10:00 A.M. to 11:30 A.M., Tokyo Time on March 9, 2020).

In recent years, the foreign exchange market has seen a growing presence of algorithmic trading. Additionally, the observed characteristics may change in the future, reflecting advancement in information technology[27] and potential change in risk perception by algorithmic traders. Accordingly, it would be important to continue deepening the understanding of evolving algorithmic trading, including implications on market functioning, from a diverse perspective. In achieving this, international collaboration and discussion would be needed, reflecting on the nature of FX's 24-hour global trading. The Global Foreign Exchange Committee (GFXC), consisting of local FX committees represented by private and central bank members, could make an important contribution. For reference, the GFXC is now reviewing the FX Global Code and considering whether to modify the codes related to algorithmic trading, on the back ground of its increasing share.

* Currently at Monetary Affairs Department.

[1] For discussions about the spread of electronic trading and its impact on market functioning, see Koga, M., and Takeuchi, A., "High-speed trading and automatic trading in the foreign exchange market: changes in the market structure and new Issue" (Bank of Japan Review, 2013-J-1, 2013, available only in Japanese) and Oh, Y., Takada, Y., and Sugayama, Y., "Recent structural changes in FX markets" (Bank of Japan Review 2014-J-5, 2014, available only in Japanese), Bank for International Settlements (2018) "Monitoring of fast-paced electronic markets."

[2] See Schrimpf, A., and Sushko, V. (2019) "FX trade execution: complex and highly fragmented," *BIS Quarterly Review*.

[3] This paper categorizes algorithmic trading into "trading algorithms" and "execution algorithms" based on its objective and function. However, fixed and general algorithmic trading names and categorization are not available.

[4] High-frequency trading (HFT) entities are also called non-bank market makers. They often utilize large European and U.S. banks' prime brokerage service and make interbank market transactions in the name of the banks that provide the service.

[5] For example, the Euromoney FX Survey in 2020 shows that two non-banks are among the top 10 liquidity providers (third: XTX markets, seventh: Jump Trading) in the FX market (including not only spot market but also derivatives market).

[6] Typical types of execution algorithms include:
- Those called TWAP (time-weighted average price) in which main orders are divided into small orders and executed at equal time intervals, resulting in execution at TWAP.
- Those execute immediately when market price become more favorable than a certain pre-determined level.
- Those execute when the gap between transaction price and best quotes (spread cost) within a certain pre-determined level.

[7] Non-financial corporations sometimes use execution algorithms (e.g., when they buy out large overseas companies).

[8] The analysis of execution results is referred to as transaction cost analysis (TCA). TCA is conducted by banks that offer execution algorithms, specialized third parties, and customers.

[9] Based on the Financial Stability Board's (FSB) recommendation, the countries and regions of its members collect detailed data in which the entities of transactions can be specified to a certain extent. The data do not include FX markets' spot trading, which are the focus of analysis in this paper, though it includes FX option trading.

[10] Previous literature on fast-paced orders includes Hasbrouck, J., and Saar, G. (2009) "Technology and liquidity provision: The blurring of traditional definitions," *Journal of Financial Markets*, and Scholtus, M., Dijk, V. D., and Frijns, B. (2014) "Speed, algorithmic trading, and market quality around macroeconomic news announcements," *Journal of Banking and Finance*. Previous literature regarding fast executions includes: Scholtus et al. (2014) and Corsetti, G., Lafarguette, R., and Mehl, A. (2019) "Fast trading and the virtue of entropy: evidence from the foreign exchange market," *ECB Working Paper Series*.

[11] More specifically we use EBS data Mine Level 2.0. Information about transactions and quotes (from best bid-ask to 10th bid-ask quotes) are recorded at each 100 millisecond (0.1 second).

[12] Algorithmic trading such as execution algorithms is not necessarily characterized as high speed and frequency trading, thereby it is excluded from the discussion below.

[13] As described in note 11, the best bid–ask to the tenth bid–ask quotes are available in the data used in this paper. We calculate fast-paced orders, utilizing quotes that are newly offered by market makers at time t and remain more favorable than the tenth bid–ask quote at time t+1. The reason is to avoid misclassification. Newly emerged quotes at time t may appear to disappear at time t+1 even though they are not cancelled because they become out of the tenth bid–ask quotes due to the emergence of better quotes.

[14] Market makers hold position (inventories) temporarily when customers' orders are biased toward one direction (either buy or sell), and they are exposed to risks derived from FX fluctuations (market risk). Therefore, they conduct spot trading (or forward trading) as price-takers to eliminate the position. This transaction is referred to as cover deal.

[15] Fast executions may include human traders' transactions. They take prices by chance immediately after a new price emerge. (In addition, other types of executions that conducted immediately when market prices are within a certain range pre-determined by human traders can be included in this indicator.) However, such problem looks not so serious because fast executions indicator is not high in the Japanese time zone when human traders' share is assumed to be relatively high.

[16] When interpreting these indicators, two caveats should be kept in mind. First, data used in this paper are targeted on interbank market. Therefore algorithmic trading conducted by other than banks may not be sufficiently captured. However, non-banks and hedge funds generally utilize large European or U.S. banks' prime brokerage services and make interbank market transactions using the name of such banks (note 4). This fact implies that the data used in this paper satisfy the coverage to a certain degree. Second, the threshold time (100

milliseconds) used in this paper for constructing algorithmic trading's indicators is kept unchanged over the sample period. Considering the general improvement in telecommunication speed, algorithmic trading quality in terms of speed captured by the indicators worsens over time (In other words, 100 milliseconds in recent years is not as fast as that in 10 years ago.). Therefore, the indicators tend to increase over time.

[17] For example, see Hendershott, T., Jones, M. C., and Menkveld, J. A. (2011) "Does algorithmic trading improve liquidity?," *Journal of Finance* and Hasbrouck, J., and Saar, G. (2013) "Low-latency trading," *Journal of Financial Markets.*

Quality of algorithmic trading's liquidity has no clear consensus. Bank for International Settlements (2011) "High-frequency trading in the foreign exchange market," and other literature indicate the following quality problems. First, algorithmic trading's liquidity volume per transaction is small and insufficient in terms of depth. Second, algorithmic traders provide quotes simultaneously to various platforms (venues). When the quotes are taken at one of the platforms, algorithmic traders often cancel those provided in other platforms. This situation leads to a misperception of available liquidity (called "liquidity mirage").

[18] We refer to Hendershott et al. (2011) in note 17, Corsetti et al. (2019) in note 10, and Kumano, Y., and Goshima, K., (2018) "Monetary policy announcement and algorithmic trading: the analysis using access information to webpage" (Institute for monetary and economic studies Bank of Japan discussion paper series, 2018, available only in Japanese).

[19] Strictly speaking, we use effective spread divided by mid-quote price in the regression (estimated in basis point value (bps) unit, 0.01%). Effective spread, as well as bid-ask spread (the spread between dealers' bid quote and ask quote), is categorized as "tightness" indicator of market liquidity. It is assumed that lower value of the indicator (tighter spread) means better liquidity condition because traders are likely to make their transaction at better price.

[20] The amount of best quotes (depth) shows the amount of bid–ask quotes around the current price. Larger depth indicates higher possibility in which traders can transact at their desired volume with better price. This situation means higher market liquidity. This paper uses the amount of best quotes (best bid–ask) as depth.

[21] Algorithmic trading may also increase through a certain channel where market liquidity improves as the reverse causality of the estimation assumed in this paper. To deal with such endogeneity problem, this paper uses effective spread, referring to Corsetti et al. (2019) in note 10 and others. The mid-quote price at the time of execution used to calculate effective spread is not available when the decision to use algorithmic trading is made. Alternatively, the spread between traded and mid-quote price 5 minutes after the transaction (realized spread) is also used as a liquidity indicator in previous literature. As a robustness check, we also use realized spread as a dependent variable, and obtain approximately the same estimation results (The coefficient on fast-paced orders is significantly negative.). In addition, to deal with the endogeneity problem, Scholtus et al. (2014) in note 10 assume that if the data are limited to only 1 minute after the event, the decision to use algorithmic trading is determined before the event and not affected by liquidity condition after the event. We also estimate based on the same method (i.e., using the data only 1 minute after the release of the U.S. employment report) and obtain approximately similar results (The coefficient on fast-paced orders is significantly negative.).

[22] For example, see Bank for International Settlements (2017) "Foreign exchange liquidity in the Americas."

[23] All market makers, including but not limited to algorithmic traders, can conduct such behavior.

[24] For example, see Bank for International Settlements (2011) referred to note 17.

[25] A "resiliency" is one of liquidity indicators in FX markets, together with tightness and depth. For example, a "price impact" captures the degree of new order flows' impact on FX rate (either appreciation or depreciation). We also estimated price impact, and obtained approximately similar developments to tightness and depth indicators, though they are not illustrated in this paper.

[26] This paper conducts t-test based on the methods by Breedon, F., Chen, L., Ranaldo, A., and Vause, N. (2018) "Judgement Day: algorithmic trading around the Swiss franc cap removal," *Bank of England Staff Working Papers.*

Fast executions on the event day do not significantly decrease compared with before and after the event. Hedge funds (price-takers and liquidity consumers) that use directional algorithmic trading included in fast executions may have traded more actively as market volatility increases.

[27] For example, further speeding up transactions and the programs' sophistication can be assumed.

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