Simple measures of market efficiency:
A study in foreign exchange markets

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ABSTRACT

Previous studies on the stock market consider the degree of market efficiency to be an inverse of the predictive power of order flow. Following this notion, I propose simple market efficiency measures in foreign exchange (FX) markets. The first measure considers the market to be inefficient when positive (negative) order flows predict the appreciation (depreciation) of a base currency. The second measure considers whether predictions using order flow result in tangible gains. These measures are related to liquidity levels and information factors in FX markets, unlike the measures in previous studies.

JEL classification: F31; G14

Keywords: Liquidity; Information asymmetry; Market efficiency; Order flows; Stealth trading

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Highlights

I find order flows to have short–lived predictability and FX markets to be efficient to some extent.

I propose measures of efficiency in FX markets.

These measures decline largely around periods of financial turmoil.

These measures are related to market liquidity and information factors.

An increase in medium-size trading enhances the predictive power of order flows.

1. Introduction

Globally, the foreign exchange (FX) market is the largest financial market, with an average of approximately $5.3 trillion transactions per day (BIS, 2013). This large market has special characteristics. First, the market is composed of a handful of participants. In interdealer FX markets, trading is concentrated among a handful of large financial institutions (King et al., 2013). Second, unlike a stock market, trading is not centralized. Although the recent spread of the electronic broking system has centralized trading to some extent, no unique system is used to trade a certain currency pair, and decentralized transactions for one currency pair occur through different systems. Additionally, BIS (2010) reports that approximately 60% of trades still occur through non-electronic broking systems, and most of these trades are over-the-counter (OTC). A handful of participants engage in decentralized trading in the FX market, and Menkhoff et al. (2013) call this opaque market a "dark" one.

Does this dark market achieve informational efficiency? Compared with a stock market, is this market more (less) efficient? As reported in studies on stock markets (e.g., Chordia et al., 2005, 2008; Chung and Hrazdil, 2010), is a market's efficiency related to its conditions, such as liquidity? These questions motivate this research on the EUR/USD and USD/JPY markets. Because the measure proposed by the extant literature provides little information on the third question, I introduce alternative measures. To the best of my knowledge, this paper is the first to examine the issue of FX market efficiency using these measures. Previous studies on stock markets consider a market to be inefficient when a lagged order imbalance (net buyer-initiated trade) (OIB) predicts a current price change (Chordia et al., 2005, 2008; Chung and Hrazdil, 2010). Alternatively, I propose two simple measures of market efficiency. The first measure takes the value of 1 when lagged order flow is positive (negative) and the current base currency appreciates (depreciates), and 0 otherwise. The second measure takes the value of 1 when order flow brings tangible gains. These two measures are not based on conventional statistical criteria but on the practical predictive power of order flow and are correlated with liquidity proxies (effective spread and price impact) and information factors (information asymmetry and stealth trading). Moreover, the graphical analysis shows that the proposed measures decline largely around periods of financial turmoil, such as the bankruptcy of Lehman Brothers and the Eurozone crisis. This finding and the empirical results indicate that market efficiency deteriorates when market uncertainty becomes large and liquidity dampens.

When researchers approach the issue of market efficiency in an FX market, they consider that no information can predict a future FX rate change in an efficient market and that no excess returns exist. Regarding this issue, vast literature reports persistent deviations from the uncovered interest rate parity (UIP) and purchasing power parity (PPP) that indicate excess returns and inefficiencies in an FX market. Meanwhile, the following empirical studies provide economic interpretations and some justifications for the existence of excess returns. Mancini et al. (2013) construe the deviation from UIP as a premium for market liquidity risk. They find that high interest rate currencies depreciate sharply when FX market liquidity deteriorates and propose that excess returns (deviations from UIP) realized through short U.S. dollar positions and long positions in a high interest rate currency are premiums for the liquidity risk of holding such high interest rate currencies. Regarding PPP, Michael et al. (1997) use a smooth transition auto-regressive (STAR) model and support the transaction cost hypothesis as an explanation for deviations from PPP. Their STAR model suggests that the real FX rate (deviation from PPP) shows a mean-reverting pattern toward PPP through arbitrage once the deviation exceeds the transaction cost.[1] Moreover, many players use technical analysis to map past and current FX rates and trading volume data into trading decisions (Neely and Weller, 2012). Although the former two deviations may have some economic justifications, the last fact is inconsistent with the efficient market hypothesis, which denies the usefulness of past information to predict a future FX rate.

To examine market efficiency as information that predicts an FX rate, I consider order flows, which reflect net buyer-initiated trades and demand pressure (e.g., Evans and Lyons, 2002). Recent developments in the microstructure approach in an FX market motivate me to consider order flow as information because this approach proposes that order flow is the key variable to convey information in an FX rate. Unlike traditional FX models that assume a representative agent, the microstructure approach considers heterogeneous agents whose trading processes affect an FX

[1] Chapters 2 and 3 of Sarno and Taylor (2002) provide surveys of the literature on UIP and PPP, respectively.

rate. Order flows aggregate different opinions among market participants and convey aggregated market expectations. If participants are homogeneous, other things being equal, a rise in U.S. interest rates instantly changes the expectation of the representative agent through the UIP condition, and an FX rate archives its new equilibrium value without trading. Carlson and Lo (2006) use one-minute data for the DEM/USD and show that intensive trading and volatile rate changes follow the unexpected interest rate increase by the Bundesbank for the next two hours. This result suggests that heterogeneous traders have different opinions about that increase, and an FX rate gradually archives its new equilibrium value through transactions. I consider that this result is not appropriate for the assumption of a representative agent and heterogeneous agents should be adopted. Moreover, Ito et al. (1998) report information asymmetry in an FX market and support heterogeneous agents in the market. These results lead me to consider the microstructure approach for the issue of market efficiency.

When order flows are positive, buyer-initiated trades dominate seller-initiated trades. What motivates net buyers initiating their purchases: private information or the need for liquidity? If the order flow has a persistent effect on an FX rate, it is caused by private information. If the order flow is caused by a liquidity factor, that effect is transitory and an FX rate moves back to its previous equilibrium level eventually. Regarding this issue, the empirical evidence is mixed. Rime et al. (2010) find that order flow is significantly related to fundamentals and is a powerful predictor of a future FX rate. Their study confirms that order flow can raise tangible economic gains, which they evaluate using Sharp ratios and utility calculations. Froot and Ramadorai (2005) find that order flows are less related to fundamentals in the long term, although they are related to short-term currency returns. King el al. (2013) suggest that the three mutually consistent theories of focus on a dealer's inventory management, a finite price elasticity of asset demand, and private information can explain the transit and persistent effects of order flows on an FX rate.

From where does private information originate? The three round model developed by Evans and Lyons (2002) assumes that private information comes from a dealer's customer (Round 1). In the interbank market (Round 2), the dealer who trades with its customer in Round 1 exploits that information and passes her inventories—that originally come from the customer in Round 1—to dealers to unwind it. In Round 3, a dealer who processes and is not reluctant to carry over these inventories trades with her customers to unwind her inventories. Because the customer's demand curve is downward, an FX rate should change with the direction of the order flows of the Round 1 customer. The literature finds evidence for the model of Evans and Lyons (2002) that deals with the customer as a source of private information. Menkhoff et al. (2013) examine order flows of various end users and find that asset managers whose order flows have a persistent effect on the FX rate are informed traders. Moore and Payne (2011) find that the order flows of dealers belonging to large trading floors have a significant effect on an FX rate, a result that indicates that these dealers can access more customer order flows than other dealers. Osler et al. (2011) show that dealers strategically narrow their quoting spreads when they trade with their customers to attract customers and obtain information. They also find that a dealer trades aggressively in the interdealer market after her customers trade to exploit information gained through such customer trading. This finding indicates that order flows in an interdealer market contain some information. Rime et al. (2010), who use interdealer order flows, support this view; interdealer order flows significantly predict a future FX rate change. I also postulate the informativeness of interdealer order flows and use these flows to measure the efficiency of FX markets. Figure 1 shows that the predictive power of order flows is statistically significant even in short periods (one and two minutes). The short-lived predictive power of order flows indicates that the studied FX markets achieve some efficiency.

The proposed measures contribute to the microstructure analysis in the following respects. First, these measures are available at high frequencies and help microstructure researchers. For example, when one considers one-minute order flow predictability, these proposed measures are available at every one-minute interval, allowing researchers to engage in high frequency analysis (e.g., Tables 3 and 5 in this study). Second, the measures seem economically more relevant than the previous ones when one considers the predictability of order flows given that the proposed measure ($EF2$) considers tangible gains from the order flow signal. Third, the proposed measures are simple for calculations and easily applied to research on other markets in which order flow information is available. Fourth, FX market efficiency has been discussed primarily in terms of UIP holding (see Sarno and Taylor (2002)), and I expect that the proposed measures provide additional insights into an analysis of FX market efficiency.

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 proposes two measures of market efficiency. Section 3 measures the proxies for liquidity and information asymmetry. Section 4 presents the empirical results and considers a proxy for the number of informed trades. Section 4 checks the robustness of the main result. Section 5 concludes this paper.

2. The Data

2.1. Data

I purchased EBS data mine 2.0 from ICAP, which provides the Electronic Broking Service (EBS) electronic trading platform. EBS is dominant in electronic trading of EUR/USD and USD/JPY over Reuters D 2000–2, which is also popular with interdealers, particularly in transactions in Commonwealth and Scandinavian currencies (McGroarty et al., 2009). I focus on EUR/USD and USD/JPY, the most popular in international financial markets (BIS, 2013). Trading through EBS is electronic and occurs in an interdealer market. The sample period ranges from July 26, 2008 to May 20, 2010. The data are recorded in one-second slices. I use the data recorded during GMT 0–19 because FX markets are dormant after GMT 20 (Ito and Hashimoto, 2006). Data from the weekends are also excluded. Following Berger et al. (2009), I exclude several holidays and days with unusually light volume near those holidays, including December 24–26, December 31–January 2, Good Friday, Easter Monday, Memorial Day, Labor Day, Thanksgiving, and Independence Day. The original data record the best bid and ask prices quoted and the transaction prices that occur on the bid and/or ask sides. When a transaction occurs, the data record the amount of money in that transaction using a base currency unit. The minimum trading size and trading unit is one million euros (dollars) for the EUR/USD (USD/JPY) market.

2.2. *Order flow*

Throughout this paper, order flow and order imbalance (OIB) are used interchangeably. The former is used in FX market research, and literature on stock markets uses the latter. Following

Chordia et al. (2005), I calculate OIB as the amount of net buyer-initiated trades (order flow) in each interval. This money-based OIB is labeled OIBM, which is calculated using the amount of money paid and given. In addition to OIBM, Chordia et al. (2005) consider number-based OIB, which is calculated using the number of net buyer-initiated transactions. I label this OIB as OIB#. I confirm that the empirical result of OIB# is consistent with that of OIBM (the result is reported in the robustness check). Therefore, the following empirical section reports only the result for OIBM. Moreover, the EBS live screen shows only the direction of a deal (bid- or ask-side trade) but not the deal amount for each transaction, and EBS allows dealers who can monitor EBS and who are not counterparties involved in a deal to calculate OIB# but not OIBM in real time. Therefore, OIBM reflects more asymmetric information than OIB# because the amount of money in each deal is information only for the counterparties involved. This asymmetry of OIBM may play a more significant role in price discovery than OIB#. This expectation is supported by the empirical result that lagged OIBM more correctly predicts a current FX rate change than OIB# in terms of the R-square. I do not report the result of the OIB# regression for the sake of space. Keeping these points in mind, I use OIBM as OIB in the following empirical section. For the EUR/USD market, the Pearson coefficient correlations between OIBM and OIB# are 0.284 and 0.297 at one- and two-minute data frequencies, respectively. For the USD/JPY market, these correlation coefficients are 0.364 and 0.381 at one- and two-minute data frequencies, respectively. As subsequently explained, one and two minutes are the data frequencies I select to consider the forecasting power of OIB. In 63 and 62% of the EUR/USD cases, OIBM and OIB# show the same direction at one- and two-minute data frequencies, respectively. For the USD/JPY market, these percentages are 65 and 63% at the one- and two-minute data frequencies, respectively. These differences in OIBM and OIB# suggest that the selection between them significantly affects the proposed measures because the sign of OIB is crucial for the measures.

As previously mentioned, OIB# is public information for participants in the EBS market, and OIBM is private information for them. Therefore, the empirical test using OIBM is for the strong form of efficiency, which considers whether current asset prices reflect all information known to any market participant. Meanwhile, the result with OIB# is for the semi-strong form of efficiency and is reported in the robustness check.

3. Measures of market efficiency and their explanatory factors

3.1. Measures of market efficiency

This study differs from previous studies in that it considers positive (negative) order flow as a *signal* of the future appreciation (depreciation) of a base currency, although previous studies measure market efficiency using the linear predictive power of order flow. For example, Chung and Hrazdil (2010) calculate the R-square for the regression of a current price change onto a lagged order imbalance to measure market efficiency—called the R-square measure throughout this study. In my study, the predictive power of OIB for a future FX rate change is very short-lived and small. This low forecasting power may make it difficult to measure market efficiency using R-square values.

To address this issue, I apply Merton (1981) and Henriksson and Merton (1981), who derive a statistical framework for the market-timing (macroforecasting) ability of portfolio managers. They measure the market-timing ability of a manager by considering whether her forecasting is consistent with a realized future return. If she is able to forecast, then she has access to special information that allows her to exploit the market, indicating that the market is not efficient in terms of the strong form of efficiency. In the following analysis, I consider when a lagged OIB represents exploitable information and forecasts an FX rate change; if so, then the market is inefficient. Additionally, I consider whether a lagged OIB raises tangible gains when I examine market efficiency.

The first measure considers that a market is *inefficient* when lagged OIB correctly predicts the direction of a current FX rate change. This measure takes the value of +1 when the sign of the lagged OIB corresponds to that of a current FX rate change; otherwise, it takes the value of 0. This measure is labeled $INEF1$:

$$INEF1_t = +1 \text{ if } \mathrm{OIB}_{t-1} > 0 \text{ and } r_t > 0, \text{ or } \mathrm{OIB}_{t-1} < 0 \text{ and } r_t < 0$$

$$INEF1_t = 0 \text{ otherwise} \qquad (1)$$

where r_t is the FX rate change in period t. An FX rate change is calculated using the log difference of the quote midpoint ((bid + ask) / 2). I use the prevailing quote midpoints at the first and last timings in period t when calculating an FX rate change.[2]

The second measure considers whether lagged OIB results in a tangible gain. This second measure takes the value of +1 when positive (negative) lagged OIB not only predicts a positive (negative) current FX rate change but also when market participants exploit OIB and earn a profit. This second measure considers the efficiency of an FX market through the exploitability of OIB. I assume that market participants who observe and exploit a positive OIB in period t–1 buy a base currency at the prevailing ask rate at the first timing of period t and sell at the highest bid rate using a marker order in period t. For a negative OIB, the case is reversed. Let $p_t^{*,i}$ (i = ask or bid) be the prevailing rate at the first timing of period t. $p_t^{H,bid}$ and $p_t^{L,ask}$ are the highest bid and lowest ask rates prevailing during period t, respectively. I define the second variable, *INEF*2, as a measure of market *inefficiency* as follows:

$$INEF2_t = +1 \text{ if } \mathrm{OIB}_{t-1} > 0 \text{ and } p_t^{H,bid} - p_t^{*,ask} > 0, \text{ or}$$
$$\mathrm{OIB}_{t-1} < 0 \text{ and } p_t^{*,bid} - p_t^{L,ask} > 0$$
$$INEF2_t = 0 \text{ otherwise.} \quad (2)$$

*INEF*2 considers that the exploitability of lagged OIB is the inverse of market efficiency. When compared with *INEF*1, *INEF*2 provides a less (more) strict definition for market efficiency (inefficiency) because it may consider a market as efficient even when lagged OIB predicts the direction of a current FX rate change.

*****Figure 1 around here*****

I calculate these two measures related to market inefficiency in both one- and two-minute frequencies per day. The reason for adopting these frequencies is in the result of a regression of a current FX rate change on lagged OIB and constant terms from one- to 60-minute frequencies. I

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[2] One might consider that if the signal is to buy, then the ask price should be used, and if the signal is to sell, then the bid price should be used. In the following empirical section, I consider spread as an explanatory variable for *INEF*1, and returns calculated in one-sided quotes (bid/ask) are highly correlated with spread. Naturally, in this case, *INFE*1 is highly correlated with spread, which leads me to use the midpoint quote in equation (1). As a robustness check, I use the ask (bid) price for the calculation of the FX rate change if the signal is to buy (sell). The result remains unchanged (see Table 12).

calculate rate change and order flow at one- to ten-minute frequencies and do regressions at each frequency. Figure 1 presents the t-statistics for the estimated coefficient of lagged OIB at each frequency. I select ten minutes as the maximum frequency in Figure 1 to ensure easy viewing. This selection does not change in the subsequent discussion. As shown in Figure 1, two minutes is the maximum frequency at which the estimator of the lagged OIB is positive and statistically significant at least at the 5% level for the USD/JPY.[3] For the EUR/USD market, only the result at the one-minute frequency is significant. Figure 1 implies that the predictive power of the lagged OIB is quite short-lived in the FX markets compared with the stock market (e.g., a 15-minute data frequency in Chordia et al., 2005). This short-lived predictive power of the order flow indicates that the studied FX markets achieve efficiency to some extent. I convert *INEF*1 and *INEF*2 into daily measures to eliminate the effect associated with microstructure noise, aggregate these two measures, and calculate inefficiency ratios for each day. For example, the daily inefficiency ratio for 120 cases of *INEF*1=1 and 1,200 one-minute frequencies in a day is 0.1 (=120/1200). Because these ratios are bounded between 0 and 1, I apply a logit transformation to the ratios and multiply them by –1 to obtain market efficiency measures. Higher values of these measures, labeled *EF*1 and *EF*2, respectively, represent higher market efficiency levels. Thus, daily *EF*1 and *EF2* are derived using *INEF*1 and *INEF*2, respectively.

$$EF1_i = -1 \times \text{logit transformation of } \sum_{t=1}^{T} INEF1_t^i / T \quad (3)$$

$$EF2_i = -1 \times \text{logit transformation of } \sum_{t=1}^{T} INEF2_t^i / T, \quad (4)$$

where T represents the number of observations per day. For example, T is $60 \times 20 - 1$ for one-minute data during GMT 0–19. The minus one is required because I drop the data at the opening of each day to avoid the prediction of an overnight FX rate change using equations (1) and (2). $INEF1_t^i$ represents *INEF*1 during period *t* on the *i*th day. Following Chung and Hrazdil (2010), the R-square value is also considered a measure of market efficiency and is calculated using the

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[3] The negative OIB coefficient possibly indicates a price reversal effect. To absorb an OIB foisted on a market, market makers temporally set their bid and ask rates excessively low or high. After absorption, price reversal occurs. Pástor and Stambaugh (2003) adopt a negative estimator of lagged OIB as a proxy for illiquidity because this reversal is likely to occur when the market is illiquid.

regression of a current FX rate change onto the lagged OIB and constant term for each day. I adopt the logit transformation of the R-square, multiply this figure by –1, and label this variable *EF*0 (the R-square measure). Iwatsubo and Kitamura (2008) also use the R-square measure calculated using a 30-second data frequency to examine market efficiency levels in the EUR/USD and USD/JPY markets.

*****Table 1 around here*****

Table 1 shows the summary statistics of these three measures, which are calculated using the variables before the logit transformation and are multiplied by –1. Therefore, in Table 1, *EF*0, *EF*1, and *EF*2 range from 0 to 1. Table 1 indicates that *EF*0 (R-square) is absolutely small, thus suggesting that the EUR/USD and USD/JPY markets are efficient at all times in terms of a lack of forecasting power of a linear OIB. The small R-square may not correctly detect a change in market efficiency in these two markets.

*****Figure 2 around here*****

Figures 2a, 2b, and 2c show the times series of *EF*0, *EF*1, and *EF*2, respectively. The series are calculated using one-minute EUR/USD data.[4] From Figures 2b and 2c, the proposed measures indicate that the efficiency of the EUR/USD market deteriorates around the two periods of financial turmoil: the bankruptcy of Lehman Brothers and the Eurozone crisis. The sharp declines in *EF*1 and *EF*2 correspond to the bankruptcy of Lehman Brothers. On Sunday, May 9, 2010, the 27 EU member states agree to create the European Financial Stability Facility (EFSF). Just before the agreement, *EF*1 and *EF*2 reach bottom on Friday, May 7, 2010, indicating that, before its announcement, international financial markets were less confident that EU members would create the EFSF to ease fears surrounding the Eurozone crisis. This uncertainty possibly dampens market liquidity and market efficiency deteriorates. To investigate the predictability of currency markets, Bekiros and Marcellino (2013) adopt the wavelet methodology, which find that currency markets might not be efficiently priced, particularly during crisis periods, and Figures 2b and 2c in this study are consistent with their finding. Figures 2b and 2c also show the day (December 8, 2009) on which Fitch, a major international credit agency, downgrades Greece's

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[4] The other time series using different data frequencies for both FX rates show quite similar patterns to Figure 2.

credit rating before a rating cut by S&P (December 16, 2009) and Moody's (December 22, 2009). After this downgrading, *EF*1 and *EF*2 seem to become volatile, and their volatile behavior may reflect market uncertainty driven by the fear of Greece's default risk. Compared with these figures, the R-square measure (*EF*0) in Figure 1a does not clearly show its historical trend corresponding to such an event in the international financial market. Intuitively, I postulate that market efficiency around the financial turmoil differs from that in a normal period. The time-series behavior of the proposed measures is consistent with my postulation, and I expect that these measures can capture time-varying efficiency and are useful for analyzing market efficiency. In the following section, I examine the relationship between market efficiency and market conditions, such as liquidity and information asymmetry.

3.2. Explanatory variables for market efficiency levels

This subsection considers the explanatory variables for market efficiency. First, I consider effective spread and price impact as proxies for market liquidity. Second, I consider information asymmetry.

3.2.1 Effective spread and *price impact*

I hypothesize that a market's liquidity affects its efficiency. Chordia et al. (2008) propose three hypotheses on the relationship between liquidity and the predictive power of OIB. The first hypothesis predicts that they are negatively correlated: the predictive power of an OIB is an inverse of market liquidity because a liquid market can quickly absorb an OIB. If a market is too illiquid to absorb an OIB, we observe price movements to absorb that OIB during a relatively long period. Therefore, the predictive power of an OIB in an illiquid market remains for a while and a negative correlation is observed between liquidity and this predictive power. Second, if uninformed market makers cannot detect the information contained in an OIB because of their cognitive limitations, price discovery is not completed, which motivates other agents to collect and exploit the information contained in an OIB. This motivation encourages agents to enter a market, which brings competition among these agents to enhance the speed of price discovery. Meanwhile, this competition dissuades uninformed traders from providing liquidity because they protect themselves against informed traders who detect the information within an OIB. As a result, the second hypothesis suggests that the predictive power of an OIB in an illiquid market is short-lived and that it is positively correlated with liquidity. Third, if market makers always perfectly detect the information within and quickly absorb an OIB, no relationship exists between liquidity and the predictive power of the OIB.

I construct proxies for liquidity to test these three hypotheses. As in Banti and Phylaktis (2012), I find no unique definition for liquidity. In general, liquidity indicates a situation in which a market participant finds a counterparty to trade at a low trading cost and her normal transaction amount has minimal price impact (e.g., Kyle, 1985). I consider these two concepts of liquidity: trading cost and price impact. I also consider the effective spread as trading cost in an FX market, as do previous studies (e.g., Chordia et al., 2008). Let q_j and p_j be indicator variables that take the value of +1 (–1) when the *j*th trade is a buyer- (seller-) initiating trade and the transaction price at the *j*th trade, respectively. Using these variables, I calculate the effective spread, *e_spread*, as follows:

$$e\_spread_j = 2 \times q_j(p_j - m_j), \tag{5}$$

where m_j represents the quote midpoint prevailing at the *j*th trade. After dropping negative values, I calculate the effective spread for each trade and measure an average effective spread per day. I multiply this average by –1 to ensure that the higher value of this average represents higher liquidity. I label this variable *LiqCost*:

$$LiqCost_i = -1 \times \sum_{j=1}^{J_i} e\_spread_j / J_i, \tag{6}$$

where the *i*th day has J_i transactions. *LiqCost* measures daily liquidity using transaction cost, which is calculated using the average effective spread.

To measure the price impact, I adopt the method suggested by Amihud (2002) and construct the price impact using an absolute FX rate change divided by trading volume (labeled *AMIHUD*). Let the sample size and trading volume on the *i*th day be T and V_i, respectively; then, daily *AMIHUD* is calculated as follows:

$$AMIHUD_i = |\sum_{t=1}^{T} r_t| / V_i. \tag{7}$$

where r_t represents an FX rate change defined in equation (1). Similar to *LiqCost*, I also multiply

AMIHUD by –1 to ensure that a higher value represents higher liquidity. This variable is labeled *LiqPIm*:

$$LiqPIm_i = -1 \times AMIHUD_i. \tag{8}$$

LiqPIm measures daily liquidity using the price impact from the daily trading volume.

3.2.2. Information asymmetry

I also hypothesize that information asymmetry in a market affects market efficiency. The sign of the causality from information asymmetry to market efficiency is not unique. 1) A high information-adverse selection corresponds to significant new information and, generally, market participants underreact to news and gradually incorporate news into price (Chung and Hrazdil, 2010). Therefore, price does not quickly reflect the information contained in an OIB, the predictive power of the OIB is relatively long-lived, and a negative relationship is found between information asymmetry and market efficiency. 2) Meanwhile, uninformed market makers who post bid and ask rates excessively incorporate the information contained in incoming order flows to protect themselves from possible informed trading in a high information asymmetry situation; market makers excessively increase (reduce) their bid and ask rates when they observe positive (negative) incoming order flows. This pricing erodes the predictive power of an OIB and possibly causes price reversals to adjust excessive price movements in subsequent periods, and a positive relationship is found between information asymmetry and market efficiency. In sum, the sign of the effect of information asymmetry on the predictive power of OIBs is ambiguous; therefore, I rely on the empirical results of this study to interpret the effect that information asymmetry is more dominant regarding the efficiency of FX markets.

I decompose the bid and ask spread to construct a proxy for information asymmetry. One component of the bid–ask spread is compensation for a market participant who loses her money in a transaction with informed traders, and the other component earns profits in a transaction with uninformed traders (e.g., Glosten, 1987; Hung and Stoll, 1997; Madhavan et al., 1997). The former component is information asymmetry and the latter is liquidity. To decompose the bid–ask spread and measure the information asymmetry, I adopt the method suggested by Chung and Hrazdil (2010), who estimate the following two models:

$$\Delta m_{j+1} = \lambda(p_j - m_j) + \varepsilon_{j+1} \tag{9}$$

$$\Delta m_{j+1} = \alpha\left(\frac{S_j}{2} Q_j\right) + \upsilon_{j+1}, \tag{10}$$

where m_j represents the quote midpoint prevailing in the jth transaction, $\Delta m_{j+1} = m_{j+1} - m_j$, p_j represents the jth transaction price, S_j represents the quoted bid–ask spread prevailing in the jth transaction, and Q_j takes the value +1 (–1) when the jth trade is buyer (seller) initiated. ε and υ are i.i.d. error terms. The proportions of the spread attributable to information asymmetry, λ and α, are bounded above by 0 and below by 1. Equations (9) and (10) are models that Lin et al. (1995) and Huang and Stoll (1997) individually suggest to extract the information asymmetry component. Intuitively, the direction of an incoming trade and deviation of the transaction price from the quote midpoint contain private information, and a market maker uses this incoming transaction to revise her quote midpoint. For example, in equation (9), when the jth transaction is a buyer-initiated trade, p_j is the ask-side price and is higher than the quote midpoint m_j. A market maker pulls up her quote midpoint with $\lambda(p_j - m_j)$ (λ × the effective half–spread) because she takes into account the possibility that the incoming buyer is driven by good private information about a base currency. If the information asymmetry between a market maker and informed traders is large, the market maker revises her quote to hedge her losses against informed traders and λ becomes large. Equation (10) assumes this quote midpoint revision and that a market maker revises her quote using some ratio of the quoted half-spread. I estimate equations (9) and (10) per day with one-second slice data and obtain estimators related to information asymmetry: $\hat{\lambda}$ and $\hat{\alpha}$. Following Chung and Hrazdil (2010), I introduce the $HiAdvSel_i$ variable, which takes the value of +1 when both the estimated $\hat{\lambda}$ and $\hat{\alpha}$ for the ith day are higher than their own medians across days, and 0 otherwise.

*****Table 2 around here*****

Finally, Table 2 reports the summary statistics for *LiqCost*, *LiqPIm*, *HiAdvSel*, $\hat{\lambda}$ and $\hat{\alpha}$. The next section considers *LiqCost*, *LiqPIm*, and *HiAdvSel* as possible explanatory variables for market efficiency.

4. Empirical results

4.1. Results of the intraday analysis

Prior to conducting a daily analysis, I examine the relationship between liquidity and market efficiency using intraday data. The result in Figure 1 suggests that one- and two-minute frequencies should be considered, for which the predictive power of OIB is supported using statistical evidence. This section adopts these two data frequencies.

Unlike the daily analysis reported in the following section, this intraday analysis does not allow me to estimate the models of equations (9) and (10) for each interval given the practical reason of a short sample in an interval. Alternatively, to consider the effect of informed trading on an intraday basis, I focus on the medium-size trade as a proxy for informed trading. The stealth trading hypothesis suggests that informed traders choose a medium-size trade because a repeating small-size trade is burdened with excess transaction costs. In turn, a large-size trade reveals, and causes the decay of, the information advantage of a trade initiator. Barclay and Warner (1993) are the first study to report empirical evidence for stealth trading in a financial market. Regarding an FX market, Menkhoff and Schmeling (2010) find stealth trading in the USD/RUB market. Meanwhile, Ligon and Liu (2013) do not find empirical evidence for stealth trade in the Taiwanese FX voice brokered market. Therefore, the empirical results for stealth trading in FX markets are mixed. In line with Menkhoff and Schmeling (2010), I assume that the following regressions accommodate a possible informed medium-size trade:

$$Prob(INEF\#_t = 1) = F(\gamma_0 + \gamma_1 Esp_t + \gamma_2 trade\ size_t + \gamma_3 trade\ size_t^2) + error\ term_t \quad (11)$$

$$Prob(INEF\#_t = 1) = F(\gamma_0 + \gamma_1 Esp_{t-1} + \gamma_2 trade\ size_{t-1} + \gamma_3 trade\ size_{t-1}^2) + error\ term_t. \quad (12)$$

Equations (11) and (12) consider the effects of market liquidity and informed medium-size trading during periods *t* and *t–1*, respectively. *Prob*$(INEF\#_t = 1)$ is the probability that $INEF\#_t$ takes the value of +1. $INEF\#_t$ (# = 1, 2) is a binary variable defined by equations (1) and (2), respectively. When $INEF\#_t$ takes the value of +1, a market is considered *inefficient* in period *t* because the OIB predict a future FX rate change. *F*(.) is a cumulative normal distribution function and γ_i (i=0,…,3) is a parameter that I estimate by fitting a probit model. Esp_t represents the mean of the effective spread calculated using equation (5) during period *t*, and is considered a proxy for market liquidity: the wider the *Esp*, the less liquid a market. I expect that an estimated γ_1 is positive if market *inefficiency* increases with transaction costs, which are measured using the effective spread.

The variable *trade size* represents the mean of the absolute amount of each transaction in each interval. The terms for single and squared trade sizes in equations (11) and (12) are proxies for stealth trading. The stealth trade hypothesis predicts a U-shape effect or the reverse of trade size in equations (11) and (12). The former effect is that medium-size trading enhances competition among informed traders and positively contributes to market efficiency in FX markets, and implies that the estimators of γ_2 and γ_3 are negative and positive, respectively (U-shape effect). This former effect indicates that the high frequency of medium-size trading corresponds to competition among informed traders that enhances market efficiency (Admati and Pfleiderer, 1988). Meanwhile, a reverse U-shape effect is also postulated because an OIB caused by informed traders engaged in medium-size trading is likely to predict a future FX rate change; therefore, $INEF\#_t$ takes the value of +1 when informed traders engaging in medium-size trading exist, and I expect that the estimators of γ_2 and γ_3 are positive and negative, respectively. Because no theoretical model indicates the effect that is stronger than the other, I empirically examine this situation.

*****Table 3 around here*****

Table 3 shows the empirical results of equations (11) and (12). The result of the likelihood ratio test in Table 3 supports the notion that effective spread and trade size are promising determinant factors for $INEF\#_t$. Table 3 shows that the estimators of *Esp* are positive and statistically significant in all cases. I consider that this result in Table 3 indicates that a high transaction cost dampens market efficiency.

Reverse U-shape effects of trade size are found in all cases, and a positive γ_2 and a negative γ_3 are statistically significant. This result indicates that medium-size trades are able to predict a future FX rate change in the EUR/USD and USD/JPY markets. Therefore, I conclude that the predictive power of the medium-size trade dominates the competition of that trade in my high-frequency analysis. The row "max. trade" is the trade size that has a maximum positive effect on $INEF\#_t$. The values of "max. trade" show similarity across regressions for each FX rate. In Table 3, the medians for "max. trade" in the EUR/USD and USD/JPY markets are 4.5 and 4.7, respectively, leading to the postulation that the four- and five-million euros/dollars trade sizes are related to informed trading because they possibly predict a future FX rate change.

*****Table 4 around here*****

As shown in Table 4, trade sizes are concentrated in the €1 million and $1 million range for the EUR/USD and USD/JPY markets, respectively. Compared with stock markets, the trade size range in FX markets is much narrower (Ligon and Liu, 2013). The result in Table 4 indicates that the mean trade size used in Table 3 is likely affected by large trades; in other words, the calculated mean may be affected by outliers. This result may cast doubts on the reliability of trade size mean as a proxy for stealth trading and, therefore, on the result in Table 3. For this issue, I consider the four- and five- million euros (dollars) trade size as a proxy for stealth trading for the EUR/USD (USD/JPY) market. Because the result of Table 3 indicates that trades of four- and five-million euros (dollars) have a maximum positive effect on the dependent variables, I postulate that these trade sizes are related to informed trading. If an increase in these trade sizes has a positive and significant effect on the dependent variable $INEF\#_t$ (# = 1, 2), then the result in Table 3 may be safely considered to be consistent with the stealth trading story.

*****Table 5 around here*****

$$Prob(INEF\#_t = 1) = F(\gamma_0 + \gamma_1 Esp_t + \gamma_2 stealth\, trade_t) + e_t \qquad (13)$$

$$Prob(INEF\#_t = 1) = F(\gamma_0 + \gamma_1 Esp_{t-1} + \gamma_2 stealth\, trade_{t-1}) + e_t \qquad (14)$$

Table 5 shows the result of the probit regressions of equations (13) and (14), for which the explanatory variables are effective spread (*Esp*) and the number of four- and five-million euros/dollars trades (*stealth trading*), and the dependent variable is $INEF\#_t$ (# = 1, 2). The estimators of *stealth trading* are positive and statistically significant at the 1% level in all cases, an empirical result that is also consistent with the stealth trading story in the studied FX markets; an increase in medium-size trades enhances the predictive power of OIB.

4.2. Results of daily analysis

This section examines on a daily basis the relationship between market efficiency and information asymmetry. The previous intraday analysis indicates stealth trading in the studied FX markets. I also examine whether the effect of stealth trading is observed on a daily basis and consider the following regression:

$$EF_i = \beta_0 + \beta_1 LiqCost_i + \beta_2 HiAdvSel_i + \beta_3 LiqCost_i \times HiAdvSel_i + \beta_4 Stealth_i + e_i, \quad (15)$$

$$EF_i = \beta_0 + \beta_1 LiqCost_i + \beta_2 HiAdvSel_i + \beta_3 LiqCost_i \times HiAdvSel_i + \beta_4 Stealth_i + e_i, \quad (16)$$

where $EF0_i$, $EF1_i$, and $EF2_i$ are adopted as EF_i in the left term of equations (15) and (16). *LiqCost* and *LiqPIm* are variables related to transaction cost and are calculated using equations (6) and (8), respectively. *HiAdvSel* is binary variable that takes the value of +1 when both the estimated parameters in equations (9) and (10) are higher than their medians. "$Stealth_i$" is the number of four- and five-million euro or dollar trades in *i*th day. $LiqCost_i \times HiAdvSel_i$ and $LiqPIm_i \times HiAdvSel_i$ are interaction terms. These terms are used to examine whether high information asymmetry changes the liquidity effect on price discovery. $Stealth_i$ is the number of four- and five-million euros/dollars on the *i*th day. From the intraday result of Table 5, I expect that $\beta_4<0$; in other words, an increase in stealth trading enhances the predictive power of OIBs because these OIBs are partially caused by informed trading. e_i is an error term. The effects of *LiqCost* and *LiqPIm* on market efficiency are examined separately using equations (15) and (16) because these two proxies are significantly positively correlated to the multicollinearity result.

*****Table 6 around here*****

*****Table 7 around here*****

*****Table 8 around here*****

Table 6 presents the Pearson coefficient correlations among the variables of equations (15) and (16) and shows positive correlations for *LiqCost* and *LiqPIm* with $EF1_i$ and $EF2_i$. Meanwhile, overall, the estimated parameters of *LiqPIm* are negative when both *LiqCost* and *LiqPIm* are included as explanatory variables for market efficiency (the result is not reported). This negative sign is inconsistent with the results in Table 6, and *LiqCost* and *LiqPIm* are adopted separately in equations (15) and (16). Tables 7 and 8 show the estimation results for equations (15) and (16), respectively.

First, compared with *EF*0, Tables 7 and 8 show that the R-squares for *EF*1 and *EF*2 are much larger for both currency pairs. In particular, these large R-squares are found when I use *LiqCost* as a proxy for liquidity in Table 7. These results possibly imply that *EF*1 and *EF*2 are more adequate for measuring market efficiency insofar as my proxies for liquidity and information factors are well measured and market efficiency is closely related to liquidity and information factors.

For the liquidity effect, the estimated parameters of *LiqCost* are positive values and are statistically significant except for four cases of *EF*0 in Table 7. This result indicates that market efficiency, which is measured using *EF*1 and *EF*2, is relatively high when the transaction cost is low (the market is highly liquid) in the EUR/USD and USD/JPY markets. Moreover, I overlook such a positive relationship between market efficiency and liquidity in the FX markets when I use *EF*0 (the R-square measure), which Chung and Hrazdil (2010) use in their stock market study. In other words, the results suggest that these FX markets have a similar characteristic with a stock market in which market efficiency is positively correlated with that of market liquidity (e.g., Chordia et al., 2008; Chung and Hrazdil, 2010) when I use the alternative measures instead of R-square.

The estimated parameters for *LiqPIm* also show an overall positive sign except for the two cases in Table 8, and seven cases are positive and statistically significant. In the exceptional two negative cases, the negative estimators of *LiqPIm* are not statistically significant; therefore, I consider that the result in Table 8 is consistent with that in Table 7: liquidity and efficiency are positively correlated. I also measure the impact of the intraday price using one-, two-, and five-minute data frequencies. I calculate the daily average of these price impacts and replace *LiqPIm* in equation (16) with them. The results of these impacts are scarcely different from those in Table 8. The R-square values in Table 7 are much larger than those in Table 8, particularly when I use *EF*1 and *EF*2 as a dependent variable. Amihud (2002) proposes a price impact to measure liquidity and admits that the daily price impact is a less accurate proxy for liquidity when microstructure data are available to measure intraday liquidity proxies. The comparative results of Tables 7 and 8 lead me to suggest that effective spread is a more adequate proxy for liquidity than the daily price impact. Next, I focus only on the result in Table 7 because the result in Table 8 is consistent with that in Table 7 and *LiqCost* may be a better proxy than *LiqPIm* for market liquidity.

Table 7 shows the positive estimators of *HiAdvSel* in all eight cases of *EF*1 and *EF*2, and seven of them are statistically significant. These positive figures are consistent with the correlation analysis in Table 6 and suggest that information asymmetry enhances market efficiency when *EF*1 and $EF2$ measure market efficiency in both currency pair markets. As discussed in section 3.2.2, this result indicates that high information asymmetry leads market makers to excessively revise their prices in line with the direction of incoming order flows and, therefore, OIB predictability is likely to decay in the next period. This result is opposite of the result in Chung and Hrazdil (2010), who study stocks listed on the NYSE and indicate a gradual price discovery. This opposite result indicates that the speed of price discovery in the studied EUR/USD and USD/JPY markets is much faster than for the NYSE. Meanwhile, the negative values of *HiAdvSel* in *EF*0's three cases in Table 7 are consistent with Chung and Hrazdil (2010). However, these negative effects are not statistically significant, and the result of Table 7 leads me to propose that information asymmetry enhances market efficiency in the EUR/USD and USD/JPY markets.

In Table 7, the estimators of $LiqCost \times HiAdvSel$ are positive in all cases of $EF1$ and $EF2$, and the estimators of *HiAdvSel* are also positive. These positive estimators of the interaction term indicate that high information asymmetry enhances the liquidity effect on market efficiency, or vice versa. However, the $LiqCost \times HiAdvSel$ estimator is statistically significant only for the one-minute frequency of *EF*1 for both currency pairs, although it is statistically significant in all cases of *EF*2. For the EUR/USD market, the $HiAdvSel$ estimator is statistically insignificant for the two-minute frequency of $EF1$. These results may imply that information asymmetry weakly affects market efficiency in both currency pair markets.

Finally, Table 7 shows that the stealth trading estimator is negative and statistically significant for all cases of $EF1$ and $EF2$, a result that supports stealth trading on a daily basis. In particular, the sign condition for adverse selection (*HiAdvSel*) is positive, whereas that for stealth trading is negative. These different sign conditions indicate that the number of informed traders is not necessarily large even when information asymmetry is high.[5]

4.3. Robustness checks

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[5] On a daily basis, the coefficient of the correlation for the number of medium-size trades with information asymmetry $\hat{\lambda}$ and $\hat{\alpha}$ are 0.20 and –0.05 (–0.08 and 0.29) for the EUR/USD (USD/JPY) market, respectively.

This section checks the robustness of Table 7.

*****Table 9 around here*****

First, as Rime et al. (2010) suggest, I use intraday data for GMT 7–17 to calculate explanatory and dependent variables for equation (15). Table 9 shows the result of the regression analysis of equation (15) using these variables, which is consistent with that of Table 7, although the $HiAdvSel$ and $LiqCost \times HiAdvSel$ estimators become less statistically significant for most cases of $EF1$ and $EF2$. As noted in the previous section, the effect of information asymmetry might be relatively low in the studied markets. Additionally, Table 9 indicates that the effect becomes much weaker in the most active part of the trading day than in other parts.

*****Table 10 around here*****

Second, I calculate $EF0$, $EF1$, and $EF2$ using OIB# (net number of buyer initiated trade) and regress them onto the explanatory variables of equation (15). As explained in section 2.2, OIB# is public information for participants in the EBS market because they can count these numbers in real time by monitoring the EBS screen. Therefore, I construe that the result in Table 10 is related to the semi-strong form of efficiency in the studied markets. Table 10 presents the result and confirms the robustness of Table 7. Therefore, the studied markets appear to perfectly achieve neither the strong nor the semi-strong form of efficiency within one- and two-minute data frequencies, and liquidity, information asymmetry, and informed trading affect the degree of these efficiencies.

*****Table 11 around here*****

Third, I calculate $EF0$, $EF1$, and $EF2$ using an unexpected OIB. Chordia et al. (2008) suggest that a rational market maker revises her quote in advance to incorporate a predictable imbalance, and only an unexpected OIB can predict a future price change. To address this issue, I estimate an autoregressive OIB model with 15 lags (AR(15)) and use residuals to calculate $EF0$, $EF1$, and $EF2$. As shown in Table 11, the results of these regressions are consistent with Table 7. I also estimate the AR(5) and AR(10) models and confirm that these results remain unchanged (the results are not reported).

*****Table 12 around here*****

Finally, I calculate $EF1$ in equations (1) and (3) using bid and ask rates instead of the midpoint quote: if order flow is positive (negative), I use the ask (bid) rate to calculate $EF1$ because market makers who observe buying (selling) pressure may begin with revising their ask (bid) rates. In equation (1), $r_t = p_t^{**,ask} - p_t^{*,ask}$ if $OIB_{t-1} > 0$. $p_t^{**,ask}$ and $p_t^{*,ask}$ are the prevailing ask rates at the first and last timings of period t, respectively. If $OIB_{t-1} < 0$, r_t is calculated similarly using bid rates and is labeled $EF1$ as $EF1^*$, which considers that liquidity providers revise their ask (bid) rates upwardly (downwardly) when they expect net buying (selling) pressure. Table 12 presents the result of the regression using this $EF1^*$; the signs of all of the estimators are the same as those of Table 7 and most are statistically significant.

5. Conclusion

During the recent decade, popularization of electronic trading in an FX market enables researchers to access tick-by-tick transaction data and assist in the development of a microstructure approach to an FX market. This approach emphasizes the crucial role of order flows during the price discovery process of an FX market. Order flow is a conduit through which relevant information is transmitted to an FX rate. Thus, order flow contains information and is a predictor of future FX rates. Given the predictability of order flows, I measure the efficiency in an FX market.

First, I find the short-lived predictive power of order flow in the studied FX markets, and the result indicates that FX markets achieve informational efficiency to some extent. Next, I propose two simple measures of, and examine the effects of liquidity and information factors on, market efficiency. The proposed measures decline largely around the bankruptcy of Lehman Brothers and the Eurozone crisis, indicating that financial turmoil deteriorates liquidity and market efficiency in the studied FX markets. Moreover, the proposed measures provide rich information on the relationship between FX market efficiency and market conditions, such as liquidity and information asymmetry, although the measure used in the extant literature does not.

High liquidity enhances market efficiency in the EUR/USD and USD/JPY markets. This result implies that these markets are able to quickly absorb the order flow when their liquidity is high. A liquid market enhances competition among informed traders, and the speed of price discovery is much faster than in an illiquid market.

Information asymmetry also enhances market efficiency for the EUR/USD and the USD/JPY markets, although the results of the robustness checks weakly support the effect of information asymmetry. This result suggests that an excessive response by uninformed market makers to incoming order flows results in a weak predictive power of OIBs in a high information asymmetry situation.

Finally, possible stealth trading is analyzed in the studied FX markets, and empirical evidence is found for such trading in these markets; when informed traders with medium-size trades increase in the markets, the order flow possibly driven by them predicts a future FX rate change. The daily analysis indicates that an increase in the number of informed traders does not necessarily correspond to an increase in information asymmetry because their effects on the predictability of order flow show different directions.

Overall, the studied markets achieve efficiency to some extent, and their efficiencies are affected by market conditions, such as liquidity and information factors. This finding suggests that future research will consider the effects of these market conditions on the price discovery process of FX markets.

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Table 1

Summary of statistics for market efficiency measures: *EF*0, *EF*1, and *EF*2 (before logit transformation and multiplied by −1)

*EF*0, *EF*1, and *EF*2 are variables used to measure market efficiency. *EF*0 is calculated using the R-square value, which is measured for the regression of a current rate change onto a lagged order imbalance and constant term. *EF*1 and *EF*2 are calculated using equations (3) and (4), respectively. In Table 1, *EF*0, *EF*1, and *EF*2 are variables before a logit transformation and are multiplied by −1; the values of all three variables range from 0 to 1.

	Panel A. EUR/USD					
	EF 0		*EF* 1		*EF* 2	
Data frequency	1min.	2min.	1min.	2min.	1min.	2min.
Mean	0.002	0.003	0.412	0.442	0.322	0.389
Median	8.2E-04	0.001	0.413	0.442	0.319	0.385
Max	0.016	0.025	0.490	0.510	0.535	0.548
Min	5.0E-10	2.9E-09	0.321	0.375	0.093	0.163
Std. dev.	0.002	0.004	0.029	0.026	0.075	0.060

	Panel B. USD/JPY					
	EF 0		*EF* 1		*EF* 2	
Data frequency	1min.	2min.	1min.	2min.	1min.	2min.
Mean	0.002	0.004	0.377	0.418	0.215	0.295
Median	0.001	0.002	0.375	0.420	0.203	0.283
Max	0.035	0.038	0.495	0.508	0.533	0.542
Min	6.8E-10	6.7E-10	0.219	0.260	0.030	0.077
Std. dev.	0.004	0.005	0.042	0.033	0.085	0.080

Table 2

Summary of statistics for liquidity and information asymmetry variables

LiqCost is the negative effective spread, and is calculated using equation (6). *LiqPIm* is the negative price impact calculated using equation (8). *HiAdvSel* is a binary variable that takes the value of +1 when both the estimated $\hat{\lambda}$ and $\hat{\alpha}$ values for a given day are higher than their own medians. $\hat{\lambda}$ and $\hat{\alpha}$ are estimated parameters of equations (9) and (10), respectively, and are related to information asymmetry levels.

	EUR/USD					USD/JPY				
	LiqCost (×1000)	*LiqPIm* (×1000)	*HiAdvSel*	$\hat{\lambda}$	$\hat{\alpha}$	*LiqCost* (×1000)	*LiqPIm* (×1000)	*HiAdvSel*	$\hat{\lambda}$	$\hat{\alpha}$
Mean	-0.126	-0.118	0.396	0.691	0.847	-12.736	-0.252	0.428	0.670	0.849
Median	-0.120	-0.095	-	0.689	0.849	-11.994	-0.213	-	0.667	0.850
Max	-0.100	-0.001	1.000	0.821	0.959	-9.859	-0.001	1.000	0.877	0.995
Min	-0.219	-0.627	0.000	0.567	0.691	-27.299	-1.294	0.000	0.435	0.496
Std. dev.	0.021	0.094	0.490	0.047	0.045	2.376	0.193	0.495	0.059	0.061

Table 3

Probit regression of market inefficiency measures on effective spread and trade size

I estimate equations (11) and (12). “Esp_t” is the mean of *e_spread* calculated using equation (5) for period *t*. “*trade size*” represents the mean of the absolute amount of each transaction in each interval. For example, the left column of *INEF*1 (1min.) presents the result of equation (11), with *INEF*1 as a dependent variable and for a one-minute data frequency. Bold figures are statistically significant at least at the 5% level. The numbers in parentheses are p-value for the estimators. “p < .01” indicates that the p-value is less than .01. The row “*max. trade*” is the trade size that has a maximum positive effect on $INEF\#_t$. “p-value for LR test” is a p-value for the likelihood ratio test statistics for which the null is the coefficients of *Esp* and *trade size*, and *trade size* squared is zero. NOB is the number of observations.

Panel A. EUR/USD

Dependent Variable	*INEF* 1 (1min.)		*INEF* 2 (1min.)		*INEF* 1 (2min.)		*INEF* 2 (2min.)	
Intercept	**-0.280**	**0.061**	**-1.950**	**-1.128**	**-0.590**	**-0.346**	**-1.768**	**-1.259**
	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)
Esp_t	**203.900**		**815.352**		**277.555**		**788.358**	
	(<.01)		(<.01)		(<.01)		(<.01)	
Esp_{t-1}		**41.682**		**417.463**		**112.481**		**463.949**
		(<.01)		(<.01)		(<.01)		(<.01)
$trade\ size_t$	**0.310**		**0.942**		**0.168**		**0.690**	
	(<.01)		(<.01)		(<.01)		(<.01)	
$trade\ size_t^2$	**-0.027**		**-0.104**		**-0.011**		**-0.076**	
	(<.01)		(<.01)		(<.01)		(<.01)	
$trade\ size_{t-1}$		**0.153**		**0.554**		**0.108**		**0.503**
		(<.01)		(<.01)		(<.01)		(<.01)
$trade\ size_{t-1}^2$		**-0.018**		**-0.063**		**-0.016**		**-0.065**
		(<.01)		(<.01)		(<.01)		(<.01)
max. trade	5.8	4.3	4.5	4.4	7.7	3.5	4.5	3.9
mean log-likelihood	-0.647	-0.660	-0.647	-0.677	-0.685	-0.687	-0.655	-0.666
p-value for LR test	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
NOB	518904	518903	518904	518903	253846	253845	253846	253845

Panel B. USD/JPY

Dependent Variable	*INEF* 1 (1min.)		*INEF* 2 (1min.)		*INEF* 1 (2min.)		*INEF* 2 (2min.)	
Intercept	**-0.319**	**0.055**	**-1.743**	**-1.120**	**-0.628**	**-0.351**	**-1.886**	**-1.192**
	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)
Esp_t	**2.648**		**8.462**		**2.186**		**9.928**	
	(<.01)		(<.01)		(<.01)		(<.01)	
Esp_{t-1}		**0.004**		**6.735**		**1.261**		**6.871**
		(<.01)		(<.01)		(<.01)		(<.01)
$trade\ size_t$	**0.248**		**0.573**		**0.205**		**0.582**	
	(<.01)		(<.01)		(<.01)		(<.01)	
$trade\ size_t^2$	**-0.015**		**-0.057**		**-0.019**		**-0.065**	
	(<.01)		(<.01)		(<.01)		(<.01)	
$trade\ size_{t-1}$		**0.084**		**0.240**		**0.066**		**0.234**
		(<.01)		(<.01)		(<.01)		(<.01)
$trade\ size_{t-1}^2$		**-0.009**		**-0.028**		**-0.008**		**-0.029**
		(<.01)		(<.01)		(<.01)		(<.01)
max. trade	8.1	4.9	5.0	4.3	5.4	4.3	4.5	4.1
mean log-likelihood	-0.665	-0.682	-0.610	-0.629	-0.681	-0.682	-0.607	-0.613
p-value for LR test	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
NOB	505464	505463	505464	505463	241968	241967	241968	241967

Table 4

Number of trades by size classification

The unit for trade size is one million euros (dollars) for EUR/USD (USD/JPY) markets. The relative proportion of trades is the ratio of the number of trades for a trade size to all trades.

	EUR/USD		USD/JPY	
Trade size	Number of trades	Relative proportion of trades	Number of trades	Relative proportion of trades
1	4,321,148	0.47	2,622,781	0.51
2	1,980,225	0.22	1,116,187	0.22
3	986,345	0.11	523,307	0.10
4	533,586	0.06	266,328	0.05
5	518,279	0.06	239,207	0.05
6	204,679	0.02	88,213	0.02
7	137,959	0.02	58,063	0.01
8	98,089	0.01	40,210	0.01
over 9	365,519	0.04	139,934	0.03
Total	9,145,829	1.00	5,094,230	1.00

Table 5

Probit regression of market inefficiency measures on effective spread and medium-size trades

I estimate equations (13) and (14). "*stealth trade*" is the number of four- and five-million trades in each interval. "Esp_t" represents the mean of *e_spread* calculated using equation (5) during period *t*. For example, the left column of *INEF*1 (1min.) presents the result of equation (13), with *INEF*1 as a dependent variable and for a one-minute data frequency. Bold figures are statistically significant at least at the 5% level. The numbers in parentheses are p-value for the estimators. "p < .01" indicates that the p-value is less than .01. "p-value for LR test" is the p-value for the likelihood ratio test statistics for which the null is that the coefficients of *Esp* and *stealth trade* are 0. NOB is the number of observations.

Panel A. EUR/USD

Dependent Variable	*INEF* 1 (1min.)		*INEF* 2 (1min.)		*INEF* 1 (2min.)		*INEF* 2 (2min.)	
Intercept	**0.229**	**0.291**	**-0.517**	**-0.303**	**-0.252**	**-0.188**	**-0.575**	**-0.459**
	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)
Esp_t	**158.570**		**658.125**		**229.447**		**625.675**	
	(<.01)		(<.01)		(<.01)		(<.01)	
Esp_{t-1}		**20.673**		**330.001**		**96.499**		**371.283**
		(<.01)		(<.01)		(<.01)		(<.01)
stealth trade $_t$	**0.072**		**0.241**		**0.003**		**0.010**	
	(<.01)		(<.01)		(<.01)		(<.01)	
stealth trade $_{t-1}$		**0.027**		**0.134**		**0.003**		**0.009**
		(<.01)		(<.01)		(<.01)		(<.01)
mean log-likelihood	-0.650	-0.661	-0.656	-0.678	-0.687	-0.687	-0.671	-0.672
p-value for LR test	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
NOB	518904	518903	518904	518903	253846	253845	253846	253845

Panel B.USD/JPY

Dependent Variable	*INEF* 1 (1min.)		*INEF* 2 (1min.)		*INEF* 1 (2min.)		*INEF* 2 (2min.)	
Intercept	**0.086**	**0.121**	**-0.991**	**-0.769**	**-0.294**	**-0.254**	**-0.967**	**-0.847**
	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)	(<.01)
Esp_t	**2.707**		**9.761**		**2.224**		**9.657**	
	(<.01)		(<.01)		(<.01)		(<.01)	
Esp_{t-1}		**1.075**		**5.949**		**1.232**		**6.642**
		(<.01)		(<.01)		(<.01)		(<.01)
stealth trade $_t$	**0.113**		**0.345**		**0.004**		**0.011**	
	(<.01)		(<.01)		(0.01)		(<.01)	
stealth trade $_{t-1}$		**0.046**		**0.164**		**0.006**		**0.017**
		(<.01)		(<.01)		(<.01)		(<.01)
mean log-likelihood	-0.670	-0.681	-0.608	-0.626	-0.682	-0.682	-0.618	-0.614
p-value for LR test	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
NOB	505464	505463	505464	505463	241968	241967	241968	241967

Table 6

Contemporaneous correlations (Pearson product-moment coefficient correlation)

*EF*0 is calculated using R-square, which is measured from the regression of a current rate change onto a lagged order imbalance and constant term. *EF*1 and *EF*2 are calculated using equations (3) and (4), respectively. The number of minutes in parentheses represents the data frequency adopted to calculate each variable. For example, *EF*0 (1min.) is calculated using a one-minute data frequency. *LiqCost* is a variable related to transaction cost and is obtained using equation (6). *LiqPIm* is a variable related to the price effect and is calculated using equation (8). *HiAdvSel* is a binary variable that takes the value of +1 when both estimated parameters in equations (9) and (10) are higher than their own medians.

	Panel A. EUR/USD								
	EF 0 (1min.)	*EF* 0 (2min.)	*EF* 1 (1min.)	*EF* 1 (2min.)	*EF* 2 (1min.)	*EF* 2 (2min.)	*LiqCost*	*LiqPIm*	*HiAdvSel*
LiqCost	0.03	-0.07	0.57	0.45	0.73	0.67			
LiqPIm	0.01	-0.08	0.12	0.08	0.18	0.15	0.34		
HiAdvSel	-0.11	0.03	0.16	0.10	0.14	0.13	0.23	0.12	
Stealth	-3.E-03	0.04	-0.51	-0.39	-0.60	-0.58	-0.17	0.02	0.10
	Panel B. USD/JPY								
	EF 0 (1min.)	*EF* 0 (2min.)	*EF* 1 (1min.)	*EF* 1 (2min.)	*EF* 2 (1min.)	*EF* 2 (2min.)	*LiqCost*	*LiqPIm*	*HiAdvSel*
LiqCost	4.E-03	-0.04	0.64	0.52	0.73	0.70			
LiqPIm	0.02	0.01	0.10	0.13	0.09	0.08	0.23		
HiAdvSel	-0.05	-0.01	0.29	0.23	0.27	0.26	0.42	0.17	
Stealth	-0.01	-0.05	-0.48	-0.39	-0.53	-0.52	-0.21	0.11	0.04

Table 7

Regression of market efficiency measures on liquidity, information asymmetry, and stealth trading (equation (15))

Table 7 shows the estimation result of regression of equation (15): $EF_i = \beta_0 + \beta_1 LiqCost_i + \beta_2 HiAdvSel_i + \beta_3 LiqCost_i \times HiAdvSel_i + \beta_4 Stealth_i + e_i$. *EF* is replaced with *EF*0, *EF*1, and *EF*2. *EF*0 is calculated using R-square values, which are measured from the regression of a current rate change onto a lagged order imbalance and a constant term. *EF*1 and *EF*2 are calculated using equations (3) and (4), respectively. The column labeled "Data frequency" corresponds to the data frequency adopted when calculating each dependent variable. *LiqCost* is a variable related to the transaction cost measured using effective spread and calculated from equation (6). *HiAdvSel* is binary variable that takes the value of +1 when both the estimated parameters in equations (9) and (10) are higher than their medians. "$Stealth_i$" is the number of four- and five-million euro or dollar trades on the *i*th day. Bold figures indicate statistical significance at least at the 5% level. The numbers in parentheses are p-values for the estimators. "p < .01" indicates that the p-value is less than .01. To calculate the p-values, I use the heteroskedasticity and autocorrelation (HAC) standard errors. NOB is the number of observations.

Panel A. EUR/USD

Dependent variable	*EF* 0		*EF* 1		*EF* 2	
Data frequency	1min.	2min.	1min.	2min.	1min.	2min.
Intercept	**8.409**	**5.949**	**0.836**	**0.579**	**2.636**	**1.702**
	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)
LiqCost	5775.961	-7290.582	**2441.804**	**1813.583**	**10245.670**	**6601.400**
	(.286)	(.306)	(< .01)	(< .01)	(< .01)	(< .01)
HiAdvSel	-0.135	-0.636	**0.204**	0.090	**0.417**	**0.350**
	(.924)	(.697)	(< .01)	(.159)	(.012)	(< .01)
LiqCost ×*HiAdvSel*	3594.995	-7129.975	**1461.520**	645.410	**3141.766**	**2655.746**
	(.751)	(.591)	(.015)	(.194)	(.017)	(< .01)
Stealth (×1,000)	0.062	0.085	**-0.077**	**-0.051**	**-0.249**	**-0.178**
	(.709)	(.524)	(< .01)	(< .01)	(< .01)	(< .01)
NOB	444	444	444	444	444	444
R-square	0.015	0.009	0.525	0.312	0.775	0.681

Panel B. USD/JPY

Dependent variable	*EF* 0		*EF* 1		*EF* 2	
Data frequency	1min.	2min.	1min.	2min.	1min.	2min.
Intercept	**8.020**	**6.010**	**1.090**	**0.691**	**3.294**	**2.368**
	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)
LiqCost	25.426	-87.916	**31.339**	**18.841**	**107.645**	**82.224**
	(.685)	(.107)	(< .01)	(< .01)	(< .01)	(< .01)
HiAdvSel	-0.322	2.367	**0.240**	**0.143**	**0.731**	**0.502**
	(.853)	(.157)	(< .01)	(.041)	(< .01)	(< .01)
LiqCost ×*HiAdvSel*	0.229	192.525	**18.580**	10.971	**62.582**	**42.810**
	(.999)	(.167)	(< .01)	(.055)	(< .01)	(< .01)
Stealth (×1,000)	-0.094	-0.137	**-0.170**	**-0.109**	**-0.493**	**-0.370**
	(.633)	(.672)	(< .01)	(< .01)	(< .01)	(< .01)
NOB	444	444	444	444	444	444
R-square	0.004	0.005	0.607	0.402	0.749	0.692

Table 8

Regression of market efficiency measures on liquidity, information asymmetry, and stealth trading (equation (16))

Table 8 shows the estimation result of the regression of equation (16):
$EF_i = \beta_0 + \beta_1 LiqPIm_i + \beta_2 HiAdvSel_i + \beta_3 LiqPIm_i \times HiAdvSel_i + \beta_4 Stealth_i + e_i$. $LiqPIm$ is a variable related to transaction cost measured using price impact and calculated from equation (8). The other details for Table 8 are presented in Table 7.

Panel A. EUR/USD

Dependent variable	*EF* 0		*EF* 1		*EF* 2	
Data frequency	1min.	2min.	1min.	2min.	1min.	2min.
Intercept	**7.722**	**6.581**	**0.569**	**0.381**	**1.526**	**0.987**
	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)
LiqPIm	-205.975	-1528.731	**122.311**	**105.040**	**637.396**	**411.889**
	(.887)	(.384)	(.027)	(.049)	(< .01)	(< .01)
HiAdvSel	-0.249	-0.075	**0.056**	0.020	**0.136**	**0.077**
	(.444)	(.834)	(< .01)	(.224)	(< .01)	(.044)
LiqPIm ×*HiAdvSel*	2436.750	-2465.506	55.434	-91.105	44.766	-118.144
	(.278)	(.396)	(.637)	(.355)	(.874)	(.558)
Stealth (×1,000)	0.022	0.138	**-0.092**	**-0.062**	**-0.311**	**-0.218**
	(.892)	(.284)	(< .01)	(< .01)	(< .01)	(< .01)
NOB	444	444	444	444	444	444
R-square	0.014	0.013	0.319	0.182	0.426	0.386

Panel B. USD/JPY

Dependent variable	*EF* 0		*EF* 1		*EF* 2	
Data frequency	1min.	2min.	1min.	2min.	1min.	2min.
Intercept	**7.889**	**7.223**	**0.750**	**0.496**	**2.101**	**1.448**
	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)
LiqPIm	589.326	572.866	**84.701**	**76.825**	**209.311**	131.284
	(.448)	(.366)	(.030)	(.021)	(.032)	(.100)
HiAdvSel	-0.478	-0.344	**0.080**	**0.058**	**0.208**	**0.170**
	(.219)	(.365)	(< .01)	(< .01)	(< .01)	(< .01)
LiqPIm ×*HiAdvSel*	-751.883	-1300.928	14.221	56.352	79.848	101.069
	(.626)	(.334)	(.826)	(.313)	(.603)	(.468)
Stealth (×1,000)	-0.136	-0.016	**-0.223**	**-0.142**	**-0.672**	**-0.506**
	(.443)	(.955)	(< .01)	(< .01)	(< .01)	(< .01)
NOB	444	444	444	444	444	444
R-square	0.005	0.002	0.465	0.327	0.526	0.485

Table 9

Regression of equation (15) for GMT 7–17

I use the data within GMT 7–17 and carry out the regression for Table 7. Table 9 shows the estimation result of the regression of equation (16): $EF_i = \beta_0 + \beta_1 LiqCost_i + \beta_2 HiAdvSel_i + \beta_3 LiqCost_i \times HiAdvSel_i + \beta_4 Stealth_i + e_i$. The other details for Table 9 are presented in Table 7.

	Panel A. EUR/USD					
Dependent variable	*EF* 0		*EF* 1		*EF* 2	
Data frequency	1min.	2min.	1min.	2min.	1min.	2min.
Intercept	**7.991**	**7.012**	**0.631**	**0.466**	**2.557**	**1.507**
	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)
LiqCost	4692.218	4410.799	**2096.541**	**1574.473**	**12523.301**	**7457.433**
	(.423)	(.394)	(< .01)	(< .01)	(< .01)	(< .01)
HiAdvSel	1.280	-1.159	**0.203**	0.100	0.301	0.183
	(.356)	(.332)	(< .01)	(.141)	(.108)	(.201)
LiqCost ×*HiAdvSel*	13185.879	-8720.309	**1493.398**	725.628	2354.307	1386.639
	(.205)	(.362)	(.017)	(.168)	(.116)	(.222)
Stealth (×1,000)	0.042	0.150	**-0.053**	**-0.042**	**-0.254**	**-0.173**
	(.755)	(.284)	(< .01)	(< .01)	(< .01)	(< .01)
NOB	444	444	444	444	444	444
R-square	0.012	0.003	0.358	0.165	0.792	0.645

	Panel B. USD/JPY					
Dependent variable	*EF* 0		*EF* 1		*EF* 2	
Data frequency	1min.	2min.	1min.	2min.	1min.	2min.
Intercept	**7.491**	**6.663**	**0.958**	**0.583**	**3.285**	**2.286**
	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)
LiqCost	70.106	-6.326	**27.154**	**14.814**	**117.784**	**86.635**
	(.205)	(.915)	(< .01)	(< .01)	(< .01)	(< .01)
HiAdvSel	0.496	1.302	0.123	0.118	0.344	0.308
	(.699)	(.360)	(.141)	(.118)	(.180)	(.140)
LiqCost ×*HiAdvSel*	58.615	117.584	8.426	8.150	31.418	27.900
	(.547)	(.287)	(.204)	(.182)	(.120)	(.087)
Stealth (×1,000)	0.399	-0.206	**-0.159**	**-0.086**	**-0.523**	**-0.372**
	(.042)	(.303)	(< .01)	(< .01)	(< .01)	(< .01)
NOB	444	444	444	444	444	444
R-square	0.012	0.006	0.572	0.230	0.763	0.677

Table 10

Regression of equation (15) using the efficiency measures calculated on the basis of net number of buyer-initiated trades

I use net number of buyer-initiated trades as order imbalance and calculate $EF0$, $EF1$, and $EF2$. Table 10 shows the estimation result of the regression of equation (15): $EF_i = \beta_0 + \beta_1 LiqCost_i + \beta_2 HiAdvSel_i + \beta_3 LiqCost_i \times HiAdvSel_i + \beta_4 Stealth_i + e_i$. The other details for Table 10 are presented in Table 7.

	Panel A. EUR/USD					
Dependent variable	*EF* 0		*EF* 1		*EF* 2	
Data frequency	1min.	2min.	1min.	2min.	1min.	2min.
Intercept	**7.723**	**6.654**	**0.746**	**0.594**	**2.597**	**1.709**
	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)
LiqCost	1004.158	1195.631	**2533.157**	**2057.695**	**10331.123**	**6807.063**
	(.856)	(.858)	(< .01)	(< .01)	(< .01)	(< .01)
HiAdvSel	-0.546	-0.192	**0.156**	0.041	**0.420**	**0.275**
	(.734)	(.895)	(.023)	(.508)	(.015)	(.029)
LiqCost ×*HiAdvSel*	-7609.087	-1157.172	**1122.438**	298.885	**3190.641**	**2131.024**
	(.565)	(.921)	(.036)	(.538)	(.019)	(.028)
Stealth (×1,000)	-0.044	**0.296**	**-0.057**	**-0.036**	**-0.236**	**-0.163**
	(.760)	(.041)	(< .01)	(< .01)	(< .01)	(< .01)
NOB	444	444	444	444	444	444
R-square	0.008	0.008	0.483	0.260	0.761	0.644

	Panel B. USD/JPY					
Dependent variable	*EF* 0		*EF* 1		*EF* 2	
Data frequency	1min.	2min.	1min.	2min.	1min.	2min.
Intercept	**7.993**	**7.920**	**1.015**	**0.705**	**3.291**	**2.374**
	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)
LiqCost	26.370	68.132	**34.135**	**19.492**	**111.601**	**81.851**
	(.563)	(.096)	(< .01)	(< .01)	(< .01)	(< .01)
HiAdvSel	2.209	**-4.218**	**0.227**	**0.199**	**0.745**	**0.548**
	(.060)	(.014)	(.015)	(.015)	(< .01)	(< .01)
LiqCost ×*HiAdvSel*	**210.782**	**-360.580**	**17.961**	**15.725**	**64.374**	**47.374**
	(.023)	(.014)	(.016)	(.016)	(< .01)	(< .01)
Stealth (×1,000)	0.037	-0.008	**-0.130**	**-0.102**	**-0.470**	**-0.364**
	(.841)	(.966)	(< .01)	(< .01)	(< .01)	(< .01)
NOB	444	444	444	444	444	444
R-square	0.011	0.016	0.572	0.410	0.748	0.696

Table 11

Regression of equation (15) using the efficiency measures calculated on the basis of unexpected order imbalance

I use the residuals from AR(15) as the unexpected order imbalance and calculate $EF0$, $EF1$, and $EF2$. Table 11 shows the estimation result of the regression of equation (15): $EF_i = \beta_0 + \beta_1 LiqCost_i + \beta_2 HiAdvSel_i + \beta_3 LiqCost_i \times HiAdvSel_i + \beta_4 Stealth_i + e_i$. The other details for Table 11 are presented in Table 7.

	Panel A. EUR/USD					
Dependent variable	*EF* 0		*EF* 1		*EF* 2	
Data frequency	1min.	2min.	1min.	2min.	1min.	2min.
Intercept	**8.281**	**6.447**	**0.631**	**0.453**	**2.544**	**1.628**
	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)
LiqCost	4668.260	-6257.845	**2529.961**	**1865.479**	**10398.833**	**6724.518**
	(.396)	(.283)	(< .01)	(< .01)	(< .01)	(< .01)
HiAdvSel	0.830	1.422	**0.210**	0.082	**0.458**	**0.362**
	(.536)	(.326)	(< .01)	(.212)	(< .01)	(< .01)
LiqCost ×*HiAdvSel*	10207.651	11076.966	**1541.691**	615.554	**3471.781**	**2760.173**
	(.333)	(.328)	(< .01)	(.230)	(< .01)	(< .01)
Stealth (×1,000)	0.029	-0.071	**-0.040**	**-0.027**	**-0.234**	**-0.165**
	(.862)	(.541)	(< .01)	(< .01)	(< .01)	(< .01)
NOB	444	444	444	444	444	444
R-square	0.012	0.003	0.496	0.251	0.771	0.671

	Panel B. USD/JPY					
Dependent variable	*EF* 0		*EF* 1		*EF* 2	
Data frequency	1min.	2min.	1min.	2min.	1min.	2min.
Intercept	**8.099**	**5.984**	**0.771**	**0.504**	**3.154**	**2.265**
	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)	(< .01)
LiqCost	42.421	-101.951	**28.948**	**16.621**	**108.727**	**82.277**
	(.383)	(.066)	(< .01)	(< .01)	(< .01)	(< .01)
HiAdvSel	-1.692	2.373	**0.263**	**0.175**	**0.775**	**0.559**
	(.270)	(.137)	(< .01)	(.020)	(< .01)	(< .01)
LiqCost ×*HiAdvSel*	-101.072	184.568	**20.771**	**13.512**	**66.262**	**47.472**
	(.432)	(.155)	(< .01)	(.028)	(< .01)	(< .01)
Stealth (×1,000)	0.082	-0.386	**-0.076**	**-0.060**	**-0.446**	**-0.341**
	(.688)	(.133)	(< .01)	(< .01)	(< .01)	(< .01)
NOB	444	444	444	444	444	444
R-square	0.011	0.010	0.545	0.307	0.749	0.692

Table 12

Regression of equation (15) with $EF1^*$ calculated using bid and ask rates

I calculate $EF1$ in equations (1) and (3) using bid and ask rates instead of the midpoint quote: if order imbalance is positive (negative), I use the ask (bid) rate to calculate $EF1$. In equation (1), $r_t = p_t^{**,ask} - p_t^{*,ask}$ if $OIB_{t-1} > 0$. $p_t^{**,ask}$ and $p_t^{*,ask}$ are the prevailing ask rates at the first and last timings in period t, respectively. If $OIB_{t-1} < 0$, r_t is calculated similarly using bid rates. I label this $EF1$ as $EF1^*$. Table 12 shows the estimation result of the regression of equation (15): $EF1_i^* = \beta_0 + \beta_1 LiqCost_i + \beta_2 HiAdvSel_i + \beta_3 LiqCost_i \times HiAdvSel_i + \beta_4 Stealth_i + e_i$. The other details for Table 12 are presented in Table 7.

	EUR/USD		USD/JPY	
Dependent variable	*EF1**		*EF 1**	
Data frequency	1min.	2min.	1min.	2min.
Intercept	**0.501**	**-0.079**	**1.044**	**0.307**
	(< .01)	(.392)	(< .01)	(< .01)
LiqCost	**8831.938**	**8791.478**	**97.886**	**91.805**
	(< .01)	(< .01)	(< .01)	(< .01)
HiAdvSel	**0.358**	**0.373**	**0.497**	**0.489**
	(.030)	(.032)	(< .01)	(< .01)
LiqCost ×*HiAdvSel*	2566.693	2670.927	**41.001**	**39.271**
	(.051)	(.053)	(< .01)	(< .01)
Stealth (×1,000)	**-0.213**	**-0.190**	**-0.412**	**-0.335**
	(< .01)	(< .01)	(< .01)	(< .01)
NOB	444	444	444	444
R-square	0.708	0.645	0.768	0.725

Figure 1

Statistical significance of lagged order imbalance

I regress a current rate change onto a lagged order imbalance and constant term. I calculate the rate change and order imbalance from one- to ten-minute frequencies and regress at each frequency. The vertical axis presents the t-statistics for a lagged order imbalance at each data frequency. The horizontal axis presents the data frequency (minute).

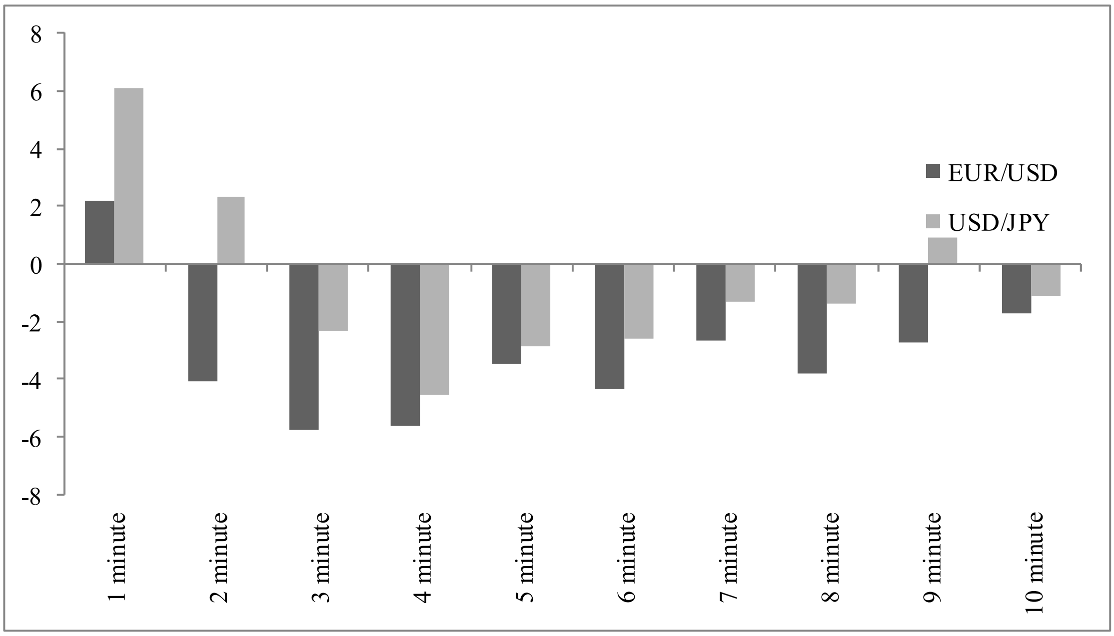
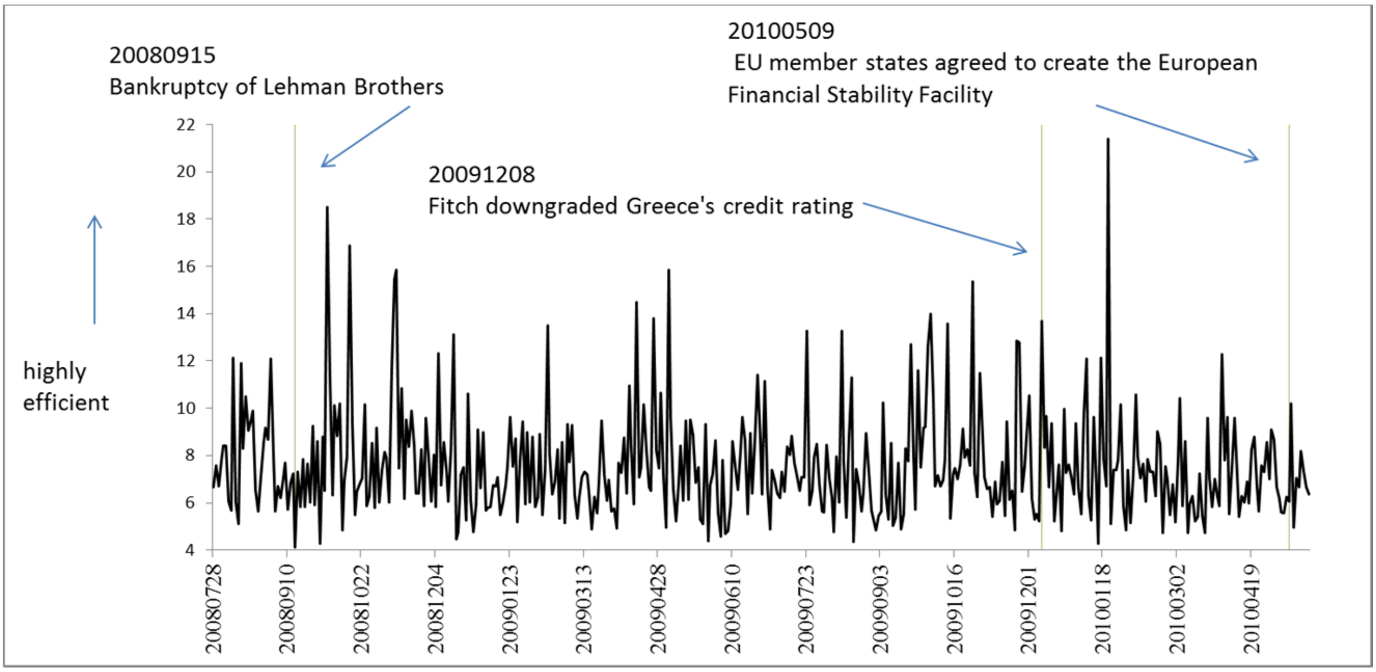


Figure 2

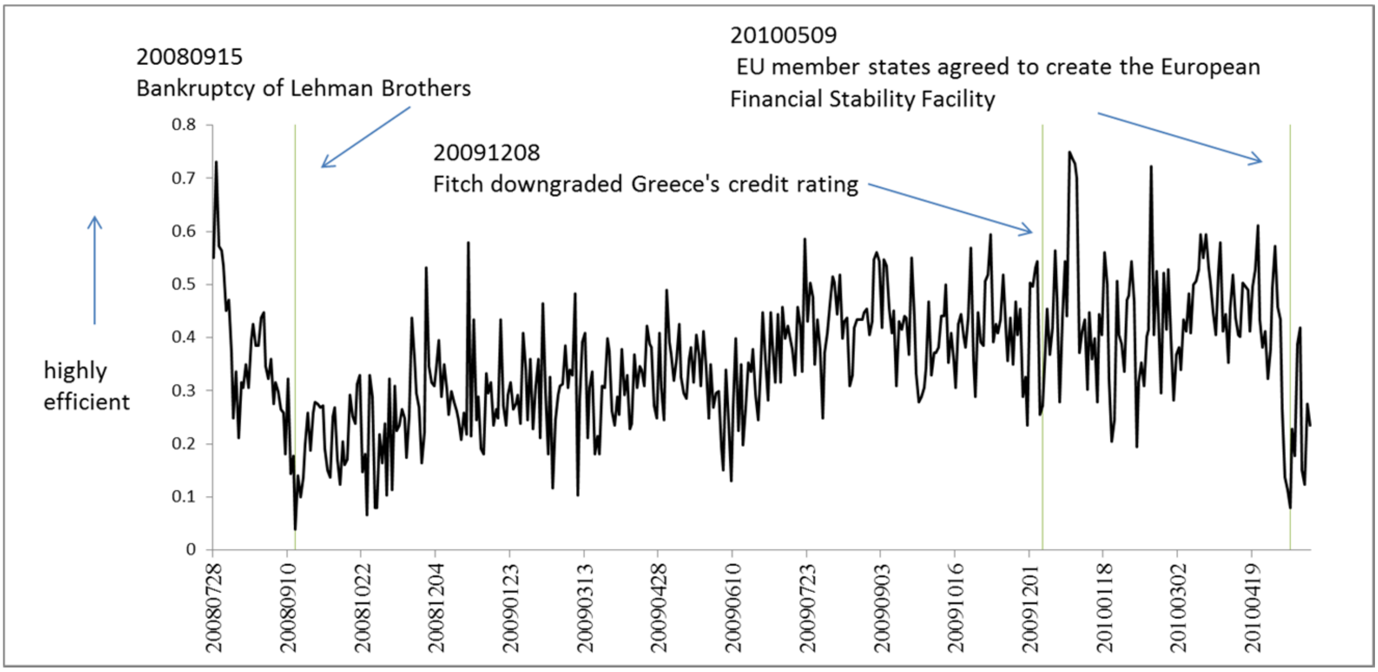
Time series of *EF*0, *EF*1, and *EF*2

*EF*0, *EF*1, and *EF*2 are variables used to measure the level of market efficiency. *EF*0 is calculated using R-square, which is measured from the regression of a current rate change onto a lagged order imbalance and constant term. *EF*1 and *EF*2 are calculated using equations (3) and (4), respectively. All of the measures are calculated using one-minute data for the EUR/USD.

2a *EF*0 series



2b *EF*1 series



2c *EF*2 series