



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.

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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 few of large financial institutions (King et al., 2013). Second, unlike a stock market, trading is not centralized in FX markets. 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 the USD/JPY markets.

To examine these questions, I propose measures of market efficiency in an FX market. 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, these proposed measures seem economically more relevant than previous ones when one considers the predictability of order flows given that one of the proposed measures (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 uncovered interest rate parity (UIP) holding (see Sarno and Taylor (2002)), and I expect that the proposed measures provide additional insights into an analysis of FX market efficiency.

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

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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, a 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, in an efficient market, no information can predict a future FX rate change and that no excess returns exist. Regarding this issue, the vast body of literature reports persistent deviations from 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 conveying 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 rate. Order flows aggregate different opinions among market participants and convey aggregated market expectations. Other things being equal, if participants are homogeneous, an increase 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 followed an unexpected interest rate increase by the Bundesbank for the subsequent two

hours. This result suggests that heterogeneous traders have different opinions about that increase, and an FX rate gradually achieves its new equilibrium value through transactions. I consider this result to be inappropriate 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 the FX rate eventually moves back to its previous equilibrium level. 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 long-term fundamentals, although they are related to short-term currency returns. King et 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—originally 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), which deals with the customer as a source of private information. Menkhoff et al. (2013) examine the 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, when trading with their customers, dealers strategically narrow their quoting spreads 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. Fig. 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 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

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

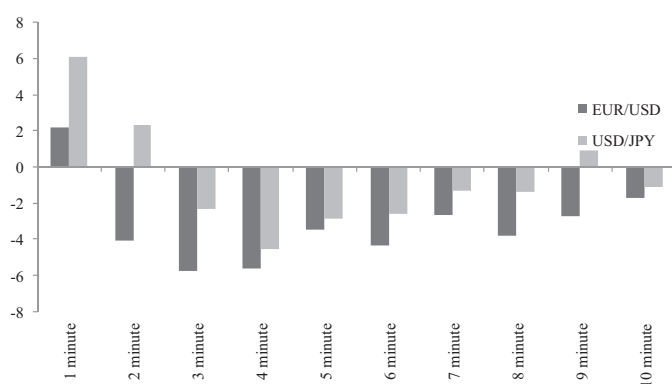


Fig. 1. Statistical significance of lagged order imbalance.

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).

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 Group, 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 currency pairs in the 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 the 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 in real time OIB# but not OIBM. 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 than OIB# in price discovery. 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 minute and two minutes are the data frequencies selected to consider the forecasting power of OIB. OIBM and OIB# show the same direction at one- and two-minute data frequencies in 63 and 62% of the EUR/USD cases, 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

Following previous studies (e.g., Kyle (1985), Admati and Pfleiderer (1988)), I assume that buying and selling through liquidity trading occurs randomly. This assumption enables me to assume that informed trading causes order imbalance. Therefore, order imbalance can predict price changes. Throughout the paper, market efficiency corresponds to a situation in which order imbalance information cannot predict future prices. When order flow is observable for all market participants, researchers test the semi-strong form of market efficiency. In turn, if the flow is private information, they test the strong form 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 (macro forecasting) 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*:

$$\begin{aligned} INEF1_t &= +1 \text{ if } OIB_{t-1} > 0 \text{ and } r_t > 0, \text{ or } OIB_{t-1} < 0 \text{ and } r_t < 0 \\ INEF1_t &= 0 \text{ otherwise} \end{aligned} \quad (1)$$

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. For example, the second measure takes the value of +1 if a positive order imbalance is followed by a period in which the highest bid exceeds the lowest ask at the beginning of the period, and similarly for a negative order imbalance. 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 $p_t^{*,i}$ ($i = \text{ask or bid}$) 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, *INEF2*, as a measure of market *inefficiency* as follows:

$$\begin{aligned} INEF2_t &= +1 \text{ if } OIB_{t-1} > 0 \text{ and } p_t^{H,bid} - p_t^{*,ask} > 0, \\ &\text{or } OIB_{t-1} < 0 \text{ and } p_t^{*,bid} - p_t^{L,ask} > 0 \\ INEF2_t &= 0 \text{ otherwise.} \end{aligned} \quad (2)$$

INEF2 considers that the exploitability of lagged OIB is the inverse of market efficiency. When compared with *INEF1*, *INEF2* 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.

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-min frequencies. I calculate rate change and order flow at one- to ten-minute frequencies and do regressions at each frequency. Fig. 1 presents the t-statistics for the estimated coefficient of lagged OIB at each frequency. I select ten minutes as the maximum frequency in Fig. 1 to ensure easy viewing. This

² One might consider that if the signal is to buy, then the ask price should be used. 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 *INEF1*, and returns calculated in one-sided quotes (bid/ask) are highly correlated with spread. Naturally, in this case, *INEF1* is highly correlated with spread, which leads me to use the midpoint quote in Eq. (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).

selection does not change in the subsequent discussion. As shown in Fig. 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. Fig. 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-min 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 *INEF1* and *INEF2* 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 *INEF1* = 1 and 1200 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 *EF1* and *EF2*, respectively, represent higher market efficiency levels. Thus, daily *EF1* and *EF2* are derived using *INEF1* and *INEF2*, 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 Eqs. (1) and (2). $INEF1_t^i$ represents *INEF1* 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 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 *EF0* (the R-square measure). Iwatsubo and Kitamura (2008) also use the R-square measure calculated using a 30-s data frequency to examine market efficiency levels in the EUR/USD and USD/JPY markets.

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, *EF0*, *EF1*, and *EF2* range from 0 to 1. Table 1 indicates that *EF0* (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. As shown later in Table 6, *EF1* and *EF2* show significant positive correlation, although *EF0*s show weaker correlation with the proposed efficiency measures.

Fig. 2a–c show the times series of *EF0*, *EF1*, and *EF2*, respectively. The series are calculated using one-minute EUR/USD data.⁴ From Figs. 2b and c, 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 *EF1* and *EF2* correspond to

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.

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

Table 1
Summary of statistics for market efficiency measures: *EF0*, *EF1*, and *EF2* (before logit transformation and multiplied by -1).

Panel A. EUR/USD						
Data frequency	<i>EF0</i>		<i>EF1</i>		<i>EF2</i>	
	1 min.	2 min.	1 min.	2 min.	1 min.	2 min.
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						
Data frequency	<i>EF0</i>		<i>EF1</i>		<i>EF2</i>	
	1 min.	2 min.	1 min.	2 min.	1 min.	2 min.
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

EF0, *EF1*, and *EF2* are variables used to measure market efficiency. *EF0* 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. *EF1* and *EF2* are calculated using Eqs. (3) and (4), respectively. In Table 1, *EF0*, *EF1*, and *EF2* are variables before a logit transformation and are multiplied by -1 ; the values of all three variables range from 0 to 1.

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, *EF1* and *EF2* reach bottom on Friday, May 7, 2010, indicating that, before the 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 Figs. 2b and 2c in this study are consistent with their finding. Figs. 2b and 2c also show the day (December 8, 2009) on which Fitch, a major international credit agency, downgraded Greece's credit rating before a rating cut by S&P (December 16, 2009) and Moody's (December 22, 2009). After this downgrading, *EF1* and *EF2* 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 (*EF0*) in Fig. 2a does not clearly exhibit 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 creates competition among these agents to enhance the speed of the 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 with 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

Table 2
Summary of statistics for liquidity and information asymmetry variables.

	EUR/USD					USD/JPY				
	LiqCost ($\times 1000$)	LiqPlm	HiAdvSel	$\hat{\lambda}$	$\hat{\alpha}$	LiqCost ($\times 1000$)	LiqPlm	HiAdvSel	$\hat{\lambda}$	$\hat{\alpha}$
Mean	-0.126	-0.054	0.396	0.691	0.847	-12.736	-0.068	0.428	0.670	0.849
Median	-0.120	-0.050	-	0.689	0.849	-11.994	-0.065	-	0.667	0.850
Max	-0.100	-0.022	1.000	0.821	0.959	-9.859	-0.026	1.000	0.877	0.995
Min	-0.219	-0.115	0.000	0.567	0.691	-27.299	-0.164	0.000	0.435	0.496
Std. dev.	0.021	0.017	0.490	0.047	0.045	2.376	0.021	0.495	0.059	0.061
Auto(1)	0.869	0.044	0.358	0.570	0.470	0.827	0.109	0.372	0.589	0.487

LiqCost is the negative effective spread and is calculated using Eq. (6). *LiqPlm* is the negative price impact calculated using Eq. (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 Eqs. (9) and (10), respectively, and are related to information asymmetry levels. Auto(1) is the coefficient of the first-order autocorrelation.

Table 3
Probit regression of market inefficiency measures on effective spread and trade size.

Dependent Variable	Panel A. EUR/USD							
	INEF1 (1 min.)		INEF2 (1 min.)		INEF1 (2 min.)		INEF2 (2 min.)	
Intercept	-0.280 (<0.01)	0.061 (<0.01)	-1.948 (<0.01)	-1.128 (<0.01)	-0.591 (<0.01)	-0.346 (<0.01)	-1.768 (<0.01)	-1.259 (<0.01)
Esp_t	200.900 (<0.01)		815.057 (<0.01)		278.545 (<0.01)		788.343 (<0.01)	
Esp_{t-1}		41.661 (0.06)		417.461 (<0.01)		112.481 (<0.01)		463.949 (<0.01)
trade size _t	0.310 (<0.01)		0.941 (<0.01)		0.168 (<0.01)		0.690 (<0.01)	
trade size _t ²	-0.027 (<0.01)		-0.104 (<0.01)		-0.011 (<0.01)		-0.076 (<0.01)	
trade size _{t-1}		0.154 (<0.01)		0.554 (<0.01)		0.108 (<0.01)		0.503 (<0.01)
trade size _{t-1} ²		-0.018 (<0.01)		-0.063 (<0.01)		-0.016 (<0.01)		-0.065 (<0.01)
max. trade	5.8	4.3	4.5	4.4	7.8	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	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
NOB	518904	518903	518904	518903	253846	253845	253846	253845

Dependent Variable	Panel B. USD/JPY							
	INEF1 (1 min.)		INEF2 (1 min.)		INEF1 (2 min.)		INEF2 (2 min.)	
Intercept	-0.200 (<0.01)	0.055 (<0.01)	-1.743 (<0.01)	-1.104 (<0.01)	-0.628 (<0.01)	-0.351 (<0.01)	-1.886 (<0.01)	-1.193 (<0.01)
Esp_t	0.011 (<0.01)		8.462 (<0.01)		2.186 (<0.01)		9.928 (<0.01)	
Esp_{t-1}		0.004 (0.05)		6.533 (<0.01)		1.261 (<0.01)		6.850 (<0.01)
trade size _t	0.253 (0.40)		0.573 (<0.01)		0.205 (<0.01)		0.582 (<0.01)	
trade size _t ²	-0.015 (<0.01)		-0.057 (<0.01)		-0.019 (<0.01)		-0.065 (<0.01)	
trade size _{t-1}		0.084 (0.47)		0.236 (<0.01)		0.066 (<0.01)		0.236 (<0.01)
trade size _{t-1} ²		-0.009 (<0.01)		-0.027 (<0.01)		-0.008 (<0.01)		-0.029 (<0.01)
max. trade	8.2	4.8	5.0	4.4	5.4	4.3	4.5	4.0
mean log-likelihood	-0.666	-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

I estimate Eqs. (11) and (12). “ Esp_t ” is the mean of e_spread calculated using Eq. (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 INEF1 (1 min) presents the result of Eq. (11), with INEF1 as a dependent variable and for a one-minute data frequency. Bold figures are statistically significant at least at the 10% level. The numbers in parentheses are p -values for the estimators. “ $p < 0.01$ ” indicates that the p -value is less than 0.01. The row “max. trade” is the trade size that has a maximum positive effect on $INEF\#_t$. “p-value for LR test” is the p -value for the likelihood ratio test statistic for which the null is the coefficients of Esp and trade size, and trade size squared is zero. NOB is the number of observations.

Table 4
Number of trades by size classification.

Trade size	EUR/USD		USD/JPY	
	Number of trades	Relative proportion of trades	Number of trades	Relative proportion of trades
1	43,21,148	0.47	2,622,781	0.51
2	19,980,225	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

The trade size unit 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.

at the j th trade, respectively. Using these variables, I calculate the effective spread, e_spread , as follows:

$$e_spread_j = 2 \times q_j (p_j - m_j) \quad (5)$$

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

Table 5
Probit regression of market inefficiency measures on effective spread and medium-size trades.

Dependent Variable	Panel A. EUR/USD							
	INEF1 (1 min.)		INEF2 (1 min.)		INEF1 (2 min.)		INEF2 (2 min.)	
Intercept	0.201 (<0.01)	0.262 (<0.01)	-0.668 (<0.01)	-0.424 (<0.01)	-0.252 (.01)	-0.188 (.01)	-0.575 (<0.01)	-0.459 (<0.01)
Esp_t	151.165 (<0.01)		622.684 (<0.01)		229.447 (<0.01)		625.675 (<0.01)	
Esp_{t-1}		6.337 (0.49)		288.114 (<0.01)		96.499 (<0.01)		371.283 (<0.01)
$stealth\ trade_t$	0.040 (<0.01)		0.166 (<0.01)		0.003 (<0.01)		0.010 (<0.01)	
$stealth\ trade_{t-1}$		0.028 (<0.01)		0.117 (<0.01)		0.003 (<0.01)		0.009 (<0.01)
mean log-likelihood	-0.651	-0.660	-0.638	-0.664	-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

Dependent Variable	Panel B. USD/JPY							
	INEF1 (1 min.)		INEF2 (1 min.)		INEF1 (2 min.)		INEF2 (2 min.)	
Intercept	0.063 (<0.01)	0.104 (<0.01)	-1.091 (<0.01)	-0.837 (<0.01)	-0.294 (<0.01)	-0.254 (<0.01)	-0.967 (<0.01)	-0.847 (<0.01)
Esp_t	2.542 (<0.01)		8.838 (<0.01)		2.224 (<0.01)		9.657 (<0.01)	
Esp_{t-1}		0.815 (<0.01)		5.280 (<0.01)		1.232 (<0.01)		6.643 (<0.01)
$stealth\ trade_t$	0.062 (<0.01)		0.233 (<0.01)		0.004 (0.01)		0.011 (<0.01)	
$stealth\ trade_{t-1}$		0.043 (<0.01)		0.142 (<0.01)		0.006 (<0.01)		0.017 (<0.01)
mean log-likelihood	-0.670	-0.681	-0.593	-0.618	-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

I estimate Eqs. (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 Eq. (5) during period t . For example, the left column of INEF1 (1 min) presents the result of Eq. (13), with INEF1 as a dependent variable and for a one-minute data frequency. Bold figures are statistically significant at least at the 10% level. The numbers in parentheses are p -value for the estimators. " $p < 0.01$ " indicates that the p -value is less than 0.01. "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.

Table 6
Contemporaneous correlations (Pearson product-moment coefficient correlation).

	Panel A. EUR/USD									
	EFO (1 min.)	EFO (2 min.)	EF1 (1 min.)	EF1 (2 min.)	EF2 (1 min.)	EF2 (2 min.)	LiqCost	LiqPlm	HiAdvSel	
EFO (1 min.)	1									
EFO (2 min.)	0.09	1								
EF1 (1 min.)	-0.04	-0.10	1							
EF1 (2 min.)	-0.01	-0.06	0.62	1						
EF2 (1 min.)	-0.03	-0.10	0.87	0.62	1					
EF2 (2 min.)	-0.03	-0.09	0.83	0.75	0.95	1				
LiqCost	0.01	-0.01	0.60	0.45	0.74	0.67	1			
LiqPlm	-0.06	-0.04	0.54	0.44	0.65	0.62	0.74	1		
HiAdvSel	0.08	0.00	0.16	0.09	0.14	0.12	0.23	0.10	1	
Stealth	-0.01	0.09	-0.43	-0.30	-0.57	-0.54	-0.17	-0.14	0.10	1

	Panel B. USD/JPY									
	EFO (1 min.)	EFO (2 min.)	EF1 (1 min.)	EF1 (2 min.)	EF2 (1 min.)	EF2 (2 min.)	LiqCost	LiqPlm	HiAdvSel	
EFO (1 min.)	1									
EFO (2 min.)	0.07	1								
EF1 (1 min.)	0.00	-0.03	1							
EF1 (2 min.)	0.04	-0.01	0.78	1						
EF2 (1 min.)	0.04	-0.03	0.92	0.76	1					
EF2 (2 min.)	0.03	-0.03	0.91	0.83	0.97	1				
LiqCost	0.03	0.02	0.67	0.53	0.74	0.71	1			
LiqPlm	0.15	-0.06	0.52	0.44	0.56	0.54	0.63	1		
HiAdvSel	-0.04	0.02	0.29	0.24	0.27	0.25	0.42	0.27	1	
Stealth	0.00	-0.02	-0.57	-0.51	-0.68	-0.66	-0.37	-0.19	-0.10	1

EFO is calculated using R-square, which is measured from the regression of a current rate change onto a lagged order imbalance and constant term. EF1 and EF2 are calculated using Eqs. (3) and (4), respectively. The number of minutes in parentheses represents the data frequency adopted to calculate each variable. For example, EFO (1 min) is calculated using a one-minute data frequency. LiqCost is a variable related to transaction cost and is obtained using Eq. (6). LiqPlm is a variable related to the price effect and is calculated using Eq. (8). HiAdvSel is a binary variable that takes the value of +1 when both estimated parameters in Eqs. (9) and (10) are higher than their own medians.

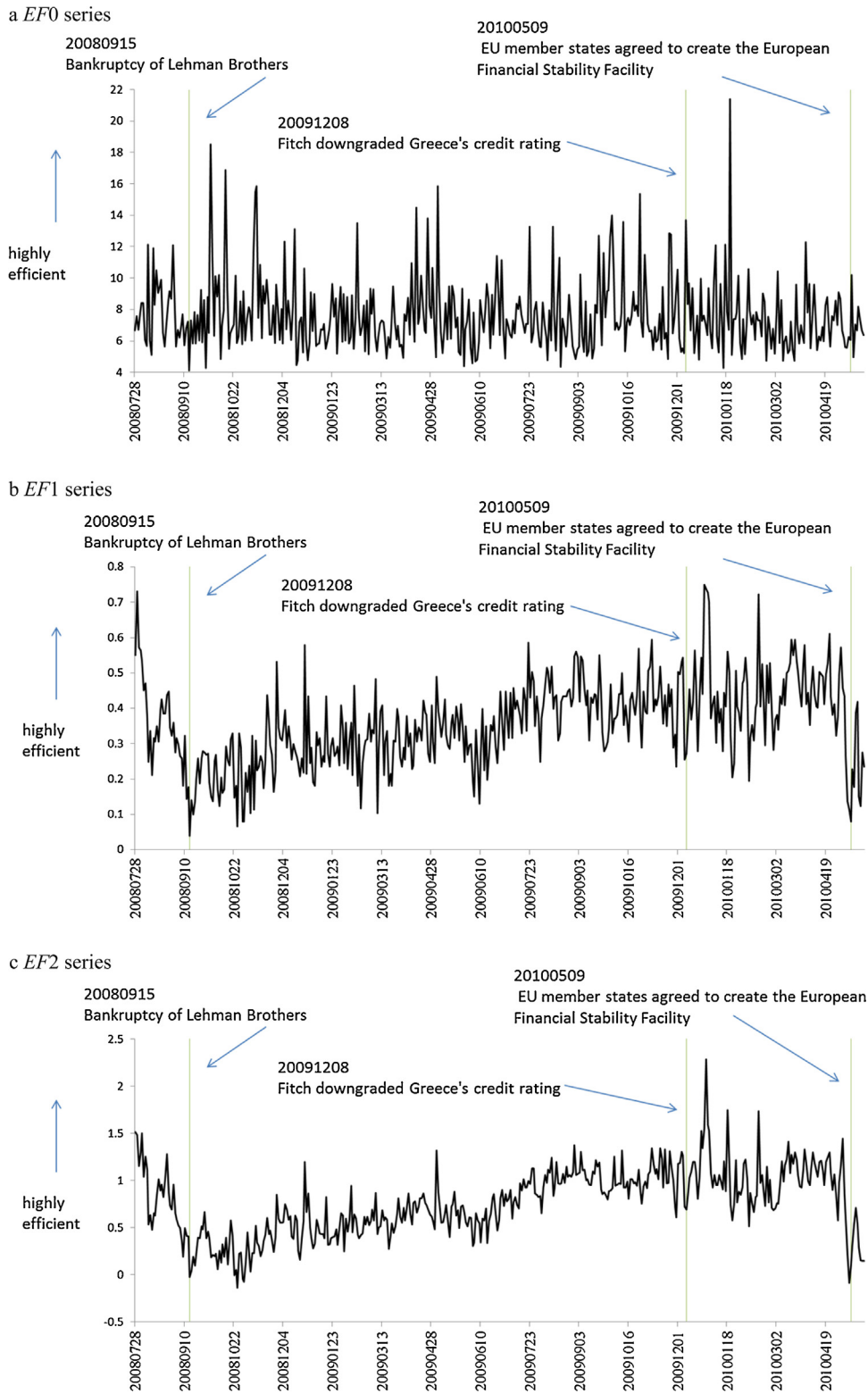


Fig. 2. Time series of EF_0 , EF_1 , and EF_2 .

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 Eqs. (3) and (4), respectively. All of the measures are calculated using one-minute data for the EUR/USD.

average represents higher liquidity. I label this variable $LiqCost$:

$$LiqCost_i = -1 \times \sum_{j=1}^{J_i} e_{spread_j} / J_i \quad (6)$$

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 Hasbrouck (2009). I calculate the five-minute price impact regressing an FX rate change onto constant and squared order flow. Let the five-minute FX rate change and aggregate order flow on the j th interval of i th day be $R_{i,j}$ and $x_{i,j}$, respectively. Then, the impact for the i th day is obtained from the following regression:

$$R_{i,j} = \gamma_{0,i} + \gamma_{1,i} \times \text{sign}(x_{i,j}) \times \sqrt{|x_{i,j}|} + \text{error term}, \quad (7)$$

where $R_{i,j}$ is the five-minute FX rate change calculated using the $1000 \times \log$ difference of the quote midpoint. I use the prevailing quote midpoints at the last timings in j and $j-1$. $x_{i,j}$ is the five-minute aggregated amount of net buyer-initiated trades (order flow) in the j th interval of the i th day. I run the regression of Eq. (7) for each day and obtain $\hat{\gamma}_{1,i}$. Similar to *LiqCost*, I also multiply $\hat{\gamma}_{1,i}$ by -1 to ensure that a higher value represents higher liquidity. This variable is labeled *LiqPlm*:

$$\text{LiqPlm}_i = -1 \times \hat{\gamma}_{1,i}. \quad (8)$$

LiqPlm measures daily liquidity using the five-minute price impact.

I also consider the alternative measure of price impact proposed by Amihud (2002). This measure is absolute price change divided by trading volume. Instead of Eq. (7), the previous version of this paper used the Amihud (2002) measure. The price impact of Eq. (7) is more informative than Amihud (2002) because the former considers the directions of both price change and transaction. This result encourages me to adopt Eq. (7). Huh (2014) uses intraday order flows and estimates price impact as a measure of liquidity. He suggests that impact well explains the return premium for illiquidity because it incorporates incremental information included in high-frequency data. His suggestion also motivates me to adopt Eq. (7) instead of the Amihud (2002) measure.

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

Table 7
Regression of market efficiency measures on liquidity, information asymmetry, and stealth trading (Eq. (15)).

Dependent variable	Panel A. EUR/USD					
	EF0		EF1		EF2	
	1 min.	2 min.	1 min.	2 min.	1 min.	2 min.
Intercept	8.194 (<0.01)	6.050 (<0.01)	0.760 (<0.01)	0.509 (<0.01)	2.424 (<0.01)	1.535 (<0.01)
<i>LiqCost</i>	273.750 (.980)	-5664.114 (.675)	740.103 (.045)	255.711 (.521)	5491.875 (<0.01)	2870.519 (<0.01)
<i>LiqPlm</i>	8.064 (.571)	-2.676 (.865)	2.564 (<0.01)	2.348 (<0.01)	7.170 (<0.01)	5.631 (<0.01)
<i>HiAdvSel</i>	1.672 (.253)	1.378 (.469)	0.150 (.033)	0.034 (.630)	0.207 (.087)	0.150 (.126)
<i>LiqCost</i> × <i>HiAdvSel</i>	36307.300 (.038)	27481.534 (.275)	928.697 (.258)	39.171 (.961)	623.360 (.668)	78.241 (.946)
<i>LiqPlm</i> × <i>HiAdvSel</i>	-40.894 (.050)	-41.040 (.177)	0.130 (.890)	0.261 (.750)	1.599 (.394)	1.976 (.177)
<i>Stealth</i> (×1000)	0.046 (.776)	0.066 (.618)	-0.076 (<0.01)	-0.050 (<0.01)	-0.246 (<0.01)	-0.176 (<0.01)
NOB	444	444	444	444	444	444
R-square	0.022	0.020	0.567	0.359	0.818	0.735

Dependent variable	Panel B. USD/JPY					
	EF0		EF1		EF2	
	1 min.	2 min.	1 min.	2 min.	1 min.	2 min.
Intercept	8.137 (<0.01)	6.013 (<0.01)	1.061 (<0.01)	0.669 (<0.01)	3.219 (<0.01)	2.307 (<0.01)
<i>LiqCost</i>	93.287 (.204)	-86.322 (.274)	14.459 (<0.01)	5.847 (.230)	64.088 (<0.01)	46.954 (<0.01)
<i>LiqPlm</i>	-10.621 (.276)	-0.334 (.972)	2.633 (<0.01)	2.019 (<0.01)	6.796 (<0.01)	5.488 (<0.01)
<i>HiAdvSel</i>	0.113 (.956)	2.017 (.288)	0.095 (.336)	-0.001 (.994)	0.360 (.095)	0.136 (.468)
<i>LiqCost</i> × <i>HiAdvSel</i>	36.793 (.881)	126.823 (.583)	2.686 (.817)	-7.257 (.474)	22.158 (.339)	-1.963 (.925)
<i>LiqPlm</i> × <i>HiAdvSel</i>	0.156 (.994)	6.794 (.733)	0.655 (.522)	1.115 (.195)	1.629 (.431)	2.547 (.154)
<i>Stealth</i> (×1000)	-0.071 (.713)	-0.142 (.659)	-0.176 (<0.01)	-0.114 (<0.01)	-0.509 (<0.01)	-0.384 (<0.01)
NOB	444	444	444	444	444	444
R-square	0.008	0.006	0.650	0.453	0.786	0.736

Table 7 shows the estimation result of the regression of Eq. (15): $EF_i = \beta_0 + \beta_1 \text{LiqCost}_i + \beta_2 \text{LiqPlm}_i + \beta_3 \text{HiAdvSel}_i + \beta_4 \text{LiqCost}_i \times \text{HiAdvSel}_i + \beta_5 \text{LiqPlm}_i \times \text{HiAdvSel}_i + \beta_6 \text{Stealth}_i + e_i$. EF is replaced with EF0, EF1, and EF2. EF0 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. EF1 and EF2 are calculated using Eqs. (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 Eq. (6). *LiqPlm* is the five-minute price impact of the squared order flow. This impact is calculated from Eq. (7). *HiAdvSel* is a binary variable that takes the value of +1 when both the estimated parameters in Eqs. (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 10% level. The numbers in parentheses are p -values for the estimators. “ $p < 0.01$ ” indicates that the p -value is less than 0.01. To calculate the p -values, I use the Newey-West standard errors. NOB is the number of observations.

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; Huang 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:

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

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

where m_j represents the quote midpoint prevailing in the j th transaction, $\Delta m_{j+1} = m_{j+1} - m_j$, p_j represents the j th transaction price, S_j represents the quoted bid–ask spread prevailing in the j th transaction, and Q_j takes the value +1 (–1) when the j th trade is buyer (seller) initiated. ε and ν 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. Eqs. (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 the 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,

Table 8
Regression of Eq. (15) for GMT 7–17.

Dependent variable	Panel A. EUR/USD					
	EF0		EF1		EF2	
	1 min.	2 min.	1 min.	2 min.	1 min.	2 min.
Intercept	7.976 (<0.01)	6.993 (<0.01)	0.592 (<0.01)	0.411 (<0.01)	2.437 (<0.01)	1.398 (<0.01)
LiqCost	4221.066 (.625)	3620.485 (.649)	1131.258 (<0.01)	168.882 (.750)	9505.539 (<0.01)	4706.205 (<0.01)
LiqPlm	0.741 (.954)	1.185 (.922)	1.613 (<0.01)	2.329 (<0.01)	5.027 (<0.01)	4.580 (<0.01)
HiAdvSel	1.398 (.354)	–0.768 (.561)	0.130 (.100)	0.062 (.404)	0.129 (.443)	0.036 (.771)
LiqCost×HiAdvSel	15410.840 (.387)	–1598.854 (.918)	521.202 (.537)	525.992 (.562)	310.496 (.858)	–303.685 (.815)
LiqPlm×HiAdvSel	–2.916 (.890)	–9.036 (.605)	0.790 (.355)	–0.337 (.730)	1.252 (.480)	0.930 (.511)
Stealth (×1000)	0.039 (.774)	0.142 (.309)	– 0.052 (<0.01)	– 0.041 (<0.01)	– 0.250 (<0.01)	– 0.170 (<0.01)
NOB	444	444	444	444	444	444
R-square	0.012	0.004	0.393	0.203	0.817	0.687

Dependent variable	Panel B. USD/JPY					
	EF0		EF1		EF2	
	1 min.	2 min.	1 min.	2 min.	1 min.	2 min.
Intercept	7.537 (<0.01)	6.632 (<0.01)	0.949 (<0.01)	0.575 (<0.01)	3.263 (<0.01)	2.268 (<0.01)
LiqCost	123.496 (.092)	–42.191 (.607)	16.715 (<0.01)	6.496 (.120)	91.991 (<0.01)	65.224 (<0.01)
LiqPlm	–9.066 (.337)	5.956 (.436)	1.778 (<0.01)	1.416 (<0.01)	4.390 (<0.01)	3.640 (<0.01)
HiAdvSel	0.634 (.624)	1.776 (.227)	0.071 (.340)	0.080 (.271)	0.234 (.332)	0.234 (.250)
LiqCost×HiAdvSel	55.101 (.677)	262.271 (.088)	2.951 (.692)	4.540 (.547)	22.423 (.273)	24.825 (.181)
LiqPlm×HiAdvSel	2.893 (.836)	–19.798 (.142)	0.207 (.791)	0.071 (.926)	–0.056 (.972)	–0.598 (.661)
Stealth (×1000)	0.417 (.035)	–0.227 (.250)	– 0.162 (<0.01)	– 0.089 (<0.01)	– 0.531 (<0.01)	– 0.379 (<0.01)
NOB	444	444	444	444	444	444
R-square	0.016	0.010	0.603	0.253	0.780	0.695

I use the data within GMT 7–17 and carry out the regression for Table 7. Table 8 shows the estimation result of the regression of Eq. (15): $EF_i = \beta_0 + \beta_1 \text{LiqCost}_i + \beta_2 \text{LiqPlm}_i + \beta_3 \text{HiAdvSel}_i + \beta_4 \text{LiqCost}_i \times \text{HiAdvSel}_i + \beta_5 \text{LiqPlm}_i \times \text{HiAdvSel}_i + \beta_6 \text{Stealth}_i + \varepsilon_i$. The other details for Table 8 are presented in Table 7.

in Eq. (9), when the j th 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 $\lambda(p_j - m_j)$ ($\lambda \times$ 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. Eq. (10) assumes this quote midpoint revision and that a market maker revises her quote using some ratio of the quoted half-spread. I estimate Eqs. (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 i th day are higher than their own medians across days, and 0 otherwise.

Finally, Table 2 reports the summary statistics for $LiqCost$, $LiqPlm$, $HiAdvSel$, $\hat{\lambda}$, and $\hat{\alpha}$. The next section considers $LiqCost$, $LiqPlm$, and $HiAdvSel$ as possible explanatory variables for market efficiency. Table 2 shows the first-order autocorrelation coefficient for the explanatory variables. This coefficient strongly suggests that most of these variables are persistent. In the regression analysis, this persistency possibly causes standard errors to be

underestimated. For this issue, I employ the Newey-West correction for standard errors (Tables 7–11).

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 Fig. 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 Eqs. (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, a trade initiator's information advantage. Barclay and Warner (1993) are the first study to report empirical evidence for

Table 9
Regression of Eq. (15) using the efficiency measures calculated on the basis of net number of buyer-initiated trades.

Panel A. EUR/USD						
Dependent variable	EFO		EF1		EF2	
	1 min.	2 min.	1 min.	2 min.	1 min.	2 min.
Intercept	7.985 (<0.01)	7.105 (<0.01)	0.675 (<0.01)	0.527 (<0.01)	2.387 (<0.01)	1.525 (<0.01)
LiqCost	6659.387 (.500)	11279.463 (.261)	943.543 (.014)	557.905 (.214)	5642.579 (<0.01)	2695.289 (<0.01)
LiqPlm	-8.598 (.451)	-15.213 (.276)	2.398 (<0.01)	2.263 (<0.01)	7.073 (<0.01)	6.201 (<0.01)
HiAdvSel	0.298 (.864)	0.277 (.862)	0.088 (.102)	-0.030 (.625)	0.204 (.080)	0.098 (.288)
LiqCost \times HiAdvSel	5692.008 (.783)	4572.527 (.824)	307.115 (.625)	-588.933 (.407)	559.892 (.686)	46.438 (.965)
LiqPlm \times HiAdvSel	-14.266 (.540)	-3.857 (.882)	0.503 (.550)	0.616 (.453)	1.753 (.344)	1.271 (.381)
Stealth ($\times 1000$)	-0.054 (.712)	0.290 (.043)	-0.056 (<0.01)	-0.035 (<0.01)	-0.233 (<0.01)	-0.161 (<0.01)
NOB	444	444	444	444	444	444
R-square	0.012	0.013	0.530	0.308	0.804	0.705

Panel B. USD/JPY						
Dependent variable	EFO		EF1		EF2	
	1 min.	2 min.	1 min.	2 min.	1 min.	2 min.
Intercept	7.865 (<0.01)	8.044 (<0.01)	0.991 (<0.01)	0.683 (<0.01)	3.220 (<0.01)	2.317 (<0.01)
LiqCost	-48.214 (.594)	138.733 (.021)	20.578 (<0.01)	6.930 (.109)	70.416 (<0.01)	48.942 (<0.01)
LiqPlm	11.573 (.255)	-11.452 (.104)	2.116 (<0.01)	1.965 (<0.01)	6.429 (<0.01)	5.126 (<0.01)
HiAdvSel	1.300 (.373)	-5.479 (<0.01)	0.113 (.315)	0.112 (.280)	0.407 (.065)	0.232 (.233)
LiqCost \times HiAdvSel	91.136 (.639)	-639.133 (<0.01)	5.659 (.660)	7.804 (.505)	28.597 (.233)	10.285 (.631)
LiqPlm \times HiAdvSel	7.934 (.657)	32.458 (.071)	0.478 (.648)	0.089 (.924)	1.291 (.539)	1.899 (.290)
Stealth ($\times 1000$)	0.005 (.979)	-0.011 (.953)	-0.135 (<0.01)	-0.106 (<0.01)	-0.485 (<0.01)	-0.377 (<0.01)
NOB	444	444	444	444	444	444
R-square	0.018	0.023	0.603	0.448	0.780	0.734

I use the net number of buyer-initiated trades as order imbalance and calculate EFO, EF1, and EF2. Table 9 shows the estimation result of the regression of Eq. (15): $EF_i = \beta_0 + \beta_1 LiqCost_i + \beta_2 LiqPlm_i + \beta_3 HiAdvSel_i + \beta_4 LiqCost_i \times HiAdvSel_i + \beta_5 LiqPlm_i \times HiAdvSel_i + \beta_6 Stealth_i + e_i$. The other details for Table 9 are presented in Table 7.

Table 10
Regression of Eq. (15) using the efficiency measures calculated on the basis of unexpected order imbalance.

Dependent variable	Panel A. EUR/USD					
	EF0		EF1		EF2	
Data frequency	1 min.	2 min.	1 min.	2 min.	1 min.	2 min.
Intercept	8.142 (<0.01)	7.042 (<0.01)	0.562 (<0.01)	0.393 (<0.01)	2.330 (<0.01)	1.458 (<0.01)
LiqCost	1137.473 (.915)	6988.959 (.539)	977.730 (<0.01)	531.057 (.216)	5616.878 (<0.01)	2923.404 (<0.01)
LiqPlm	5.181 (.703)	-20.007 (.231)	2.337 (<0.01)	2.013 (<0.01)	7.213 (<0.01)	5.737 (<0.01)
HiAdvSel	1.932 (.184)	2.239 (.171)	0.176 (<0.01)	0.025 (.723)	0.249 (.035)	0.160 (.120)
LiqCost×HiAdvSel	30200.324 (.085)	22096.782 (.251)	1329.489 (.044)	-48.403 (.953)	987.588 (.491)	157.858 (.894)
LiqPlm×HiAdvSel	-25.043 (.215)	-9.257 (.674)	-0.210 (.804)	0.397 (.650)	1.550 (.421)	1.985 (.189)
Stealth (×1000)	0.020 (.906)	-0.082 (.482)	-0.039 (<0.01)	-0.027 (<0.01)	-0.231 (<0.01)	-0.163 (<0.01)
NOB	444	444	444	444	444	444
R-square	0.015	0.014	0.539	0.294	0.814	0.729

Dependent variable	Panel B. USD/JPY					
	EF0		EF1		EF2	
Data frequency	1 min.	2 min.	1 min.	2 min.	1 min.	2 min.
Intercept	8.181 (<0.01)	5.938 (<0.01)	0.751 (<0.01)	0.483 (<0.01)	3.084 (<0.01)	2.205 (<0.01)
LiqCost	90.231 (.231)	-128.602 (.061)	17.350 (<0.01)	4.715 (.278)	68.314 (<0.01)	47.507 (<0.01)
LiqPlm	-7.407 (.440)	4.120 (.574)	1.800 (<0.01)	1.851 (<0.01)	6.297 (<0.01)	5.411 (<0.01)
HiAdvSel	-1.059 (.560)	1.982 (.224)	0.124 (.133)	0.046 (.604)	0.394 (.065)	0.204 (.267)
LiqCost×HiAdvSel	-15.107 (.946)	129.696 (.544)	2.530 (.793)	-2.586 (.790)	22.079 (.333)	4.183 (.834)
LiqPlm×HiAdvSel	-6.031 (.754)	4.071 (.851)	1.197 (.160)	0.960 (.217)	2.193 (.274)	2.425 (.157)
Stealth (×1000)	0.103 (.606)	-0.398 (.121)	-0.081 (<0.01)	-0.065 (<0.01)	-0.462 (<0.01)	-0.354 (<0.01)
NOB	444	444	444	444	444	444
R-square	0.014	0.011	0.588	0.365	0.785	0.738

I use the residuals from AR(15) as the unexpected order imbalance and calculate EF_0 , EF_1 , and EF_2 . Table 10 shows the estimation result of the regression of Eq. (15): $EF_i = \beta_0 + \beta_1 LiqCost_t + \beta_2 LiqPlm_t + \beta_3 HiAdvSel_t + \beta_4 LiqCost_t \times HiAdvSel_t + \beta_5 LiqPlm_t \times HiAdvSel_t + \beta_6 Stealth_t + e_t$. The other details for Table 10 are presented in Table 7.

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:

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

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

Eqs. (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 Eqs. (1) and (2), respectively. When $INEF_t$ takes the value of +1, a market is considered inefficient in period t because the OIB predicts a future

FX rate change. $F(\cdot)$ is a cumulative normal distribution function and γ_i ($i=0, \dots, 3$) is a parameter that I estimate by fitting a probit model. Esp_t represents the mean of the effective spread calculated using Eq. (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 Eqs. (11) and (12) are proxies for stealth trading. The stealth trade hypothesis predicts a U-shape effect or the reverse of trade size in Eqs. (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

Table 11
Regression of Eq. (15) with $EF1^*$ calculated using bid and ask rates.

Dependent variable	EUR/USD		USD/JPY	
	$EF1^*$		$EF1^*$	
Data frequency	1 min.	2 min.	1 min.	2 min.
Intercept	0.325 (<0.01)	-0.292 (<0.01)	0.989 (<0.01)	0.255 (.019)
LiqCost	4873.025 (<0.01)	3984.254 (<0.01)	65.946 (<0.01)	61.511 (<0.01)
LiqPlm	5.971 (<0.01)	7.242 (<0.01)	4.983 (<0.01)	4.720 (<0.01)
HiAdvSel	0.185 (.163)	0.241 (.101)	0.224 (.242)	0.204 (.269)
LiqCost \times HiAdvSel	510.096 (.755)	1538.648 (.415)	11.152 (.620)	6.321 (.769)
LiqPlm \times HiAdvSel	1.283 (.539)	-0.080 (.972)	1.216 (.508)	1.626 (.375)
Stealth ($\times 1000$)	-0.211 (<0.01)	-0.188 (<0.01)	-0.424 (<0.01)	-0.346 (<0.01)
NOB	444	444	444	444
R-square	0.745	0.690	0.795	0.756

I calculate $EF1$ in Eqs. (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 Eq. (1), $r_t = p_t^{*,ask} - p_t^{*,ask}$ if $IOB_{t-1} > 0$, $p_t^{*,ask}$ and $p_t^{*,ask}$ are the prevailing ask rates at the first and last timings in period t , respectively. If $IOB_{t-1} < 0$, r_t is calculated similarly using bid rates. I label this $EF1$ as $EF1^*$. Table 11 shows the estimation result of the regression of Eq. (15): $EF_i = \beta_0 + \beta_1 LiqCost_i + \beta_2 LiqPlm_i + \beta_3 HiAdvSel_i + \beta_4 LiqCost_i \times HiAdvSel_i + \beta_5 LiqPlm_i \times HiAdvSel_i + \beta_6 Stealth_i + e_i$. The other details for Table 11 are presented in Table 7.

negative, respectively. Because no theoretical model indicates an effect that is stronger than the other, I empirically examine this situation.

Table 3 shows the empirical results of Eqs. (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 almost all cases, and a positive γ_2 and a negative γ_3 are statistically significant. This result indicates that order flows driven by medium-size trades possibly predict a future FX rate change in the EUR/USD and USD/JPY markets. Therefore, in my high-frequency analysis, I conclude that the predictive power of the medium-size trade dominates the competition of that trade. The row “max. trade” is the trade size that has the 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.

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.

$$Prob(INEF_t = 1) = F(\gamma_0 + \gamma_1 Esp_t + \gamma_2 stealth\ trade_t) + e_t \quad (13)$$

$$Prob(INEF_t = 1) = F(\gamma_0 + \gamma_1 Esp_{t-1} + \gamma_2 stealth\ trade_{t-1}) + e_t \quad (14)$$

Table 5 shows the result of the probit regressions of Eqs. (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 the daily 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:

$$EF_i = \beta_0 + \beta_1 LiqCost_i + \beta_2 LiqPlm_i + \beta_3 HiAdvSel_i + \beta_4 LiqCost_i \times HiAdvSel_i + \beta_5 LiqPlm_i \times HiAdvSel_i + \beta_6 Stealth_i + e_i \quad (15)$$

where $EF0_i$, $EF1_i$, and $EF2_i$ are adopted as EF_i in the left term of Eq. (15). $LiqCost$ and $LiqPlm$ are variables related to transaction cost and are calculated using Eqs. (6) and (8), respectively. $HiAdvSel$ is a binary variable that takes the value of +1 when both the estimated parameters in Eqs. (9) and (10) are higher than their medians. $LiqCost_i \times HiAdvSel_i$ and $LiqPlm_i \times HiAdvSel_i$ are interaction terms 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 $\beta_6 < 0$; 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.

Table 6 presents the Pearson coefficient correlations among the variables of Eq. (15) and shows positive correlations for $LiqCost$ and $LiqPlm$ with $EF1_i$ and $EF2_i$. Table 7 shows the estimation results for Eq. (15).

First, compared with $EF0$, Table 7 shows that the R-squares for $EF1$ and $EF2$ are much larger for both currency pairs. These results possibly imply that $EF1$ and $EF2$ 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 and statistically significant except for all cases of $EF0$ and two of $EF1$ in Table 7. This result indicates that market efficiency, which is measured using $EF1$ and $EF2$, is relatively high when transaction costs are 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 $EF0$ (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 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 *LiqPlm* also show positive values and are statistically significant except for all cases of *EF0* in Table 7. Therefore, I consider that this result is consistent with that of *LiqCost*: liquidity and efficiency are positively correlated.

Table 7 shows the positive estimators of *HiAdvSel* in seven cases of *EF1* and *EF2*, and three of them are statistically significant (1 min *EF1* for EUR/USD and 1 min *EF2* for both pairs). These results may imply that information asymmetry weakly affects market efficiency in both currency pair markets. These positive estimators are consistent with the correlation analysis in Table 6 and suggest that information asymmetry enhances market efficiency when *EF1* 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. Therefore, OIB predictability is likely to decay in the next period. This result is the 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. The result in Table 7 leads me to propose that information asymmetry in the one-minute frequency may enhance market efficiency in the EUR/USD and USD/JPY markets.

In Table 7, the estimators of both interaction terms, *LiqCost* × *HiAdvSel* and *LiqPlm* × *HiAdvSel*, are statistically insignificant in all cases of *EF1* and *EF2*. When I drop *LiqPlm* from Eq. (15), the *LiqCost* × *HiAdvSel* estimator is statistically significant for the one-minute frequency of *EF1* for both currency pairs and for all cases of *EF2* (the result is available on request).⁵ Additionally, the estimated parameters of *HiAdvSel* are positive statistically significant values except for four cases of *EF0* and one of *EF1* when *LiqPlm* is dropped.

These findings may indicate that *LiqPlm* is closely related to changes in market liquidity attributable to information asymmetry and captures that asymmetry more than *HiAdvSel* does. As Eqs. (7), (9), and (10) show, both *HiAdvSel* and *LiqPlm* are price impacts of a transaction. By using a binary variable for information asymmetry, I may drop some information included in the estimators in Eqs. (9) and (10), which may weaken the explanatory power of *HiAdvSel*. To check this possibility, I replace binary *HiAdvSel* with the estimator of Eq. (9) and run the regression of Eq. (15). I confirm that this replacement enlarges the statistical significance of *HiAdvSel* and its interaction terms (the result is not reported).⁶

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 in most cases of *EF1* and *EF2*, 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.⁷

⁵ I consider the following equation: $EF_i = \beta_0 + \beta_1 LiqCost_i + \beta_2 HiAdvSel_i + \beta_3 LiqCost_i \times HiAdvSel_i + \beta_4 Stealth_i + e_i$.

⁶ Given possible multicollinearity, this replacement makes the estimators of *LiqCost* and *LiqPlm* negative and statistically insignificant in some cases. To overcome this issue, future research needs to adopt an alternative variable of information asymmetry.

⁷ On a daily basis, the coefficients of the correlation for the number of medium-size trades with information asymmetry λ and α are 0.20 and -0.05 (-0.08 and 0.29) for the EUR/USD (USD/JPY) market, respectively.

4.3. Robustness checks

This section checks the robustness of Table 7.

First, as Rime et al. (2010) suggest, I use intraday data for GMT 7–17 to calculate the explanatory and dependent variables for Eq. (15). Table 8 shows the result of the regression analysis of Eq. (15) using these variables, which is consistent with that of Table 7, although the *HiAdvSel* estimator becomes less statistically significant for all cases. As noted in the previous section, the effect of information asymmetry might be relatively low in the studied markets. Additionally, Table 8 indicates that the effect becomes much weaker during the most active part of the trading day than in other parts.

Second, I calculate *EF0*, *EF1*, and *EF2* using OIB# (net number of buyer-initiated trades) and regress them onto the explanatory variables of Eq. (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 9 is related to the semi-strong form of efficiency in the studied markets. Table 9 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.

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 10, 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).

Finally, I calculate *EF1* in Eqs. (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 Eq. (1), $r_t = p_t^{*,ask} - p_t^{*,ask}$ if $OIB_{t-1} > 0$, $p_t^{*,ask}$ and $p_t^{*,ask}$ are the lowest ask rates in 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 11 presents the result of the regression using this $EF1^*$; the signs of all of the significant estimators are the same as those of Table 7.

4.4. Discussion

This section discusses some notable points of the proposed measures.

First, the proposed measures (before logit-transformation and multiplied by -1) seem to converge to 0.5 when I consider longer intervals. As shown in Fig. 1, the predictive power of the order flow weakens in longer intervals. Therefore, positive (negative) order flows randomly predict positive and negative changes in such long intervals and adopting a longer interval makes *EF1* close to 0.5 when negative and positive changes occur with equal probability, 0.5. Moreover, the magnitude of the rate change becomes large in a long period, which also generates a random profit to make *EF2* close to 0.5. These results suggest that the proposed measure should be calculated within an interval short enough for positive (negative) order flow to predict an appreciation (depreciation) of the base currency. Additionally, the proposed measures are not

comparable when the sampling frequencies are different. When the data interval becomes long, as previously discussed, the proposed measures become large and converge to 0.5 upwardly. This phenomenon does not necessarily mean that the market is relatively inefficient in a long interval.

This first discussion may explain the negative correlation between proposed measures and R-square one. Table 6 shows that the proposed measures are often negatively correlated with R-square one. This phenomenon becomes stronger for two-minute frequency data than for one-minute frequency data. As shown in Table 1, the means of the proposed measures are less than 0.5. When the predictive power of the order flow becomes weak and the price change is volatile in the long interval, the proposed measures approach 0.5 upwardly, as discussed in the previous paragraph. In turn, R-square approaches 0 downwardly. This result may explain the negative correlation between the proposed measures and R-square one for longer intervals.

To check the validity of this explanation, Table 12 shows the coefficient of correlation between the proposed measures and R-square one for five other currency pairs (EUR/CHF; USD/CHF; EUR/JPY; AUD/USD; USD/CAD). These pairs are major currencies that follow the EUR/USD and the USD/JPY in my data set. I confirm that $EF1$ is negatively correlated with $EF0$ (R-square measure) in all cases of two-minute frequency. This negative correlation becomes stronger compared with the cases of one-minute frequency. For $EF2$, this tendency is moderate. $EF2$ considers profit exploited with order flow in addition to the direction of the rate change predicted by order flow. This consideration may moderate the convergence speed of $EF2$ to 0.5. Overall, the result of Table 12 supports the previous explanation on the negative correlation between the proposed measures and R-square one.

To examine whether the effect of random profits dominates $EF2$, I consider a reverse prediction of the order flow using the variable $INEF2rev$. This variable takes the value of +1 if a positive order imbalance is followed by a period in which the lowest ask is lower than the highest bid at the beginning of the period, and 0 otherwise, and similarly for negative order imbalance. If the effect of random profits is dominant, the number of observations of +1 for $INEF2$ (Eq. (2)) does not differ from that for $INEF2rev$ in a day.

Table 13 shows that the percentage of days for which the number of observations of +1 for $INEF2$ is larger than that for $INEF2rev$. For one-minute intervals, Table 13 does not indicate that the random effect dominates $INEF2$ because $INEF2$ takes +1 on more days than $INEF2rev$ does. In turn, the effect seems to be dominant for the two-minute interval. Moreover, for EUR/USD, $INEF2rev$ takes +1 on more days than does $INEF2$. This result is consistent with Fig. 1, which indicates that positive (negative) order flows predict the depreciation (appreciation) of the EUR against the USD with two-minute frequency. This finding is a possible recommendation to me to consider the one-minute frequency to calculate the $EF2$ measure.

Table 12
Contemporaneous correlations (Pearson product-moment coefficient correlation).

	Correlation between $EF0$ and $EF1$		Correlation between $EF0$ and $EF2$	
	1 min.	2 min.	1 min	2 min
EUR/CHF	-0.008	-0.032	0.007	-0.035
USD/CHF	0.007	-0.044	0.073	0.029
EUR/JPY	-0.081	-0.125	0.016	-0.054
AUD/USD	0.079	-0.012	0.074	0.151
USD/CAD	-0.009	-0.034	-0.042	0.011

Table 12 shows the coefficient of correlation between the proposed measures and R-square one. To calculate the correlation, I calculate these measures for the five currency pairs (EUR/CHF; USD/CHF; EUR/JPY; AUD/USD; USD/CAD). These major currency pairs follow EUR/USD and USD/JPY in my data set.

Table 13

Percentage of days in which the number of observations of +1 for $INEF2$ is larger than that for $INEF2rev$.

	1 min.	2 min.
EUR/USD	63.7%	49.8%
USD/JPY	65.8%	52.5%

Table 13 shows that the percentage of days in which the number of observations of +1 for $INEF2$ is larger than that for $INEF2rev$. $INEF2$ is the value of +1 if a positive order imbalance is followed by a period in which the highest bid exceeds the lowest ask at the beginning of the period, and similarly for a negative order imbalance (Eq. (2)). In turn, $INEF2rev$ takes the value of +1 if a positive order imbalance is followed by a period in which the lowest ask is lower than the highest bid at the beginning of the period and 0 otherwise, and similarly for a negative order imbalance. There are 444 sample days.

Second, the proposed measures drop some valuable information about the magnitude of both price change and transaction when I consider the binary variables in Eqs. (1) and (3). To do a logit transformation, I aggregate the binary variables as ratio in Eqs. (3) and (4). This transformation enables me to compare the proposed measures with the R-square measure, which is also logit-transformed. My measures and the R-square one possibly take the same range from 0 to 1 before being logit-transformed. I then show that my measures contain more information about market efficiency in the studied FX market than the R-square one does. By considering information about the magnitude of the price change and the transaction, future research may enhance the usefulness of the proposed measures.

Finally, I mention expanding this research. Given the validity of the proposed measures, researchers can use them to gauge the level of market (informational) efficiency. In turn, future research can examine whether a high level of efficiency decreases the pricing error by regressing the latter on the proposed measures. If this statement is true, publishing live information on the order flow may decrease market volatility.

5. Conclusion

During the recent decade, the popularization of electronic trading in an FX market enables researchers to access tick-by-tick transaction data and assist in developing 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. 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 factors, 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 empirical

evidence weakly supports the effect of information asymmetry. This result suggests that an excessive response by uninformed market makers to incoming order flows results in 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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