Price Discovery in Foreign Exchange Markets: A Comparison of

Indicative and Actual Transaction Prices

Abstract

In this paper, we compare four months of Reuters EFX high frequency indicative data with D2000-1 inter-dealer transaction data for DEM/USD and GBP/USD. Contrary to previous studies, we find, using various information measures, that the matched tick-by-tick indicative data bear no qualitative difference from the transaction data, and have higher information content. Expanding the system to include order flow, due to its growing importance in exchange rate theory, we find that indicative data has a similar impact on order flow as transaction data. However, order flow has no impact on either price.

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1. Introduction

With more quotes and transaction data available the value of the indicative data has gradually been downgraded. The excessive and sometimes irrelevant quotes from aggressive banks that need to build up a market presence, and the occasional quoting strategy of copying quotes from fellow banks has resulted in indicative data being treated with caution when extracting information from them. However, as the indicative data contain the identity of the banks that made the quotes, they offer great value for those studies exploring the heterogeneity of market players. Such identity information is not available in other data sets due to confidentiality concerns. Also Goodhart and O'Hara (1997) suggest that indicative quotes are better than transaction prices in demonstrating traders' heterogeneous price interpretation, as transaction price needs agreement between two parties, while the indicative quotes could be updated instantly. An empirical investigation using transaction data may turn out to be biased because it ignores the informational content of non-trading intervals. Due to such reasons, it would be useful to verify the quality of the indicative data compared to transaction data or firm quotes.

Formal and conclusive research on the issue has yet to be provided. The few earlier papers are based on a very short sample period of either one day, or one week. For example, Goodhart et al. (1996) compare one day of DEM/USD EFX data with those from D2000-2, but with no time stamp on the data. The two data sets are matched by maximising the correlation between the transaction and indicative data. They find that at 10 minute frequency the statistical discrepancy between the two data sets is largely insignificant.

Danielsson and Payne (2002) extend the time window to five days (6^{th} to the 10^{th} of October, 1997), which is still too short for any meaningful conclusion. They process the data at 20 seconds frequency as a compromise between the different frequencies of the two series. Basic statistics, such as quote frequency, spread and return moments are investigated and compared for the two data sets. Using Hasbrouck's ECM based information share, they find that D2000-2 has a dominant role in pricing the information except during midnight hours. However, all these differences disappear when they aggregate the data into 5 and 10 minute frequency.

In our paper, we use indicative data from Reuters high-frequency EFX quotes on the DEM/USD and GBP/USD. The corresponding transaction data are D2000-1 inter-dealer transaction data on the same currency pairs.[1] Our sample data span 82 trading days, increasing substantially the time window compared to previous work, and making our empirical tests more reliable. Furthermore, instead of only focusing on DEM/USD, we also introduce GBP/USD to make the comparison of the two data sets more conclusive.

In this paper, we employ various methods to compare the indicative data and their corresponding transaction data. We conduct first cross correlation tests to investigate the lead and lag relation between the indicative and transaction return series. We find that both indicative currency pair data sets lead transaction data by around 5 to 10 minutes. We then use Hasbrouck's (1995) information share technique to recover the information content of the two data sets, which further suggests that indicative data have the dominant role in mapping the fundamental information into the prices. We vary the data frequency of the data by using real transaction time, 5 and 10-minute calendar time frequency to test the robustness of our results. Furthermore, we perform our tests for different trading sessions according to the opening and closing times of major foreign exchange markets in order to eliminate the trading zone effect on the 24-hour global foreign exchange trading.

Finally, due to the growing importance of order flow in exchange rate theory, we investigate whether our indicative data are relevant to the relationship between the order flow from the D2000-1 data and transaction prices. Order flow is the difference between the volume of dollar buyers initiated trades and that of the seller initiated trades. Micro-based foreign exchange models treat order flow as an important channel to map the widely dispersed fundamental information on to exchange rates. In Lyons and Evans' various models (see e.g. Lyons 2001, 2002), the causality runs strictly

[1] The EFX and Reuters D2000-1 data sets are provided by Olsen & Associate and Martin Evans respectively.

from order flow to exchange rates. By applying generalized impulse response method to both price series and order flow, we first find that the D2000-1 prices take longer (up to 5 to 10 minutes) to absorb one standard error of shock from the EFX price, compared to the time that EFX price takes to absorb one standard error of shock from the D2000-1 price. This confirms the results of the cross-correlation test. Adding to these findings is that the shock from EFX data imposes similar impact on order flow as the shock from D2000-1. However, we find that there is no significant impact from the shock of order flow to prices at both 5 and 10 minutes frequency. Though the prices and order flows display obvious co-movements during our sample period, it seems that order flow has more of a latent response to changes in prices, which is in contrast to Lyons' (2001) claim that order flow explains exchange rates at lower frequencies (1 hour or daily frequency). Granger causality tests confirm this result and cast doubt on the importance of order flow as an important determinant of exchange rates.

The paper is structured as follows. In section 2, we give a description of our data sets and how we process them before we conduct our empirical tests. In section 3, we carry out a simple lead-lag return analysis and then the routine unit root and cointegration tests. In section 4, we estimate the Hasbrouck information share for both prices. In section 5, we introduce the order flow to the price data and perform generalized impulse response analysis and Granger causality tests. In the final section, we briefly summarize the results and the significance of our findings.

2. Data and Sample Details

A. Data

EFX indicative high-frequency indicative data are collected from Reuters EFX page. These tick-by-tick data are provided by different participating banks with each bid and ask pair stamped with time down to the second and other information, such as dealer's bank code and location. Indicative quotes are free from transaction obligations and are considered more as an advertising method to maintain the banks' market presence. However, one should also note that due to reputation concern, the quote would not deviate too much from the market price. Another important feature is that indicative data are not subjected to the consent from any other party like transaction data and hence, are capable of instant update when news hit the market.

Reuters D2000-1 data are inter-bank transaction data. An electronic record is produced because quotes and trades are executed electronically. Each deal is time stamped to seconds with transaction size and transaction signs[2]. Unlike EFX data, transaction data do not usually include detailed information on the involved counterparties; therefore not allowing any investigation on the existence of heterogeneous information.

B. Sample Details

Eight fields are included in EFX data: date, time, bid, ask, nation, city, bank and filter. Reuters D2000-1 contains nine fields: month, day, hour, minute, seconds, time index, transaction sign, price, and volume (see Table 1). At first glance, EFX data provide more information on the quoting bank's identity, while D2000-1 offer unique record of the transaction signs and trading volume, although the later figures lack accuracy[3].

The sample data span from 1st of May to 30th of August 1996, with a total of 121 calendar days, including weekends and holidays. There are 313,845 and 612,260 quotes in GBP/USD and DEM/USD respectively in the EFX data set, which are much higher than those of D2000-1, with corresponding 52,318 and 257,398 ticks of data. This difference is more obvious in GBP/USD, with the size of EFX data being nearly six times that of the D2000-1.

[2] If it is dollar buyer initiated trade, 1 is recorded. Otherwise 0 is filled in.

[3] See Evans (2002). Due to lack of information on the exact size of each trade, he aggregates the transaction signs of the trades, which took place during each time interval as a proxy for the volume figure.

To check the basic statistical characteristics of both data sets, we first plot the average intraday quote frequency of the data sets in both currency pairs in Figures 1 and 2. Each half-hour session's total quotes (trades) are divided by the daily total quotes (trades). The peaks and lows of the two data sets generally coincide with each other throughout the day. However, the transaction data reveal more concentrated trading activity during London and New York trading hours. Indicative data instead display less dramatic rise and fall of quoting activity during these sessions.

Another method to study the intensity of the quoting or transaction activities is duration, which stands for the elapsed time (in seconds) in between two neighbouring quotes or transactions. Following Engel and Russell (1997), we eliminate the impact of automatic quoting by excluding those quotes with price changes of less than 5 basis points in the indicative data. Both the EFX and D2000-1 data sets share the same highest clustering of duration under 10 seconds, nearly 17% of all quotes (see Figures 3 and 4). From 40 seconds on, the duration patterns deviate from each other, with EFX experiencing a much more gradual decline in density while D2000-1 swinging around EFX. One significant feature of D2000-1 is its relative lack of transaction duration of near 50-60 seconds. There is no explanation for this distinct feature as far as we know. However, transaction frequency clusters again between 60 and 120 seconds, counting for over 30% of total transactions.

Such differences indicate an issue of unsynchronized data when comparing these two data sets. Indicative data can be updated without any transaction taking place, while transaction data are the result of a mutual agreement of a pair of trading banks, and as a result take place at a lower frequency. Since it is deemed that transaction data bear more information and take place at lower frequency compared with their indicative counterpart, we use transaction data as the benchmark to process our indicative data.

First, we filter indicative data using transaction data time stamp. For each transaction price, we locate its nearest indicative data in terms of time and form a matching transaction and indicative data pair. The matched indicative price could be either before or after the transaction price with equal likelihood[4]. This procedure returns us with highly simultaneous price series in both currency pairs. The two data sets in GBP/USD have a time discrepancy of average 0.04 seconds and a standard deviation of 22 seconds, and the pairs in DEM/USD differ with an average of 0.1 seconds and a standard deviation of 11 seconds. The differences between the processed time stamps of the pairs of indicative and transaction data sets in both exchange rates are insignificant.

Second, to reflect the bid and ask shift of the transaction data, we choose the corresponding bid and ask price of the indicative data. This process is based on the transaction sign of each trade. For instance, for a dollar buyer initiated trade in D2000-1, the closest EFX bid is selected as the matching price.

After the above mentioned process, and excluding weekends and holidays, we have 82 trading days, 51,741 pairs of GBP/USD prices and 255,481 pairs of DEM/USD prices left. The 5 and 10-minute frequency data are obtained by choosing the last pair of prices in each time slot. Such a method sacrifices more available updated quotes in indicative data, but avoids comparing stale transaction data with indicative data. Therefore, any subsequent empirical comparison of these two data sets may underestimate the information content of the indicative data.

The descriptive statistics of both data sets are displayed in Table 2. The statistics on the first moments of the prices indicate that indicative data are generally a couple of basis points lower than transaction data. There is no documented explanation for such findings.

3. Preliminary Data Analysis

In this section, we first provide tests on the cross correlations of the return series using different data frequency and exploring the lead and lag pattern of the two data sets. Lead and lag analysis gives us a preliminary picture of the relationship between

[4] The ratio of ‘before’ quotes to ‘after’ quotes is 0.996 (25,818:25,922) for GBP/USD and 1.005 (128,047:127,434) for DEM/USD.

the returns of the prices by comparing the data at different leads and lags. Any significant lead or lag pattern may suggest that one price leads the other in mapping information on to its returns.

We then perform unit root tests for each price to investigate whether the price series are nonstationary and integrated of order one, i.e., a $I(1)$ process. Subsequently, we conduct the Johansen (1988) test to investigate whether the two sets of prices for each currency pair are cointegrated. By establishing the unit root and cointegration relation in the prices, we can investigate the information share between them, using a technique based on the Error Correction Model.

A. Cross-correlations of Return Series

If two prices are based on the same fundamental asset, their return series should be correlated due to the shared determinants. In frictionless and complete markets, there should be complete simultaneity between the price movements. However, at higher frequency, if one market processes new information faster than the other market, it is possible for it to consistently lead the other market.

Even though previous papers (see e.g. Danielsson and Payne, 1997) associate indicative data with stale or lagged quotes compared to transaction data, we hold the opposite view. One reason is that indicative quotes are in essence advertising signals to potential customers, and hence should contain fresh information to inform the market. Furthermore, theoretically indicative data could be updated in the absence of a transaction and therefore, should be more efficient in delivering information. Cross-correlation tests of the return series offers a means to prove our hypothesis.

In Figures 5 and 6, we present the cross-correlation results of the return series of both data sets for the two currency pairs at 5-minute and 10-minute frequency respectively. The 95% confidence levels are formed by calculating $\pm 2/\sqrt{T}$, with T being usable observations, which are the dotted lines in both graphs. Positive lags at the X axis indicate that EFX quotes are in the lead. At 5 minute frequency, we find that EFX leading quotes show a significant positive correlation with the lagged D2000-1 prices at lag 1 in GBP/USD and at lags 1 and 2 in DEM/USD. The 10-minute frequency results confirm that EFX quotes lead D2000-1 prices by about 10 minutes.

The lead-lag analysis demonstrates an asymmetric relation between the returns of the two data sets, with no significant correlation when D2000-1 is in the lag. Such findings are in contrast to Danielsson and Payne’s (1997). Based on 20 seconds frequency, they find that D2000-2 returns lead EFX returns by 2 and 3 minutes. However, positive correlation also exists when EFX is the one in the lag, which suggests that the cross-correlation is less asymmetric. In our case the predictive power runs only from EFX data to D2000-1, with D2000-1's return imposing no predictive power on EFX's return at all.

B. Unit Root Tests

To investigate the cointegration between the two prices, as a routine, we first test whether the time series contain unit root. Specifically, if two time series are both nonstationary at their level, but become stationary after first differencing, we denote them as $I(1)$ processes, or integrated of order one. Cointegration becomes relevant if the linear combination of both $I(1)$ series is stationary.

The augmented Dickey-Fuller (1981) test is used in our unit root tests, which extends the basic Dickey-Fuller test by including a parametric correction for higher-order correlation by assuming that the time series follows an $AR(p)$ process and adding p lagged difference terms of the dependent variable to the right-hand side of the regression. We select the lag length p by using Schwarz Information Criterion (SIC) (see Schwarz, 1978). Three types of unit root tests, including no intercept or trend, only intercept, and only trend, are conducted. We only present the result with the intercept unless otherwise results are found. Since our further empirical tests involve all three kinds of time frequency, i.e., transaction, 5 and 10-minute frequency, unit root tests are conducted on each one of them.

In Table 3, we present both t-statistics and p-value of the unit root tests. Overall, we conclude that all price series are $I(1)$ process.

C. Cointegration Tests

The object of the cointegration test is to determine whether two nonstationary series are cointegrated. As pointed out by Engle and Granger (1987), if a linear combination of two or more nonstationary series is stationary, then the series are said to be cointegrated. The stationary linear combination is called the cointegrating equation and may be interpreted as a long-run equilibrium relationship among the variables. The cointegration relationship forms the basis of the VEC specification.

The cointegration tests used are based on the methodology developed by Johansen (1991, 1995a). We first consider a VAR of order p:

$$y_t = A_1 y_{t-1} + .. + A_p y_{t-p} + \varepsilon_t \qquad (1)$$

where y_t is a k-vector of non-stationary $I(1)$ variables, and ε_t is a vector of innovations. We may rewrite this VAR as,

$$\Delta y_t = \Pi y_{t-1} + \sum_{t=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \qquad (2)$$

where

$$\Pi = \sum_{i=1}^{p} A_t - I_t \, , \;\; \Gamma_t = -\sum_{j=i+1}^{p} A_j \, .$$

Granger's representation theorem asserts that if the coefficient matrix Π has reduced rank $r < k$, then there exist $k \times r$ matrix α and β each with rank r that $\Pi = \alpha\beta'$ and $\beta' y_t$ is $I(0)$. And subsequently r is the number of cointegrating relations and each column of β is the cointegrating vector. Johansen's method is to eliminate the Π matrix from an unrestricted VAR and to test whether the restrictions implied by the reduced rank of Π could be rejected. Cointegration tests establish the fact that there exists a long term equilibrium relation between two nonstationary series, which form the basis for the VEC (Vector Error Correction) model. In Equation (2), the elements of α are known as the adjustment parameters in the VEC model.

Though there is no possible arbitrage to keep the long run equilibrium relation between the indicative prices and transaction prices, as the former prices have no binding obligation of actual transaction, reputation and commercial concerns would drive dealers to quote on the fundamental market information. As a consequence, the indicative and transaction prices are both based on the same information related to the currency pair, and these two prices are expected to be cointegrated.

We conduct the cointegration tests by choosing the lag interval that minimizes the SIC. Based on the chosen lag length, we carry out the five standard types of cointegration tests with the option of including or excluding intercept or trend in the cointegration system. We determine the number of cointegrating vectors by comparing the maximum eigenvalues with their corresponding critical values. The (nonstandard) critical values are taken from Osterwald-Lenum (1992). In Table 4, we present the cointegration results. In all of the tests, we can reject that there is no cointegrating relationship but cannot reject that there is one cointegrating vector at the 5% significance level.

In the following section, we explore the information share between the prices from the two data sets using the cointegration results.

4. Information Share

A. Error Correction Model and Fundamental Value

In economics, fundamental value is essentially an abstract concept that cannot be observed directly. However, we can always assume that, in the long run, the fundamental value would manifest itself and transient information would disappear. In this specification, fundamental value could be identified as the permanent component of a price series. Price discovery therefore describes how one price series incorporates the permanent component into the price system, either in a static or dynamic sense. We follow Lehmann (2002) to explain the information share technique suggested by Hasbrouck (1995).

We start with one pair of cointegrated price series. For most microstructure models, we assume that the efficient price follows a random walk, as stated in a structural model:

$$p_t = lm_t + s_t\,,\quad p_t = \begin{pmatrix} p_{1t} \\ p_{2t} \end{pmatrix},\quad s_t = \begin{pmatrix} s_{1t} \\ s_{2t} \end{pmatrix} = \Upsilon(L)v_t\,,\quad l = \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \tag{3}$$

where m_t is the underlying efficient price and s_t is the transient microstructure noise.

From (3) above, the first difference of p_t has the moving average representation

$$\Delta p_t = \Psi(L)\varepsilon_t = lu_t + \Delta s_t = lu_t + (1-L)\Upsilon(L)v_t\,,\quad \Psi(\mathrm{L}) = \sum_{\mathrm{j}=0}^{\infty} \Psi_j L^j \tag{5}$$

so that Δs_t is a covariance stationary but noninvertible moving average. Since

$$\Psi(L) \equiv \Psi(1) + (1-L)\Psi^*(L),\quad \Psi_{\mathrm{i}}^* = -\sum_{j=i+1}^{\infty} \Psi_j\,, \tag{6}$$

p_t and Δp_t can be rewritten as

$$p_t = \Psi(1)\sum_{s=0}^{t} \varepsilon_s + \Psi^*(L)\varepsilon_t\,,$$

$$\Delta p_t = \Psi(1)\varepsilon_t + \Psi^*(L)\Delta\varepsilon_t = \Psi(1)\varepsilon_t + (1-L)\Psi^*(L)\varepsilon_t\,, \tag{7}$$

where $\Psi^*(L)\varepsilon_t$ is covariance stationary and its first difference $(1-L)\Psi^*(L)\varepsilon_t$ is a stationary, noninvertible moving average. Since $z_t = (1\ \ -1)\,p_t$ is stationary, it must omit the stochastic trend $\Psi(1)\sum_{s=0}^{t}\varepsilon_s$, implying that $(1 \ -1)\Psi(1)=0$ and thus $\Psi(1)=l(\psi_1\psi_2)$ which is intuitively obvious since the two prices share the same implicit efficient price.

This representation underlies the Hasbrouck (1995) information shares approach. The long run impact of ε_t, u_t, and v_t on Δp_t may be found by evaluating both $\Psi(L)$ and $(1-L)\Upsilon(L)$ in (5) at $L=1$, yielding

$$\Psi(1)\varepsilon_t = lu_t \tag{8}$$

and the resulting perfect correlation arising from the relation $\psi'\varepsilon_t = u_t$ implies

$$E[ll'u_t^2] = E[\Psi(1)\varepsilon_t\varepsilon_t^{'}\Psi(1)'] = E[l\psi'\varepsilon_t\varepsilon_t'\psi l'] \Rightarrow \sigma_u^2 = \psi'\Sigma_\varepsilon\psi \quad . \tag{9}$$

Hasbrouck's information shares involve decomposing $\psi'\Sigma_\varepsilon\psi$ into components attributed to price innovations in the two markets, where in our case they are the two prices from the two data sets. This attribution is unique when said price innovations are uncorrelated, in which case the decomposition is given by:

$$1 = \frac{\psi_1^2}{\psi'\Sigma_\varepsilon\psi}\sigma_{\varepsilon_1}^2 + \frac{\psi_1^2}{\psi'\Sigma_\varepsilon\psi}\sigma_{\varepsilon_2}^2 \tag{10}$$

However, when the reduced form residuals are correlated, the decomposition is

$$1 = \frac{\psi_1^2}{\psi'\Sigma_\varepsilon\psi}\sigma_{\varepsilon_1}^2 + \frac{\psi_1^2}{\psi'\Sigma_\varepsilon\psi}\sigma_{\varepsilon_2}^2 + 2\frac{\psi_2^2}{\psi'\Sigma_\varepsilon\psi}\sigma_{\varepsilon_1}^2\sigma_{\varepsilon_2}^2 \tag{11}$$

and there is a range of possible attributions corresponding to different allocation of the covariance form to each market. Hasbrouck suggests to change the order of the prices, hence the object of the Cholesky decomposition, till all possible orderings are realized, and then calculate the average result. In our case, there are only two price series and hence only two possible rotations of the orders.

B. Information Share Results

In order to circumvent the contemporaneous residual correlation problem and the ambiguity produced by the reordering procedure, Hasbrouck used ultimate high frequency price series, to reduce this side effect on the information share formula. In our paper, the correlation issue is less serious due to the highly simultaneous data we process. Our analysis produces results with much tighter bands than most previous studies, which use the information share technique. In both currency pairs, we test the information share of the two data sets at the transaction frequency. We test the robustness of our results using 5 and 10-minute frequency.

We first test for the information share in both currency pairs. We also present the contemporaneous residual correlation in the VEC model. In GBP/USD the indicative and transaction data have a low residual correlation of 16.6% (see the last column of the third row in Table 5). The information share attributed to the indicative data EFX is as high as 83%, with relatively tight lower and upper bands of 77% and 89%, respectively. In DEM/USD, with the residual correlation as low as 4.2%, the information share attributes 85% of the total information to the EFX data. The lower and upper bands, as predicted, are only 1.5% away from the average result, indicating a much reliable decomposition. These figures suggest that EFX data take a dominant role in the price discovery process. Using 5 and 10-minute frequency, although the information shares are reduced for EFX data, the conclusion is not fundamentally changed.

We check whether the information share changes during the 24-hour trading days, by separating the trading hours into 7 sessions, which correspond to the opening and closing times of the major foreign exchange markets. The 7 sessions are: 1) 21:00 to 8:00, the period between New York and Tokyo closing times, representing the Asian trading hours; 2) 8:00-9:00, first hour of London opening with inventory effects; 3) 9:00-12:00, the period until the opening of New York; 4) 12:00-13:00, first hour of New York opening; 5) 13:00-15:00, overlapping trading hours of two major markets; 6) 17:00-18:00, London closing hour; 7) 18:00-21:00, hours until New York closes.

The results are displayed in the middle columns of Table 5.[5] We also plot them in Figures 7 and 8. The information share of EFX data peak during London trading (session 3) and overlapping hours (session 5), with GBP/USD having a higher peak in London trading hours, and DEM/USD have a higher peak in overlapping hours. During closing and opening hours, EFX price experiences a drop in information share. These patterns suggest that during two of the peak trading hours, EFX data actually possess higher information content even though there is a substantial increase in the transaction frequency of D2000-1 data.

5. Order Flow and Generalized Impulse Response Analysis

In this section, we focus on the dynamic interaction between indicative and transaction prices using impulse response analysis. Due to the importance of the order flow in recent developments in exchange rate theory, we also include in our analysis the order flow from the D2000-1 data set.

A. Order Flow Analysis: An Introduction

Order flow is a measurement of the difference between buyer initiated trades and seller initiated trades. It is a well investigated factor in microstructure research in equity markets due to the much earlier availability of the data. However, in foreign exchange markets it was introduced by Goodhart and Flood in the late 80s and early 90s. With the seminal paper by Lyons (1995) and the gradual release of data from major trading banks and systems, order flow has become the utmost key word in exchange rate theory.

In foreign exchange microstructure theory, order flow is an important channel for heterogeneously dispersed liquidity information and asymmetric private information

[5] To calculate the information share of the each session, we use SUR (seemingly unrelated regression) and delete any lagged returns that belong to last day in each equation.

on exchange rates (see e.g. Lyons, 1995, Evans, 2002, and Breedon and Vitale, 2005). In traditional canonical models (see e.g. Glosten and Milgrom, 1985) there is two-way causality between price and order flow. In Evans and Lyons (2002) model, the causality runs strictly from order flow to price. A close investigation however reveals that they use hourly frequency and prices are taken as the last price while order flow is the interim aggregate. Therefore, if the actual causality happens at higher frequency, say at 5 to 10 minute frequency as in our case, the information contained in the order flow can well lead the latent price at the end of an hour, even though the true lead and lag pattern is the other way around, i.e., from price to order flow. This mistake could be further amplified by using daily closing prices to compare intraday day accumulated order flow, as in Killeen et al. (2006) where they find the same conclusion of one way Granger causality from order flow to exchange rates. Our impulse response tests indicate that it might not be the case when using higher frequency data. Causality tests further confirm our findings.

B. Generalized Impulse Response Analysis

The order flow data in D2000-1 is the transaction sign counts of the inter-bank deal, which does not reveal the exact size of the deal involved. Though the sign of each trade itself could be random, the accumulated order flow could be non-stationary for a given time window. ADF tests indicate that order flow data in both exchange rates are $I(1)$ processes at both 5 and 10 minute frequency (see Table 6).

We first look at the movements of the three series, i.e. EFX, D2000-1 and order flow, during our sample period (see Figures 9 and 10). In order to demonstrate the positive correlation between order flow and the price levels graphically, order flows of both currency pairs are defined as net dollar seller initiated trades. Such a modification is applied in the following empirical tests. The general co-movement between the order flow and prices is apparent, especially in DEM/USD. This suggests that prices and order flow form a system and share the same fundamentals. We are more interested, however, in the dynamic interaction among the three variables.

We introduce Hasbrouck's (1991) vector autoregression (VAR) model to investigate this issue,

$$\Delta p_{DL,t} = \sum_{i=1}^{\infty} a_i \Delta p_{DL,t-i} + \sum_{i=1}^{\infty} b_i \Delta p_{EF,t-i} + \sum_{i=1}^{\infty} c_i \Delta x_{t-i} + e_{1,t} \tag{12}$$

$$\Delta p_{EF,t} = \sum_{i=1}^{\infty} a_i \Delta p_{DL,t-i} + \sum_{i=1}^{\infty} b_i \Delta p_{EF,t-i} + \sum_{i=1}^{\infty} c_i \Delta x_{t-i} + e_{2,t} \tag{13}$$

$$\Delta x_t = \sum_{i=1}^{\infty} a_i \Delta p_{DL,t-i} + \sum_{i=1}^{\infty} b_i \Delta p_{EF,t-i} + \sum_{i=1}^{\infty} c_i \Delta x_{t-i} + e_{3,t} \tag{14}$$

where $\Delta p_{DL,t}$, $\Delta p_{EF,t}$ and Δx_t stand for D2000-1, EFX price change and order flow change respectively.[6]

As both prices p_t and the order flow x_t are $I(1)$ process, the differenced variables at the left hand sides are stationary. The changes of the order flow are divided by 1,000 to make them comparable to those of prices changes. The estimations are corrected by White's heteroskedasticity consistent standard errors. The optimum lag length is chosen by SIC.

Dynamic analysis of VAR models is routinely carried out using the 'orthogonalized' impulse responses. However, the involved Cholesky decomposition is not invariant to the ordering of the variables in the VAR. Therefore we use Pesaran and Shin's (1998) generalized impulse response approach to analyze the interactions. The generalized impulse responses from an innovation to the *j*-th variable are derived by applying a variable specific Cholesky factor computed with the *j*-th variable at the top of the Cholesky ordering. It only coincides with orthogonalized approach when the investigated variable is put at the top of the ordering.

Figure 11 to 16 display the impulse response of both prices and order flow in the two currency pairs. Due to space concern, we only present the results at the 5-minute frequency. There is no qualitative difference in the results at the 10 minute frequency.

[6] It should be noted that we have not included an error correction term as the three series have not been found to be cointegrated.

In GBP/USD currency pair, we find that the response of EFX price to one standard error of D2000-1 price impulse becomes insignificant around lag 2 or 10 minutes (Figure 11). However, the effect of one standard error of EFX impulse in D2000-1 disappear after around lag 6 or 30 minutes (Figure 12). In both Figures 11 and 12, the responses of order flow to the shocks from the two prices build up from lag 1 until lag 3, and then slide to insignificance at lag 4 or 20 minutes. In stark contrast, we could not find any significant response from the two prices to the order flow shock (Figure 13).

In DEM/USD currency pair the impulse response profiles are slightly different. Again, the response of EFX price to the D2000-1 impulse dies out at lag 2 to 3 (Figure 14). However, the response of D2000-1 to the impulse of EFX takes 15 minutes (at lag 3) to reach insignificance. In both Figures 14 and 15, the responses of order flow to the price shocks quickly slide to near zero around 10 minutes, and then reach their peaks after another 5 minutes. The impacts of the prices' shocks on the order flow continue to exist even over 30 minutes, which is different from those profiles in GBP/USD currency pair. In general, the response of order flow to exchange rate shocks indicates the existence of feedback trading rules (see Love and Payne, 2008). Finally, there is no significant response of prices to the order flow shock.

To summarize, the impulse response analysis in both currency pairs indicates that the shocks from EFX have much longer impact on D2000-1 data than vice versa. EFX data' impulses also have similar significant impact like those of D2000-1 on order flow. And order flow imposes no impact on prices, in contrast to the claims that order flow contains private information that is not revealed in prices.

In Tables 7 and 8, we present the Granger causality tests on order flow with indicative and transaction data at both frequencies[7]. The causality is unambiguously one direction from prices to order flow, with literally no causality from order flow to

[7] Since there is no cointegration between prices and order flow as we have tested, the Granger causality test is not affected by the complicated issues caused by ECM (see Toda and Phillips, 1993).

prices. The results are more obvious at 10 minute frequency than 5 minute frequency. Combined with the impulse response analysis, order flow is a latent and passive response to prices at high frequency. Even if order flow does carry dispersed information among dealers, it can not happen at such high frequency, as opaque de-centralized market institution stops individuals from quickly aggregating information from disintegrated order flows.

6. Conclusion

By comparing various statistical features of the EFX and D2000-1 data sets, we find that, contrary to previous studies, the indicative data are not inferior in terms of quality of information. More precisely, both lead-lag and impulse response analyses conclude that the indicative data lead the transaction data by 5 to 10 minutes. Furthermore, information share technique indicates a dominant role for the indicative data in mapping information. By adding order flow in the trivariate generalized impulse response analysis, we find that EFX price has a similar impact on order flow as D2000-1 price.

These findings are supportive of studies using indicative data, since the quality of their data has never been formally tested. As indicative data contain important information on the identity of the banks that made the quotes, they provide unique value for the study of market heterogeneity. The different merits of indicative and transaction data in reflecting market information suggest that we should combine both types of data to reveal the hidden picture of the heterogeneously distributed information in foreign exchange markets.

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Table 1. Two ticks of sample data

EFX	Date	Time	Bid	Ask	Nation	City	Bank	Filter	
	1996-5-1	0:00:12	1.5	1.506	392	1	532	1	
D2000-1	Month	Day	Hour	Minute	Sec	T_index	B/S	Price	Vol
	5	1	1	15	35	501.05	0	1.5047	0

These two ticks of data relate to GBP/USD. In the rows of EFX data, the codes for the nation, city and bank are assigned by the Reuters system. Filter column checks whether the price is an outlier, with number 1 indicating a good data and 0 otherwise. In the rows of D2000-1 data, T_index is converted time index of the transaction time. B/S stands buyer or seller initiated trade. Vol is the volume. The corresponding DEM/USD data have the same format.

Table 2. Properties of processed data sets with transaction time

GBP/USD	Mean	Median	Max	Min	Std. D.	Skew	Kurtosis
D2000-1	1.5397	1.5450	1.5650	1.4895	0.0167	-1.0137	2.9501
EFX	1.5393	1.5445	1.5682	1.4895	0.0167	-1.0136	2.9512
DEM/USD	Mean	Median	Max	Min	Std. D.	Skew	Kurtosis
D2000-1	1.5090	1.5182	1.5510	1.4638	0.0237	-0.1285	1.4205
EFX	1.5087	1.5180	1.5488	1.4635	0.0237	-0.1282	1.4198

The statistical results include all sample data of 82 trading days. There are in total of 51,741 pairs of GBP/USD prices and 255,481 pairs of DEM/USD prices. We use D2000-1's time stamp as the benchmark time to locate the nearest EFX data. The bid-ask selection for EFX data is also based on the D2000-1 order flow sign.

Table 3. Results of unit-root tests

	Transaction Time		5-Minute		10-Minute	
GBP/USD	EFX	D2000-1	EFX	D2000-1	EFX	D2000-1
t-Sta.	-2.01	-1.97	-2.39	-2.37	-1.94	-1.95
Prob.	0.28	0.30	0.14	0.15	0.31	0.31
DEM/USD	EFX	D2000-1	EFX	D2000-1	EFX	D2000-1
t-Sta.	-1.13	-1.05	-1.08	-1.09	-1.09	-1.08
Prob.	0.71	0.74	0.73	0.72	0.72	0.73

The two currency pairs from the two data sets are converted into the three frequencies before testing for unit-root. Both t-statistics and p-values are presented.

Table 4. Results of cointegration tests

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Sta.	5% Critical Value	1% Critical Value
GBP/USD - Transaction Frequency				
None *	0.07	3931.83	11.22	0.00
At most 1	0.00	1.18	4.13	0.32
GBP/USD - 5-minute Frequency				
None *	0.24	2264.14	15.89	1.00
At most 1	0.00	6.90	9.16	0.13
GBP/USD - 10-minute Frequency				
None *	0.24	1930.19	15.89	1.00
At most 1	0.00	4.89	9.16	0.30
DEM/USD - Transaction Frequency				
None *	0.03	6907.16	15.89	1.00
At most 1	0.00	2.09	9.16	0.76
DEM/USD - 5-minute Frequency				
None *	0.24	4877.84	15.89	1.00
At most 1	0.00	2.01	9.16	0.78
DEM/USD - 10-minute Frequency				
None *	0.24	2831.07	11.22	0.00
At most 1	0.00	0.82	4.13	0.42

The methodology is based on Johansen (1991 and 1995a). The optimum lag is chosen by Schwarz Information Criterion. The critical values are taken from Osterwald-Lenum (1992).

Table 5. Information share results of EFX data

GBP/USD EFX Information Share									
	1	2	3	4	5	6	7	ALL	Resid Corr
Transaction	60.5%	77.9%	89.5%	77.8%	93.0%	89.2%	73.9%	82.9%	16.6%
5-Min	48.8%	62.3%	82.7%	70.0%	80.5%	77.5%	64.7%	73.1%	49.6%
10-Min	42.0%	54.0%	74.0%	64.0%	67.0%	62.3%	60.2%	66.9%	60.0%
DEM/USD EFX Information Share									
	1	2	3	4	5	6	7	ALL	Resid Corr
Transaction	71.0%	78.6%	90.0%	82.0%	87.4%	82.3%	80.2%	85.0%	4.2%
5-Min	67.0%	76.0%	84.0%	69.1%	81.4%	76.6%	75.2%	81.2%	34.0%
10-Min	52.6%	71.0%	77.9%	60.8%	69.8%	66.2%	64.0%	76.4%	53.7%

The information share of the EFX data is calculated using ECM based Hasbrouck's (1995) technique. The columns numbered from 1 to 7 stand for the different trading zones of a complete trading day. The last two columns are the information share of the EFX data of the whole sample period and the residual correlation of the ECM, respectively.

Table 6. Unit-root test on order flow

Null Hypothesis: Order flow has a unit root
Exogenous: Constant and trend
Lag Length: Automatic based on SIC

	GBP/USD		DEM/USD	
	5-Minute	10-Minute	5-Minute	10-Minute
t-Sta.	-1.49709	0.461431	-1.66038	-1.58001
Prob.	0.8309	0.9854	0.7687	0.8011

The order flow data are the accumulated transaction signs of each 5 or 10 minutes, depending on the converted frequency. The test includes a constant and a trend. Both t-statistics and p-value are displayed.

Table 7. Granger causality test of order flow and price series at 5-m frequency

5-Minute	Null Hypothesis:	F-Sta.	Prob.
GBP/USD Obs: 8034	Order flow does not Granger Cause EFX	1.18	0.10
	EFX does not Granger Cause Order Flow	4.63	2.40E-46
	Order flow does not Granger Cause D2000-1	1.16	0.13
	D2000-1 does not Granger Cause Order Flow	4.21	1.50E-39
DEM/USD Obs:17178	Order Flow does not Granger Cause EFX	1.08	0.22
	EFX does not Granger Cause Order Flow	10.71	2.00E-299
	Order flow does not Granger Cause D2000-1	1.12	0.13
	D2000-1 does not Granger Cause Order Flow	8.73	5.00E-230

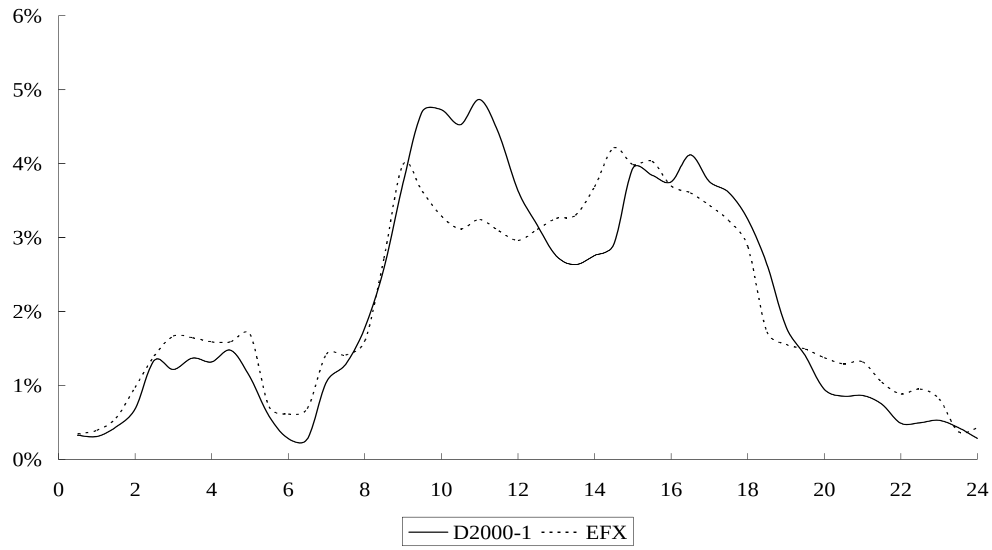
The two-way causality tests are conducted on the order flow and the two currency pairs from the two 5-minute data sets. Both F-statistics and p-value are displayed in the last two columns.

Table 8. Granger causality test of order flow and price series at 10-m frequency

10-Minute	Null Hypothesis:	F-Sta.	Prob.
GBP/USD Obs: 7206	Order flow does not Granger Cause EFX	0.94	0.66
	EFX does not Granger Cause Order Flow	5.90	5.20E-67
	Order flow does not Granger Cause D2000-1	1.03	0.39
	D2000-1 does not Granger Cause Order Flow	4.41	1.60E-42
DEM/USD Obs: 10132	Order Flow does not Granger Cause EFX	0.93	0.69
	EFX does not Granger Cause Order Flow	17.00	1.00E-263
	Order flow does not Granger Cause D2000-1	1.16	0.13
	D2000-1 does not Granger Cause Order Flow	12.99	3.00E-193

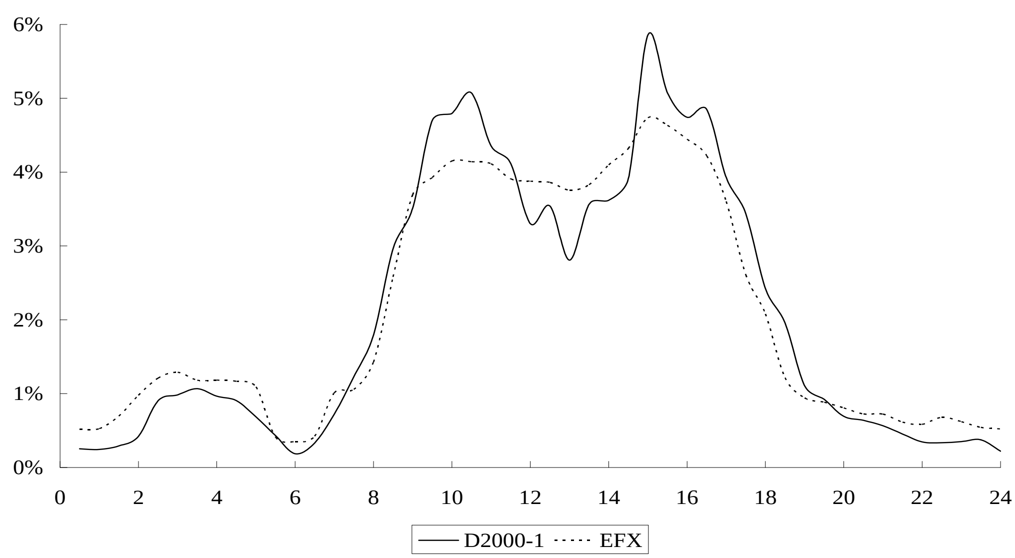
The two-way causality tests are conducted on the order flow and the two currency pairs from the two 10-minute data sets. Both F-statistics and p-value are displayed in the last two columns.

Figure 1. GBP/USD intraday quote (trade) frequency



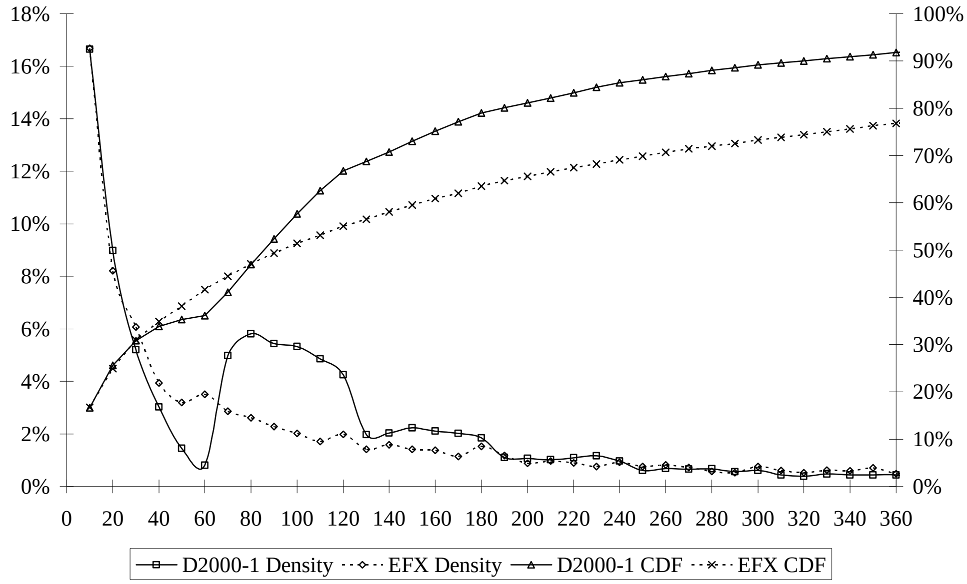
The intraday GBP/USD quote (trade) frequency is calculated by counting each half hour's prices and then dividing it by the total number of the sample average daily counts. Along the x-axis is the time index of each half hour starting from GMT 00:00.

Figure 2. DEM/USD intraday quote (trade) frequency



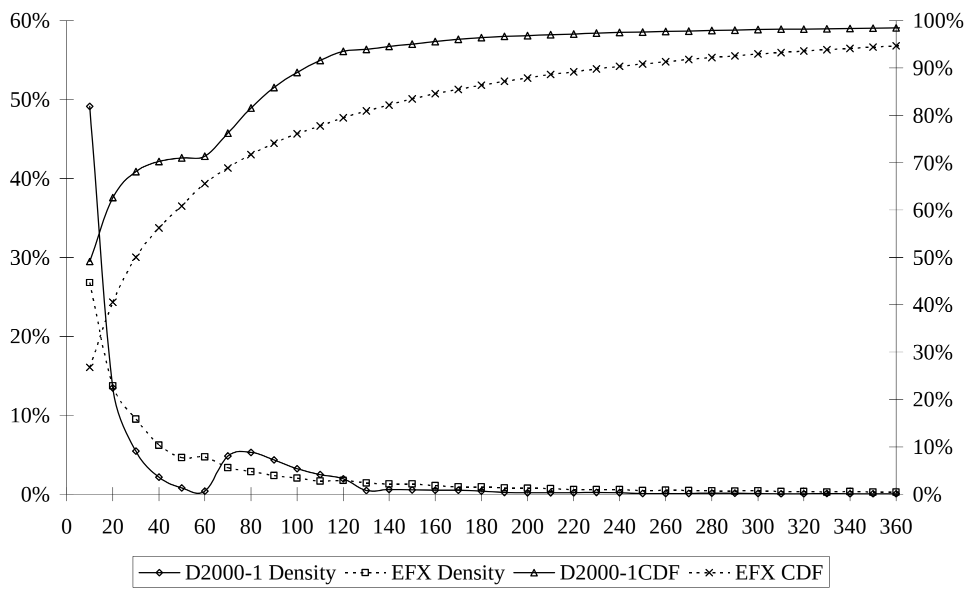
The intraday DEM/USD quote (trade) frequency is calculated by counting each half hour's prices and then dividing it by the total number of the sample average daily counts. Along the x-axis is the time index of each half hour starting from GMT 00:00.

Figure 3. Duration distribution of the GBP/USD



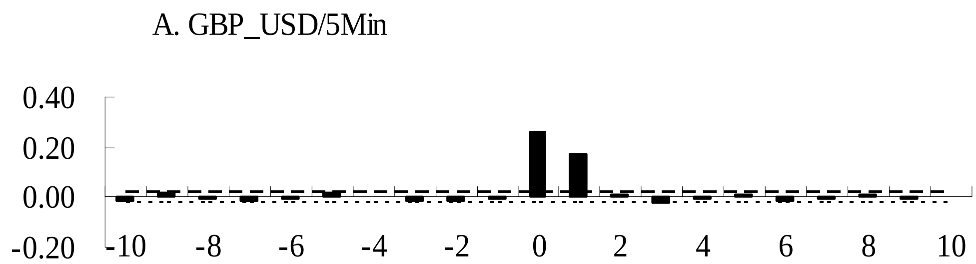
The D2000-1 density is based on the duration distribution of all prices. Cumulative distribution function (CDF) is the accumulated density for all duration. The duration density for EFX data is processed on quotes with changes larger than 5 basis points. The primary Y-axis corresponds to the density of the durations and the secondary Y-axis is the corresponding cumulative frequency. The X-axis indicates seconds.

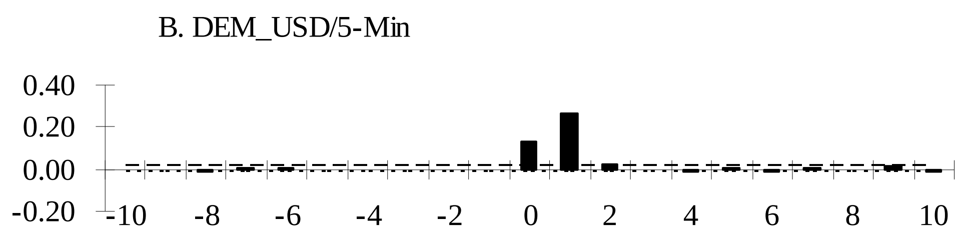
Figure 4. Duration distribution of DEM/USD



See notes to Figure 3.

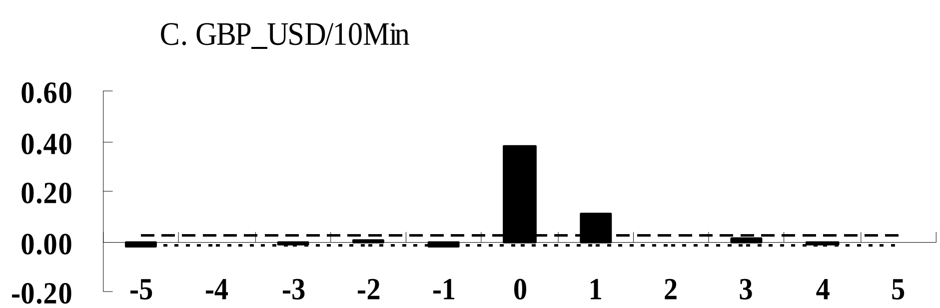
Figure 5. Cross-correlation of EFX and D2000-1 data at 5-m frequency





The 95% confidence levels are formed by calculating $\pm 2/\sqrt{T}$, with T being usable observations, which are the dotted lines in both graphs. Positive lag at the X axis indicate that EFX quotes are at the lead and vice versa.

Figure 6. Cross-correlation of EFX and D2000-1 data at 10-m frequency



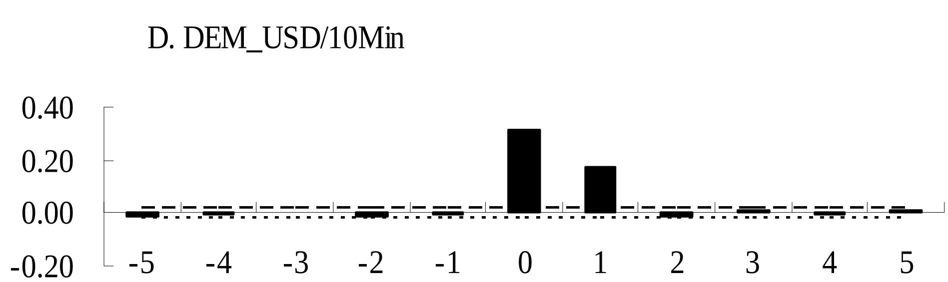
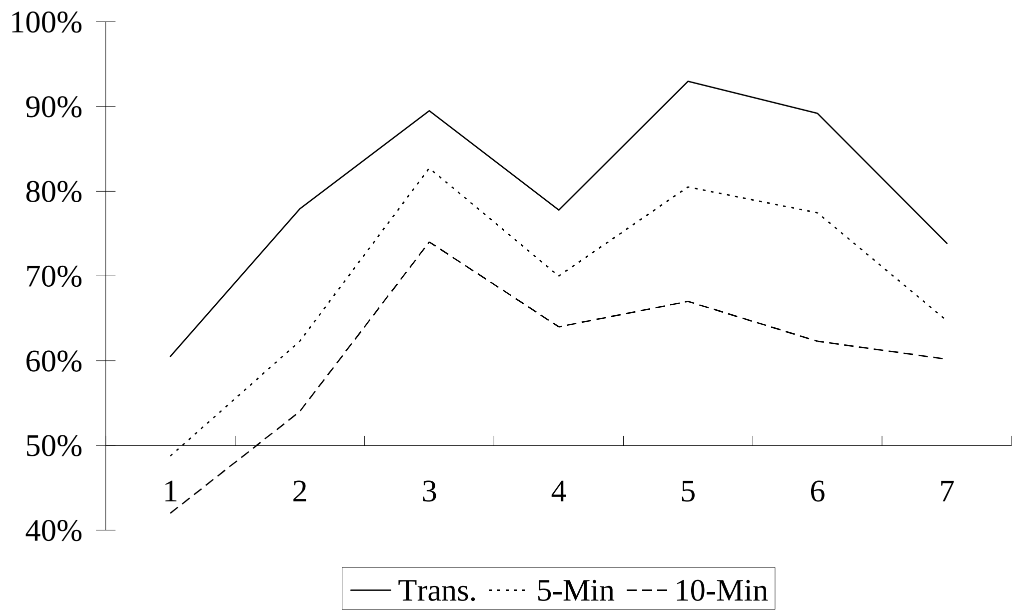


Figure 7. GBP/USD - information share of EFX during trading sessions



We separate the trading hours into 7 sessions that corresponds to major FX markets' openings and closings. The 7 sessions are 1) 21:00 to 8:00, New York closes till Tokyo closes, representing Asian trading hours; 2) 8:00-9:00, first hour of London opening with inventory effects; 3) 9:00-12:00, hours till New York opens; 4) 12:00-13:00, first hour of New York opening; 5) 13:00-15:00, overlapping trading hours of two major markets; 6) 17:00-18:00, London closing hour; 7) 18:00-21:00, hours till New York closes.

Figure 8. DEM/USD – information share of EFX during trading sessions

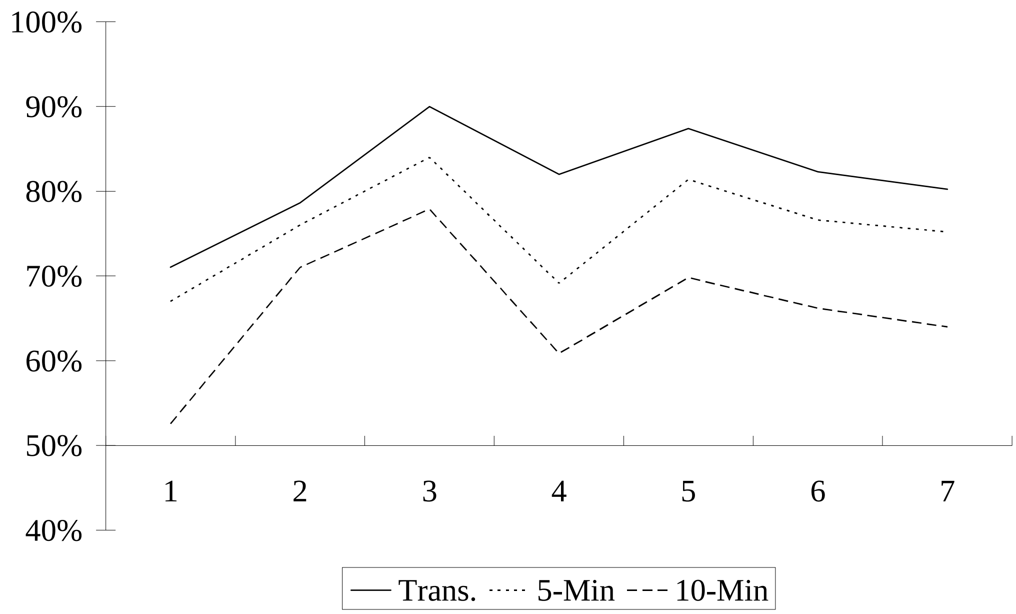
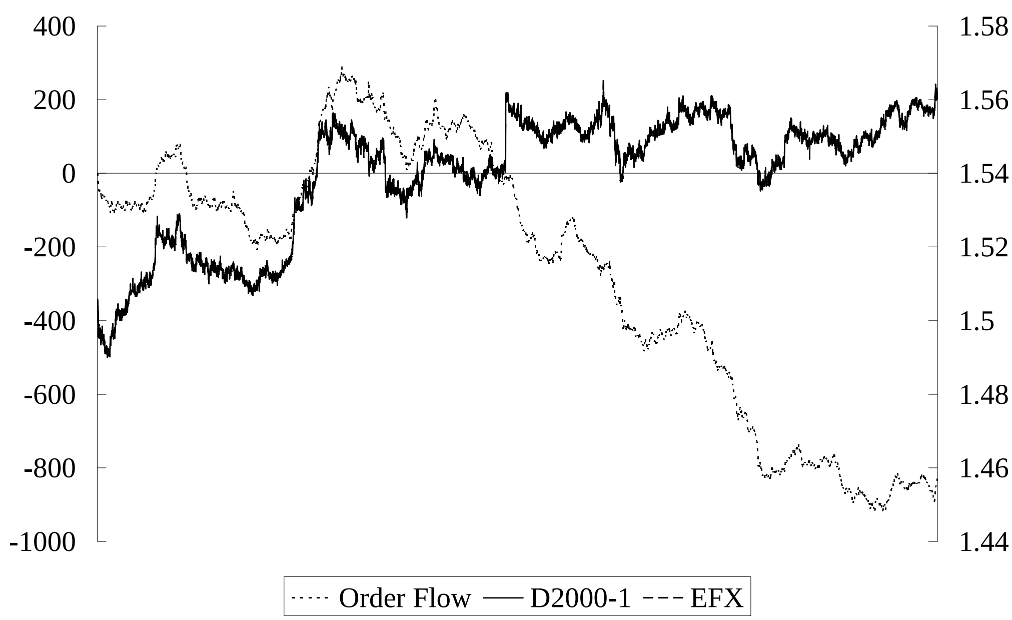


Figure 9. Order flow and prices in GBP/USD (10-M)



Order flow is the cumulative transaction signs for each 10 minute session during our sample period. The 10-minute frequency prices of the two data sets literally overlap each other due to long time window. The primary Y-axis measure the order flow while the secondary Y-axis are for the price level.

Figure 10. Order flow and prices in DEM/USD (10-M)

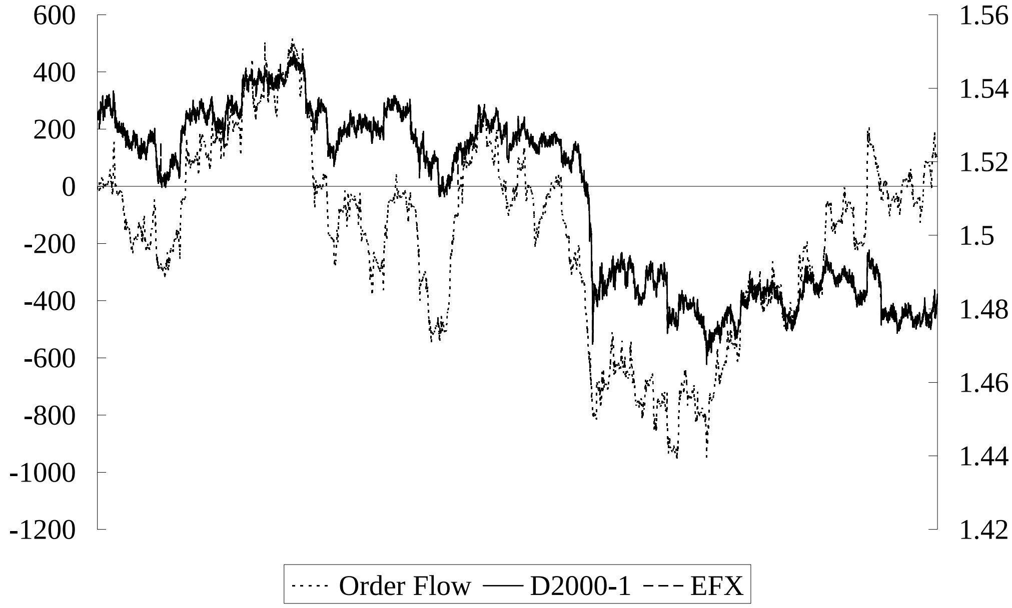
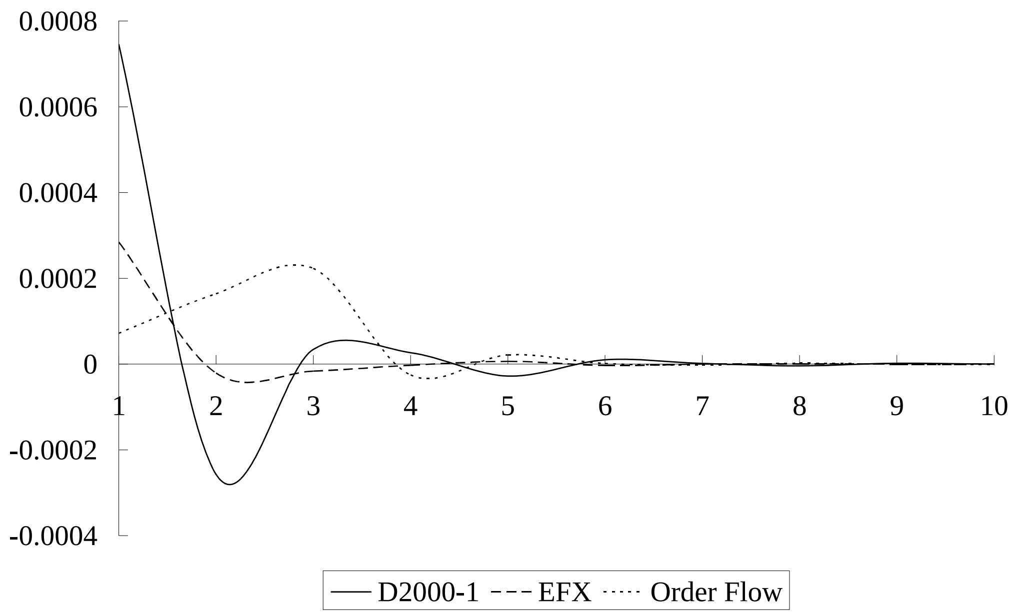
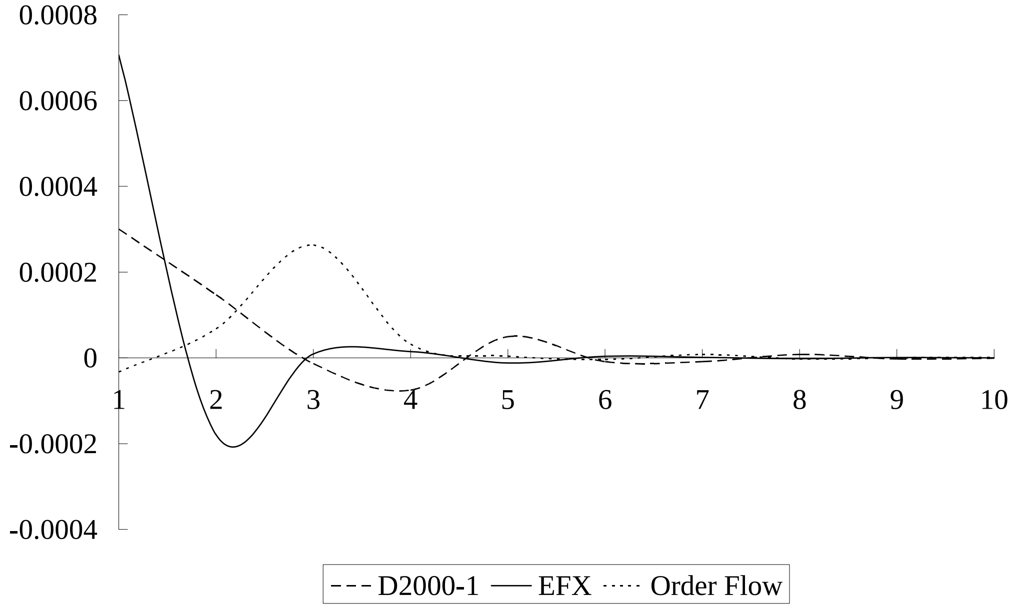


Figure 11. Generalized impulse response to one S.E. D2000-1 shock (GBP/USD)



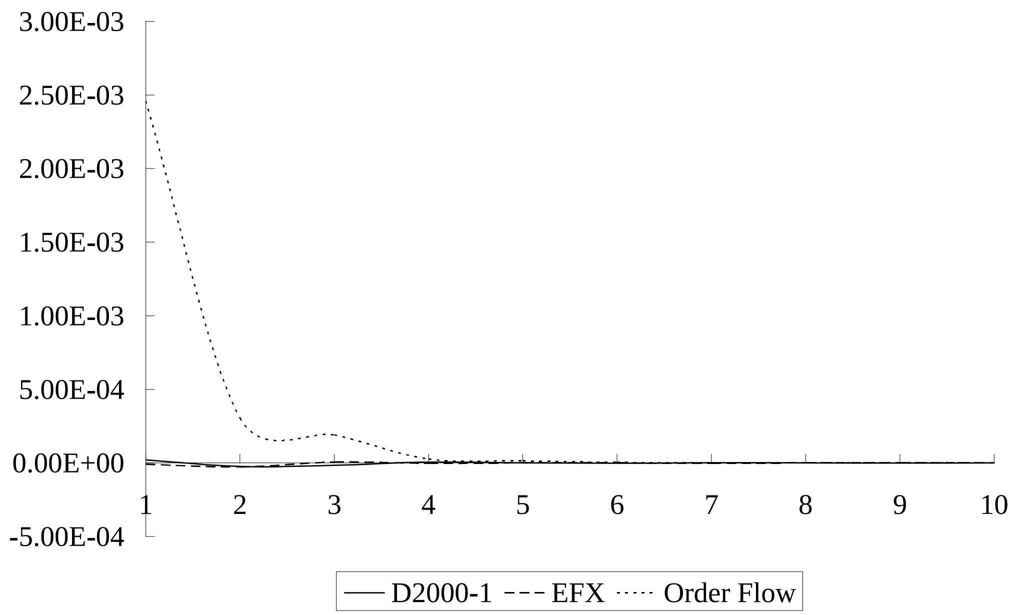
These are the generalized impulse responses to one S.E. of D2000-1 shock in GBP/USD currency pair. Each lag stands for 5 minute.

Figure 12. Generalized impulse response to one S.E. EFX shock (GBP/USD)



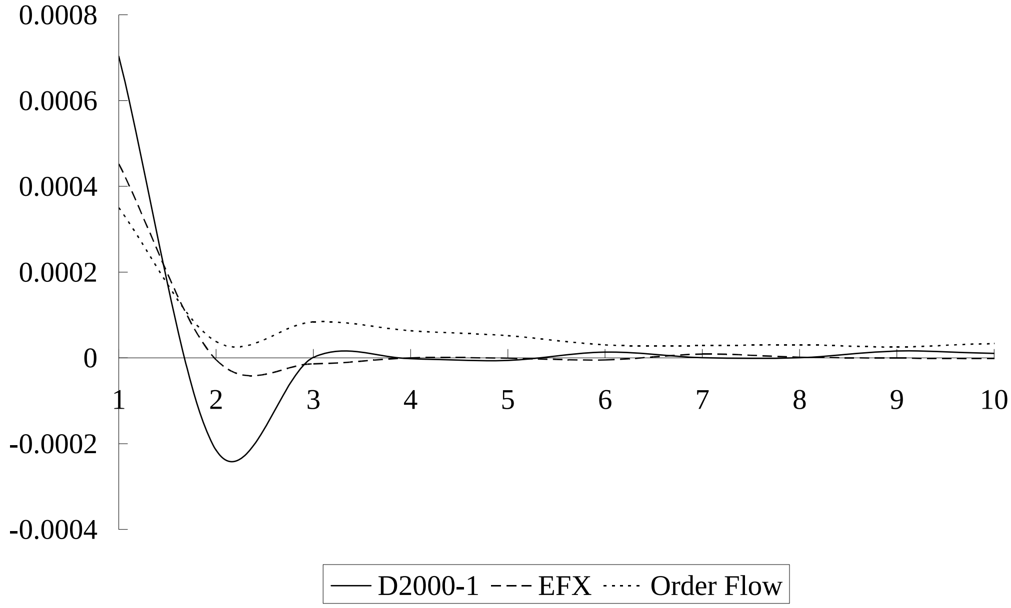
These are the generalized impulse responses to one S.E. of EFX shock in GBP/USD currency pair. Each lag stands for 5 minute.

Figure 13. Generalized impulse response to one S.E. order flow shock (GBP/USD)



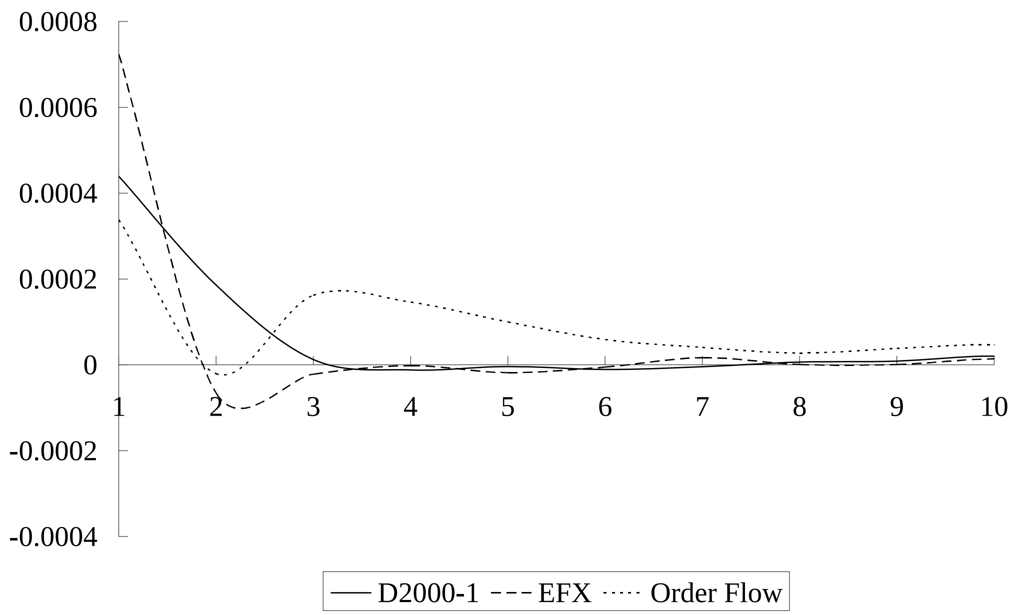
These are the generalized impulse responses to one S.E. of order flow shock in GBP/USD currency pair. Each lag stands for 5 minute.

Figure 14. Generalized impulse response to one S.E. D2000-1 shock (DEM/USD)



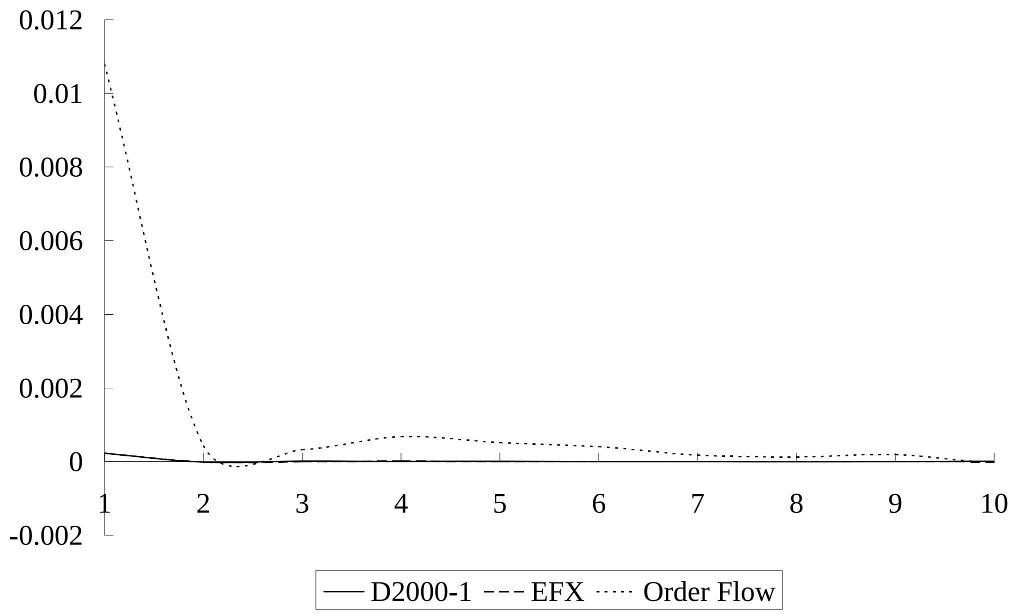
These are the generalized impulse responses to one S.E. of D2000-1 shock in DEM/USD currency pair. Each lag stands for 5 minute.

Figure 15. Generalized impulse response to one S.E. EFX shock (DEM/USD)



These are the generalized impulse responses to one S.E. of EFX shock in DEM/USD currency pair. Each lag stands for 5 minute.

Figure 16. Generalized impulse response to one S.E. order flow shock (DEM/USD)



These are the generalized impulse responses to one S.E. of order flow shock in DEM/USD currency pair. Each lag stands for 5 minute.