Forecasting the Foreign Exchange Market Using Private Information*

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Abstract

"Information is private if it's not known by all people and produces a better price forecast than public information alone" (Lyons, 2001, p. 26). This simple statement is tested for the Swedish krona vs. euro foreign exchange using a unique data set on five major banks trading with end-users. These trades satisfy the first part of the definition for the banks receiving them. We show that bank-specific forecasts of foreign exchange returns, using end-user order flow, can improve forecasts based on public information alone. Furthermore, these end-user forecasts do not dominate those based on public information alone, lending support to the view that end-user order flow represents dispersed information (as opposed to superior, insider, information). When this bank-specific, dispersed, information is aggregated across banks it a long-run relation with the exchange rate level is found, confirming that it is indeed a matter of price-relevant information.

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1 Introduction

"Information is private if it's not known by all people and produces a better price forecast than public information alone" (Lyons, 2001, p. 26). Testing this simple statement for the foreign exchange market is the objective of this paper. We also aim to shed light on what *type* of private information that may exist in the foreign exchange market: Is it information of the kind that insiders have in equity markets, or rather heterogeneous bits of information (*dispersed* information according to Evans and Lyons (2005b))?

Banks' trading with end-users satisfy the first part of the aforementioned definition of private information due to the lack of any disclosure requirements in foreign exchange markets. Using a unique data set on end-users' trading with five major banks in the Swedish krona vs. euro market (SEK/EUR), we find evidence that bank-specific end-user trades may improve forecasts of foreign exchange return that are based on public information alone, but that these end-user based forecasts do not prove to be superior to those based on public information. We take this latter result as support for the hypothesis that this private information is not of the insider kind found in equity markets, but rather represents heterogeneous bits of relevant information not captured by the publicly available data alone.

When these heterogeneous bits of dispersed information is aggregated across the banks we find that it cointegrates with the exchange rate level. The lasting effect of aggregated end-user order flow confirms that it is price relevant information.[1] The impounding of this heterogeneous information into prices may not materialize instantly but rather take some time, which in turn gives rise to its forecasting power (Evans and Lyons, 2005a).

These results are far from obvious. Over the last quarter century, exchange rates have shown substantial and persistent movements that are largely unexplained by movements in macroeconomic fundamentals (Sarno and Taylor, 2003). This again has led to the suggestion that exchange rates are not determined exclusively by macroeconomic fundamentals (Flood and Rose, 1995). Recently, Engel and West (2005) have shown that forecast failure may exist even in a world where exchange rates are determined by the discounted value of future macroeconomic fundamentals if the fundamentals are near random walks, or if discount factor are close to one.

The microstructure approach of the foreign exchange market (FX market) has emerged as an attempt to understand the apparent deviations from fundamentals. In microeconomic models of asset prices order flow plays a causal role in exchange rate determination. This arises because order flow conveys information that is not yet common knowledge. The view of the microstructure literature is that it is not necessarily the fundamentals that is the problem of standard macroeconomic approaches to foreign exchange rate determination and forecasting. Rather, it might be the assumptions about how the market is *learning* about these fundamentals.

Evans and Lyons (2002) and others[2] in the FX microstructure literature have shown

[1]Order flow is defined as signed transactions, where the sign is determined by the action of the party initiating the trade. The convention is that a purchase of base currency (euro in our case) is a positive order flow, while a sale is a negative order flow.

[2]E.g., Killeen, Lyons and Moore (2006) and Bjønnes, Rime and Solheim (2005)

that order flow explains exchange rate movements at short and medium term horizons remarkably well, and much better than the usual macro fundamentals. The interpretation suggested by the formal model of Evans and Lyons (2004) is that order flow is a function of shocks to house-holds and consumers which leads to trading (possibly for allocational reasons), and that these shocks in itself can be aggregated into shocks to macroeconomic fundamentals. Evans and Lyons takes the view that everything macro are aggregates of something from the micro-level. Observing the aggregate of the micro-shocks in real time is extremely difficult, but the banks' market makers (the ones that actually determine the prices) use the information from end-users in an attempt to learn about the macro shocks. Since each market maker only receive a subset of all end-users' trading they only get a partial picture of the macroeconomic conditions. Hence, the relevant information about current and future macroeconomic fundamentals is *dispersed* among the market makers.

This view has received some support lately. Evans and Lyons (2005a,b) show that the end-user order flow of CitiBank can forecast the exchange rate. Furthermore, they show that end-user order flows and fundamentals are linked. End-user order flow can predict (in-sample) fundamentals up to one quarter ahead. Rime, Sarno and Sojli (2006) show that it is possible to create profitable trading strategies based on order flow information.

Access to a unique data set makes it possible for us to address these issues. One contribution in this study compared to earlier work is that we evaluate end-user order flow in stead of interbank order data. End-user order flow is considered as more informative as it represents the fundamental source of demand for the currency in the economy. We have daily end-user order flow from five major banks in the spot SEK/EUR foreign exchange market over four years from beginning of 2001 to end of 2004. We have observations on the following end-users trading in the SEK/EUR market: Corporate customers, Financial customers, Treasury departments, Individuals, and two groups of non-market making interbank customers. Together these five banks may have as much as 80% of the SEK/EUR market. This enables us to both check for forecasting power over several banks, and check if the aggregate end-user order flow have persistent price impact. Under the dispersed information hypothesis it is unlikely that the end-user order flow of a single bank will cointegrate with the exchange rate.

We construct simple non-optimal forecast models for each of the five banks conditioning on end-user flows only, and forecast exchange rate return out-of-sample for one day, one week and one-month ahead. The simple forecasts perform reasonably well according to sign-tests and the projection-test of Evans and Lyons (2005a). The bank-specific forecasts are compared to several simple forecast models based on public information such as interest rate differentials, equity market return differentials, and lagged foreign exchange rate return. Using forecast encompassing tests we show that the two forecasts complement each other, confirming that end-user order flow represent some information still not reflected in the publicly available data. The price-relevant role of end-user order flows are confirmed using a maximum likelihood cointegration framework where a long-run relationship is found between customer order flow and the SEK/EUR exchange rate: Increased buying pressure for euro (the base currency) leads to a depreciation of the Swedish krona.

In the next section we discuss a conceptual framework for understanding the link between exchange rates and order flow. In the section 3 we present our data. Section 4 contains the forecasting exercise, while section 5 is devoted to cointegration analysis between the exchange rate level and aggregated end-user order flow. Section 5 concludes.

2 Exchange rates, order flow and information

The informational environment suggested by Evans and Lyons can be illustrated with Fig. 1. The large outer circle represents all information relevant for the exchange rate, while the smaller circle centered around the middle represents only publicly available information. The three remaining circles represent the information content in end-user order flow of the three banks, A, B and C. These three information sets partly overlap both each other and the public information set, but not in a way such that one bank holds an information advantage over the others. The access to end-user order flow provides each bank with some partial extra information. This extra information is thus dispersed between the banks.

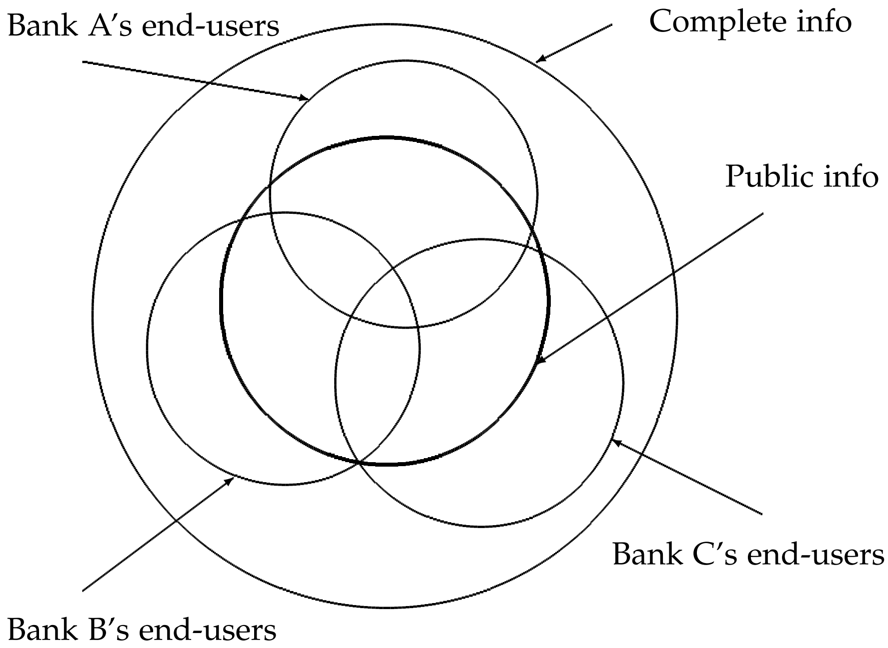

Figure 1: Information environment

The figure may illustrate the success of the FX microstructure approach in explaining exchange rate movements. Papers like Evans and Lyons (2002) and Killeen et al. (2006) have observations from a large part of the interbank market. If interbank order flow is a function of end-user order flow their empirical results may be viewed as conditioning on the union of the circles within the outer circle. Their success suggest that the bank-specific information sets lie partially outside the public information set. Bjønnes et al. (2005) study customer order flows from several banks, and as such cover a similar union. Killeen et al. (2006) and Bjønnes et al. (2005) do find that cumulative order flow cointegrates with the exchange rate. The end-user order flow of CitiBank do not, however, cointegrate with the exchange rate (Evans and Lyons, 2005a, according to private conversation), which is consistent with Fig. 1 in that, being a single bank, it has a limited market coverage and lacks some important information elements.

The information structure given by Fig. 1 suggest that there could be incremental forecasting power in bank-specific end-user order flow, but that forecasting based on end-user order flow alone should not necessarily outperform forecasts based on public information.

3 Data

Our empirical analysis utilizes a new data set that comprises end-user transaction flows, spot rates and interest rates over the sample period January 2001 to December 2004. Most previous studies of exchange rates and order flow have used inter-bank data and not customer data. The transaction data set is unique in the sense that it consists of the total amount of all executed trades in SEK/EUR performed by five major banks. Compared to previous end-user data sets (Evans and Lyons, 2005b; Marsh and O'Rourke, 2005) this data set is more complete in that it covers approximately 80 percent of the total end-user customer market in SEK/EUR and covers a time span of four years. The data set is also unusually rich in features since it includes information on the size, direction, price, and exact time of transaction, and in addition a disaggregation of the end-users into different groups. Due confidentiality reasons the names of the banks will not be revealed.

By end-users we are referring to six main segments: Corporate customers (non-financial corporations), financial customers, Treasury departments of non-financial corporations, individuals, and two interbank customers. The interbank customers are those banks that execute the FX transaction, but do not pursue FX operations on their own behalf, and those financial customers that can operate in the interbank-market, typically the markets departments of major banks. All of these customers trade for their own account and can be called end-users. The role of non-dealer customer order flow is central to microstructure theory. It is the demands of non-dealer customers that represent the underlying demands for currencies in the real economy. It is these customer orders that catalyze a market response. In this sense the interdealer trading is derived from the customer order flows. Dealers regard the customer trading as the most important source of private information for predicting exchange rate movements.

Table 1 reports the market share of each customer segment across all the banks. When we aggregate all the transactions across all the banks we see that Treasury, Corporate and Financial customers clearly dominate the market with the greatest volumes. The remaining customer types represent only a minor part of the market. When it comes to the actual number of trades we see that more than half of them are performed by the Corporate segment with Interbank Customers in second place followed by Financial and Treasury. Together we conclude that Treasury departments make large but few transactions and that the Corporate segment as well as the Financial segment make trades both large and numerous.

The market share of each bank differ quite a lot across (according to volume) the different customer segments. One bank handles the majority of transactions of both the Treasuries and Corporate segment as well as that of Individuals. The Financial flows seems to a great extent being taken care of by a different bank.

Over the sample period we have 1027 days with observations on order flow. We will use both direction- and volume-based measures of order flow, where in the former only the direction matters (a purchase is counted as 1, while a sale is counted as -1), while in the latter the we multiply the direction with the (EUR) volume of the transaction. We then aggregate from 8:00 to 16:00 in order to get daily values.

Our exchange rate data is collected by EcoWin at 16:15 every day, and denotes the amount of Swedish kronor required to buy one euro. Figure 2 shows the exchange rate evolution during the relevant time period. We see large movements in the beginning of the period, and that the SEK/EUR stabilizes towards the end of the sample. Using a HP-filter of implied volatility from one-year options, we see the sharp decrease in volatility from mid-2002 and onwards in Figure 3.

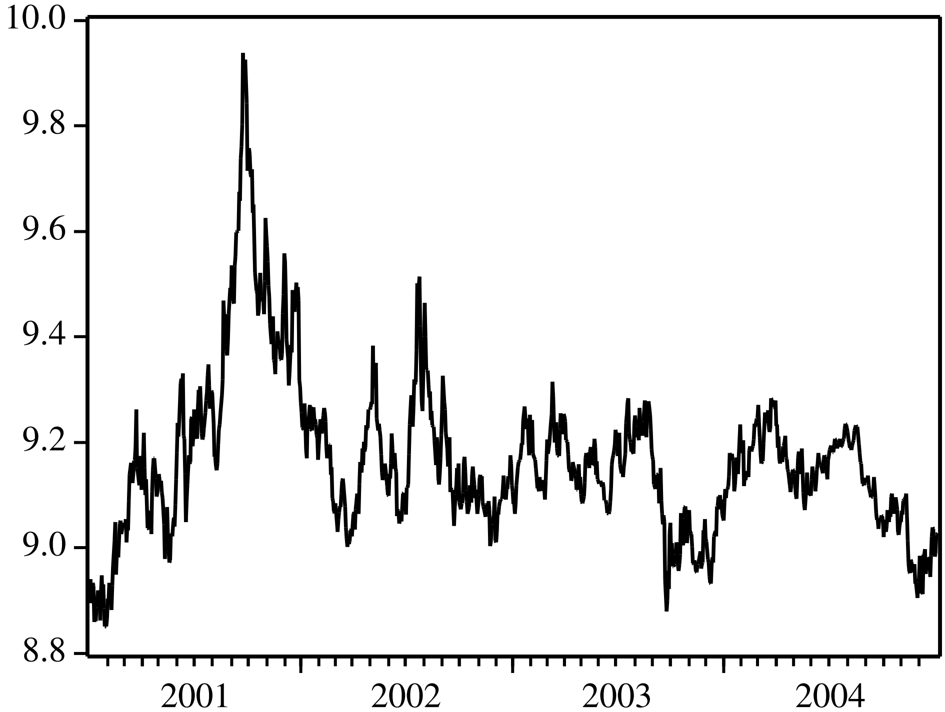

Figure 2: Swedish krona vs. euro (SEK/EUR)

Our macroeconomic variables are Swedish and Euro interest rates at different maturities. In the forecasting exercise we match the maturity of the interest rates with the forecasting horizon. In the cointegration analysis we also use the difference in slope between the Swedish and European yield to maturity curves, where slope is defined as the difference in yield between the 10-year government bond and the 3-month treasury bill. The yield to maturity curve contains information concerning market expectations of future real activity and inflation. The difference between the

Table 1: Market share for each customer type

	Treasury	Financial	Individuals	Corporate	IB Customers	IB Financials	Total
a) Volume							
Mean	32.6 %	23.6 %	0.3 %	28.2 %	15.3 %	0.03 %	294
Median	31.9 %	20.4 %	0.1 %	25.7 %	13.3 %	0.00 %	264
Maximum	84.7 %	84.7 %	12.2 %	100.0 %	100.0 %	4.12 %	1,418
Minimum	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.00 %	0
Std. Dev.	16.9 %	16.4 %	0.7 %	14.8 %	11.4 %	0.21 %	156
b) Number of trades							
Mean	8.7 %	17.9 %	1.1 %	51.5 %	20.8 %	0.1 %	135
Median	8.5 %	17.6 %	0.8 %	51.4 %	19.7 %	0.0 %	138
Maximum	50.0 %	50.0 %	16.7 %	100.0 %	100.0 %	3.3 %	270
Minimum	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	0.0 %	1
Std. Dev.	3.8 %	6.9 %	1.2 %	9.2 %	8.4 %	0.3 %	40
Observations	1023	1023	1023	1023	1023	1023	1023

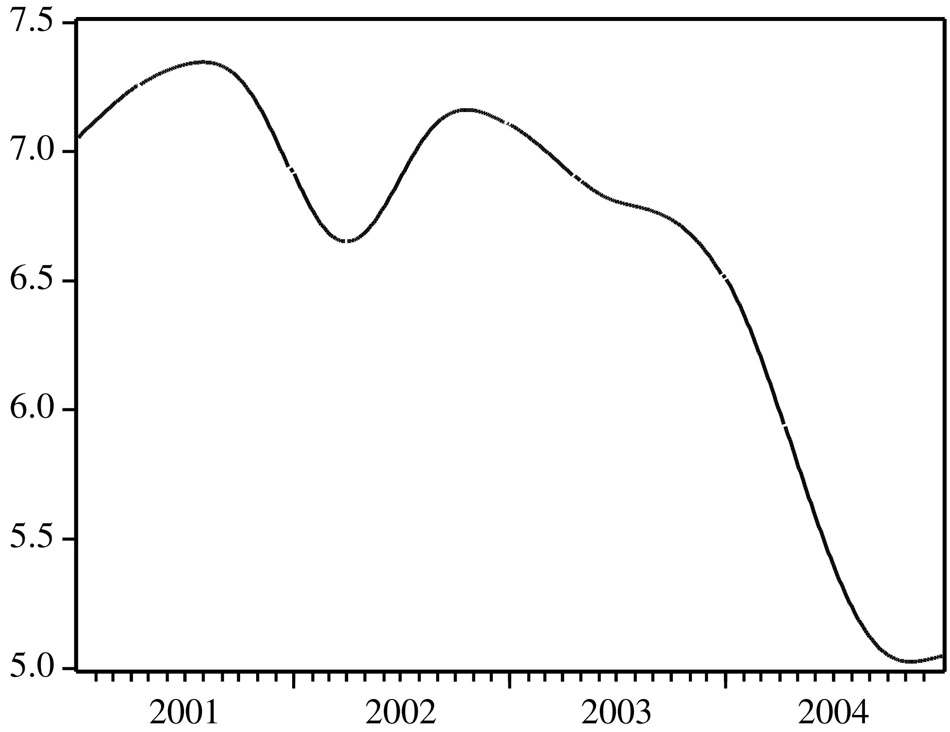

Figure 3: Market volatility trend. HP-trend of one-year implied volatility

Swedish and European yield to maturity curves thus reveals the difference in expectations regarding these two variables. A steepening of the Swedish curve relative to the European, leading to a larger positive difference, would indicate an expectation of higher inflation for the Swedish economy compared to the European economy. According to the purchasing power parity relation this should lead to an appreciation of the SEK/EUR (a depreciation of the krona).

4 Forecasting

Lyons write that information is private if (a) it is not known by all and (b) can forecast prices.[3] The end-user order flows of a particular bank satisfy part a of this definition. Since there are no disclosure requirements on banks for their foreign exchange activity, and since the bank-customer market is an over-the-counter (OTC) market, there is no way other banks can learn about these flows. The question we ask here is if these flows also can be used for forecasting by each bank.

To select models for forecasting we take Table **??** as a starting point. Although each bank can not know their exact market share, we believe they have an idea about in which customer segments they are strong. Hence, we let each bank use the order flow from the segments where they have a reasonable market share. Using market share from a segment where they have a low share would mean using highly uncertain

[3]Lyons also write that it must forecast *better* than public information. We believe that this requirement is not necessary under the dispersed information hypothesis.

information, and risk trading with a bank that have more precise information of the same kind in the interbank market.[4] A typical bank-specific forecasting model will be as follows:

$$s_{t+\tau} - s_t = \alpha + \sum_{j=1}^{n} \beta_j^{\ell} \sum_{i=t-\tau}^{t} OF_{j,i}^{\ell} + \varepsilon_{t+\tau}^{\ell}, \tag{1}$$

where s is the log exchange rate (SEK pr. EUR), τ is the forecast horizon (1, 5, or 20 days), ℓ represent the bank in question (A, B, C, D or E), and n is the number of customer segments used for forecasting.[5] We use the following flows for each bank, depending on their relative strength in customer segment: (*i*) Bank A: Treasuries and Corporates ; (*ii*) Bank B: Corporates, Treasuries and Interbank customers; (*iii*) Bank C: Financial and Interbank financials; (*iv*) Bank D: Corporates, Treasuries and Financial; and (*v*) Bank E: Financial and Interbank customers. Previous empirical research using interbank order flow have shown that it sometimes is better to disregard volume information and only use direction of trade (buyer initiated or seller initiated) when creating order flow. We therefore consider both order flow measures based on direction of trade only, and order flow measures where volume is signed.[6]

We use five different public information models:

$$\text{M1: } s_{t+\tau} - s_t = \alpha_1 + \beta_1 \left(i_t^{swe,\tau} - i_t^{eur,\tau}\right) + \varepsilon_{1,t+\tau} \tag{2}$$

$$\text{M2: } s_{t+\tau} - s_t = \alpha_2 + \beta_2 \left(s_t - s_{t-\tau}\right) + \varepsilon_{2,t+\tau} \tag{3}$$

$$\text{M3: } s_{t+\tau} - s_t = \alpha_3 + \beta_3 \left(\Delta e_t - \Delta e_{t-\tau}\right) + \varepsilon_{3,t+\tau} \tag{4}$$

$$\text{M4: } s_{t+\tau} - s_t = \alpha_4 + \beta_4 \left(i_t^{swe,\tau} - i_t^{eur,\tau}\right) + \gamma_4 \left(s_t - s_{t-\tau}\right) + \varepsilon_{4,t+\tau} \tag{5}$$

$$\text{M5: } s_{t+\tau} - s_t = \alpha_5 + \beta_5 \left(i_t^{swe,\tau} - i_t^{eur,\tau}\right) + \gamma_5 \left(\Delta e_t - \Delta e_{t-\tau}\right) + \varepsilon_{5,t+\tau} \tag{6}$$

In the above models $i^{j,\tau}$, $j = swe, eur$, is an interest rate with maturity τ, and Δe_t is equity return differential between the Stockholm stock exchange and the FTSE Europe. The latter is considered due to the "common knowledge" fact in Sweden that Ericsson and the Stockholm stock exchange lead exchange rate movements.

All forecasts are generated recursively so that the forecaster never utilize information not available at the forecast time. Coefficients are updated each period, but models stay the same during the sample. In addition to the whole sample from 2001 to end 2004 we also consider each year in isolation (reported in Appendix A). The uncertainty in the market, represented by implied volatility, have a large swing during the sample as seen from Fig. 3, and this may influence the forecasting performance. Killeen et al. (2006) show that under low uncertainty order flow is less important, and completely unimportant in the extreme of an credible fixed exchange rate regime.

Tables 2 and 3 show some forecast evaluations for each model over the whole sample. For each model/horizon we report three evaluations measures. RMSE is

[4] We have also considered forecasting based on the each banks aggregate order flow across the major customer segments (defined in Table 1). Results are omitted due to space constraints, and are available upon request.

[5] With daily data, and excluding weekends, 5 day horizon represent one week forecasting and 20 day horizon represent roughly one month.

[6] Order flow based on direction only counts each buyer initiated trade as a 1, and each seller-initiated trade as a -1.

the ratio of the model-RMSE to the RMSE of the Random walk. The accompanying t-statistic is from a Diebold Mariano test for difference in mean of squared forecast errors. The sign test reports the share of forecasts that have the same sign as actual change, together with a test for deviation from 0.5. The final test is the Prediction-test of Evans and Lyons (2005a). We report the coefficient β from the following regression:

$$\widehat{s_{t+\tau} - s_t}|_t = \alpha + \beta \left(s_{t+\tau} - s_t\right) + \varepsilon_{t+1},$$

where $\widehat{s_{t+\tau} - s_t}|_t$ is a forecast conditioned on period t information. Under the null of a random walk β should equal 0. If the model in question have forecasting power over the Random walk the coefficient β should be positive and significant. The closer to one the better.

Table 2 show the results for the five public information models. The RMSE of the public model is only better than the random walk when interest rates are part of the model (model 1, 4 and 5), and only at the one-day forecast horizon. All models do surprisingly well at the one-month horizon, with all models except model 3, equity return, beating the random walk at both the sign and projection test. These results are in accordance with some recent results that find some predictability from public information (Diebold, 2004), and in fact represents a breach of weak-form efficiency. Whether these forecasts are profitable we do not take a stand on here. Without actually testing the models against each other the results indicate that Model 3, based on equity return differentials, is doing worst, and that the two best is the ones that combine interest rate information with return information.

Table 3 show the results using order flow based on direction in panel a, while panel be show the case when volume information and trade direction is used to create order flow. From Table 3, panel b, we see that four of the five banks beat the random walk according to the RMSE-criterion, but only at the one-day horizon. When using only direction order flow, panel a, we see that three banks beat the random walk at the one-day horizon. On the one-week and one-month horizon four out of five banks beat the random walk according to the sign and projection criteria for the direction order flow, while with volume-based order flow the results are more mixed. The importance of direction is in line with evidence from the interbank market, but is somewhat surprising since one would expect that volume was more important in the end-user market than in the interbank market.

If we simply compare the share of correct signing and the value of the projection test, in cases where both are significant, between the public information models and the bank-specific models, the bank-specific models seem to perform equally well or even better. Especially Bank B and D perform better than the public information models in 2 on almost all horizons. Bank C, on the other hand, seem to perform worse.

However, this is admittedly not a statistical evaluation, and since it appears that both the Public information models and the bank-specific models performs rather well we need to compare the two sets of models more rigorously. This is the purpose of Tables 4 5. We compare the bank-specific models to each of the Public information models. The forecasting encompassing test and the Diebold-Mariano test are considered (see Diebold, 2004) . The forecast encompassing test amounts to the following

Table 2: Public information models. Whole sample, 2001-2004

Model	Horizon	Test	Stat.	*t*-test
(1) Interest rates	One day	RMSE	0.990	-2.67
		Sign	0.521	1.31
		Projection	0.015	3.13
	One week	RMSE	0.991	-0.62
		Sign	0.512	0.75
		Projection	0.028	1.74
	One month	RMSE	0.982	-0.35
		Sign	0.542	2.72
		Projection	0.109	2.24
(2) FX return	One day	RMSE	1.082	0.93
		Sign	0.542	2.69
		Projection	0.006	1.31
	One week	RMSE	0.993	-0.66
		Sign	0.579	5.07
		Projection	0.029	3.32
	One month	RMSE	1.011	0.18
		Sign	0.561	3.93
		Projection	0.065	2.80
(3) Equity return	One day	RMSE	1.093	0.95
		Sign	0.530	1.94
		Projection	0.005	1.07
	One week	RMSE	1.004	0.20
		Sign	0.521	1.35
		Projection	0.017	1.64
	One month	RMSE	1.026	0.45
		Sign	0.496	-0.23
		Projection	0.056	1.68
(4) Interest rates and FX return	One day	RMSE	0.988	-2.55
		Sign	0.531	2.01
		Projection	0.019	3.27
	One week	RMSE	0.979	-1.41
		Sign	0.545	2.91
		Projection	0.048	2.95
	One month	RMSE	0.970	-0.67
		Sign	0.554	3.48
		Projection	0.146	3.30
(5) Interest rates and equity return	One day	RMSE	0.988	-2.65
		Sign	0.520	1.25
		Projection	0.018	3.33
	One week	RMSE	0.990	-0.78
		Sign	0.495	-0.32
		Projection	0.039	2.16
	One month	RMSE	0.985	-0.31
		Sign	0.534	2.21
		Projection	0.134	2.45

Table 3: Bank-specific models, both Direction and Volume Order Flow. Whole sample, 2001-2004

			a) Direction of order flow		b) Order flow volume	
Bank	Horizon	Test	Stat.	t-test	Stat	t-test
Bank A	One day	RMSE	0.988	-2.65	0.989	-3.23
		Sign	0.543	2.75	0.538	2.43
		Projection	0.022	4.25	0.017	4.06
	One week	RMSE	0.990	-1.21	0.994	-0.93
		Sign	0.543	2.76	0.500	0.03
		Projection	0.029	2.77	0.026	2.79
	One month	RMSE	0.987	-0.43	0.983	-0.46
		Sign	0.574	4.72	0.631	8.43
		Projection	0.128	3.01	0.162	3.37
Bank B	One day	RMSE	0.986	-2.76	0.987	-2.96
		Sign	0.540	2.57	0.531	2.01
		Projection	0.025	4.49	0.025	3.70
	One week	RMSE	0.984	-1.01	0.988	-0.76
		Sign	0.569	4.42	0.564	4.11
		Projection	0.049	3.04	0.056	3.31
	One month	RMSE	0.984	-0.43	0.982	-0.58
		Sign	0.572	4.62	0.548	3.06
		Projection	0.149	3.17	0.107	3.19
Bank C	One day	RMSE	1.002	0.36	1.017	0.79
		Sign	0.507	0.44	0.513	0.82
		Projection	0.005	0.96	0.009	2.98
	One week	RMSE	1.001	-0.10	0.998	-0.31
		Sign	0.541	2.65	0.515	0.95
		Projection	0.037	2.47	0.044	2.40
	One month	RMSE	1.024	0.32	2.098	0.99
		Sign	0.518	1.14	0.562	4.00
		Projection	0.274	3.76	0.283	2.73
Bank D	One day	RMSE	0.986	-2.85	0.989	-2.20
		Sign	0.538	2.45	0.530	1.94
		Projection	0.024	3.49	0.021	3.26
	One week	RMSE	0.977	-1.41	0.986	-0.97
		Sign	0.567	4.30	0.525	1.58
		Projection	0.065	3.67	0.057	3.41
	One month	RMSE	0.961	-0.77	0.986	-0.44
		Sign	0.652	9.77	0.529	1.89
		Projection	0.222	3.71	0.114	2.98
Bank E	One day	RMSE	0.993	-1.53	0.990	-2.44
		Sign	0.534	2.16	0.517	1.10
		Projection	0.018	2.51	0.017	3.87
	One week	RMSE	0.994	-0.66	0.994	-0.67
		Sign	0.514	0.92	0.502	0.16
		Projection	0.020	1.97	0.023	2.12
	One month	RMSE	0.985	-0.56	0.976	-0.52
		Sign	0.594	6.02	0.594	6.02
		Projection	0.087	3.09	0.143	4.32

regression:

$$s_{t+\tau} - s_t = \theta_0 + \theta_B \left(\widehat{s_{t+\tau} - s_t}\big|_t^B \right) + \theta_P \left(\widehat{s_{t+\tau} - s_t}\big|_t^P \right) + \varepsilon_{t+1}, \tag{7}$$

where B and P refers to Bank-specific forecast and Public information forecast respectively. If both θ_B and θ_P is significantly different from zero a combination of forecasts are desirable.

For the Diebold-Mariano test we create the difference of squared forecast errors and difference of absolute forecast errors. We test if these differences are significant and report the Newey-West t-statistic. If the t-statistic is larger than 1.8 it suggest that the Public Information model is the preferred one, while a similar negative value suggest the opposite.

A rough inspection of the results from the encompassing tests leads us to conclude that they are equally often significantly different from zero. This is confirmed from Table 6, although we see that the two public information models that combine information, models 4 and 5, are selected more often than the bank-specific models. The results from the Diebold-Mariano test indicate that we rarely can reject either of the models. However, the t-statistics are negative on a majority of the cases indicating the bank-specific forecasts have slightly lower MSEs and MAEs. However, when we focus on the models of the two apparently best banks, Bank B and D, in Table 7 we see that they perform at least as well as the public models.

We interpret this evidence as a support that (a) end-user order flow can be useful in forecasting, and (b) that end-user order flow represents complementary information to public information. One can potentially obtain superior forecasts by combining the two.

5 Cointegration

In order to further check for information content in order flow we use the maximum likelihood cointegration test of Johansen (1995). So far we have shown that end-user order flow may be important in forecasting but to be sure that this is really due aggregation of dispersed information, we wish to confirm that there exist a long-run relationship between the exchange rate and end-user order flow. If order flow contains price relevant information its impact on prices should not be transitory. Notice that due to low transparency of the market, and strategic trading on behalf of the banks receiving end-user order flow, it may very well be that end-user flow only influence the exchange rate in the medium and long-run. Cointegration between exchange rates and order flow have previously been shown by Killeen et al. (2006) for interbank flows, and by Bjønnes et al. (2005) for end-user flows.

The model of Evans and Lyons (2002) serves as a motivation for our cointegration approach. In their model the coefficient on order flow vary with the uncertainty of the market. If there is high uncertainty in the market there is more need to aggregate information, hence order flow becomes more important. If there is little uncertainty, cointegration may either break down (as shown by Killeen et al. (2006)), or the impact may be weaker. As seen from Table 3 this may be an issue in the current sample as

Table 4: Forecast comparison, Bank-specific vs. Public model (1)-(3). Whole sample, 2001-2004

			Encompassing					
			Bank model		Public model		Diebold-Mariano	
Public	Bank	Horizon	Coeff.	*t*-value	Coeff.	*t*-value	MSE	MAE
(1) Interest rates	Bank A	One day	1.16	5.44	1.47	4.88	-0.78	-0.37
		One week	0.76	2.53	0.46	1.07	-0.36	-0.58
		One month	0.43	2.68	0.27	0.92	-0.17	-0.27
	Bank B	One day	0.93	4.35	1.26	3.87	-0.86	0.12
		One week	0.82	2.94	0.49	1.21	-0.56	-1.22
		One month	0.48	2.99	0.35	1.43	-0.19	0.01
	Bank C	One day	0.33	0.95	1.63	5.20	1.54	1.26
		One week	0.51	2.87	0.68	1.76	0.48	0.60
		One month	0.46	4.21	0.45	2.10	0.48	1.16
	Bank D	One day	1.06	3.65	1.13	3.41	-1.04	-0.66
		One week	0.73	3.60	0.41	1.09	-1.11	-0.70
		One month	0.54	3.15	0.34	1.41	-0.42	-1.10
	Bank E	One day	0.59	3.22	1.36	4.55	0.69	0.42
		One week	0.65	1.78	0.54	1.37	0.16	0.22
		One month	0.58	2.94	0.46	1.88	-0.13	0.33
(2) FX return	Bank A	One day	1.13	5.09	1.38	3.81	-1.50	-1.05
		One week	0.69	2.17	1.09	2.95	0.28	0.15
		One month	0.42	2.37	0.62	1.84	0.01	-0.83
	Bank B	One day	0.99	4.89	1.18	3.41	-1.55	-0.40
		One week	0.67	2.11	0.86	2.21	-0.15	-0.72
		One month	0.47	2.80	0.65	2.48	-0.07	-0.61
	Bank C	One day	0.36	0.96	1.57	4.69	1.38	1.10
		One week	0.53	3.26	1.28	3.48	1.15	1.41
		One month	0.47	4.52	0.81	3.19	0.63	0.97
	Bank D	One day	1.14	4.45	1.04	3.30	-1.92	-1.35
		One week	0.64	2.76	0.89	2.49	-0.57	-0.06
		One month	0.55	4.05	0.68	2.53	-0.47	-1.72
	Bank E	One day	0.64	3.68	1.17	3.26	-0.12	-0.51
		One week	0.51	1.08	1.15	3.07	0.96	1.28
		One month	0.46	1.80	0.65	1.85	-0.06	-0.24
(3) Equity return	Bank A	One day	1.16	5.35	1.04	2.35	-2.01	-0.99
		One week	0.82	2.48	0.43	0.90	-0.90	-1.30
		One month	0.46	3.42	0.33	0.96	-0.52	-0.91
	Bank B	One day	1.02	4.79	0.94	2.26	-1.57	-0.23
		One week	0.85	2.90	0.55	1.23	-0.85	-1.77
		One month	0.49	2.80	0.43	1.29	-0.32	-0.55
	Bank C	One day	0.13	0.29	1.29	3.29	1.25	1.24
		One week	0.47	2.89	0.67	1.46	0.35	0.35
		One month	0.46	4.07	0.55	1.78	0.43	1.05
	Bank D	One day	1.18	4.18	0.82	1.98	-1.73	-1.04
		One week	0.76	3.50	0.26	0.62	-1.42	-1.16
		One month	0.57	3.67	0.57	1.92	-0.52	-1.52
	Bank E	One day	0.63	2.90	0.84	1.98	-0.40	-0.20
		One week	0.69	1.73	0.52	1.24	-0.39	-0.43
		One month	0.51	2.15	0.45	1.21	-0.45	-0.15

Table 5: Forecast comparison, Bank-specific vs. Public model (4)-(5). Whole sample, 2001-2004

			Encompassing					
			Bank model		Public model		Diebold-Mariano	
Public	Bank	Horizon	Coeff.	t-value	Coeff.	t-value	MSE	MAE
(4) Interest rates and FX return	Bank A	One day	1.15	5.32	1.43	5.00	-0.12	0.03
		One week	0.59	1.91	0.81	2.41	0.75	0.61
		One month	0.30	1.66	0.47	2.08	0.42	0.26
	Bank B	One day	0.91	4.24	1.22	4.11	-0.26	0.47
		One week	0.66	2.24	0.72	2.09	0.34	-0.07
		One month	0.42	2.73	0.47	2.62	0.28	0.42
	Bank C	One day	0.43	1.24	1.53	5.04	1.74	1.46
		One week	0.54	3.18	0.96	3.01	1.21	1.49
		One month	0.49	4.73	0.62	3.98	0.73	1.34
	Bank D	One day	1.03	3.58	1.13	3.84	-0.41	-0.19
		One week	0.62	3.04	0.71	2.31	-0.11	0.40
		One month	0.51	3.15	0.44	2.34	-0.19	-0.79
	Bank E	One day	0.62	3.64	1.35	4.64	1.03	0.68
		One week	0.38	0.96	0.88	2.69	1.33	1.52
		One month	0.47	2.19	0.53	2.66	0.32	0.75
(5) Interest rates and equity return	Bank A	One day	1.16	5.50	1.39	4.36	-0.46	0.08
		One week	0.69	2.12	0.52	1.69	-0.07	-0.48
		One month	0.34	2.03	0.35	1.30	-0.01	0.08
	Bank B	One day	0.91	4.24	1.20	3.78	-0.38	0.65
		One week	0.82	2.85	0.58	2.08	-0.30	-0.99
		One month	0.44	2.73	0.38	1.74	-0.09	0.27
	Bank C	One day	0.20	0.51	1.49	4.91	1.75	1.63
		One week	0.47	2.83	0.66	2.33	0.67	0.66
		One month	0.45	4.06	0.46	2.35	0.50	1.28
	Bank D	One day	1.04	3.52	1.13	3.43	-0.51	0.08
		One week	0.69	3.49	0.46	1.78	-0.92	-0.63
		One month	0.52	2.88	0.36	1.61	-0.35	-0.89
	Bank E	One day	0.51	2.83	1.29	4.11	1.09	0.86
		One week	0.53	1.40	0.59	2.17	0.46	0.38
		One month	0.52	2.54	0.46	2.08	-0.03	0.58

Table 6: Forecast comparison: Summary of number of significant cases over all banks and samples

	Encompassing		Diebold-Mariano			
			Bank-specific		Public	
	Bank-specific	Public	MSE	MAE	MSE	MAE
Dir vs. Int.rates	63	41	8	4	2	2
OF vs. Int.rates	62	42	2	1	0	1
Dir vs. FX return	63	59	8	8	1	0
OF vs. FX return	60	58	4	8	0	1
Dir vs. Equity return	65	40	8	9	0	2
OF vs. Equity return	62	41	7	4	0	1
Dir vs. Int.rate and FX	55	67	1	1	4	3
OF vs. Int.rate and FX	58	69	1	0	2	3
Dir vs. Int.rate and equity	59	58	1	0	4	4
OF vs. Int.rate and equity	59	65	0	0	1	3
Number of cases			75			

Table 7: Forecast comparison: Summary of number of significant cases over all banks and samples

	Encompassing		Diebold-Mariano			
			Bank-specific		Public	
	Bank specific	Public	MSE	MAE	MSE	MAE
(*a*) Bank B						
Dir vs Int.rates	15	7	4	2	0	0
OF vs Int.rates	14	7	1	0	0	0
Dir vs FX returns	15	0	10	0	0	0
OF vs FX returns	14	0	11	0	0	0
Dir vs Equity returns	15	7	3	5	0	0
OF vs Equity returns	15	6	3	2	0	0
Dir vs Intrates and FX	15	13	1	1	0	0
OF vs Intrates and FX	13	13	0	0	0	0
Dir vs Intrate and equity	15	12	1	0	0	0
OF vs Intrate and equity	14	13	0	0	0	0
(*b*) Bank D						
Dir vs Int.rates	13	7	2	1	0	0
OF vs Int.rates	14	7	0	0	0	0
Dir vs FX returns	13	11	4	3	0	0
OF vs FX returns	13	11	1	2	0	0
Dir vs Equity returns	14	8	2	2	0	0
OF vs Equity returns	13	10	1	1	0	0
Dir vs Intrates and FX	13	13	0	0	0	0
OF vs Intrates and FX	11	14	0	0	1	0
Dir vs Intrate and equity	14	10	0	0	0	0
OF vs Intrate and equity	12	13	0	0	0	0
Cases		15 for each bank				

volatility, a possible proxy for uncertainty, decreased substantially after 2002. We correct for this by weighting each order flow observation by a variable measuring the ratio of current volatility to the average volatility.

The results fore Corporate customers are presented in Table 8. See Table 12 in the appendix for the Trace-statistics, and Table 13 for results on cointegration of Financial flows .

Table 8: Cointegration of exchange rate and cumulative Corporate customer order flow

Cointegration

$$SEKEUR_{t-1} = \underset{(93.74)}{8.71} + \underset{(4.55)}{0.61} \cdot Spread_{t-1} + \underset{(5.29)}{0.007} \cdot \sum_0^{t-1} OF$$

VEqM

	Δ(SEKEUR)	Δ(SPREAD-DIFF)	Δ(Cum.Agg.Corp)
CointEq1	-0.0212	0.0192	2.3026
	[-3.37]	[2.73]	[2.44]
Δ(SEKEUR(-1))	0.0373	0.0353	-7.1371
	[1.19]	[1.01]	[-1.51]
Δ(SEKEUR(-2))	-0.0201	0.0146	2.6006
	[-0.64]	[0.42]	[0.55]
Δ(SPREAD-DIFF(-1))	0.0147	-0.3178	-0.7892
	[0.53]	[-10.18]	[-0.188]
Δ(SPREAD-DIFF(-2))	-0.0015	-0.1174	6.9194
	[-0.06]	[-3.76]	[1.65]
Δ(Cum.Agg.Corp)(-1)	-0.0001	0.0000	-0.0058
	[-0.50]	[0.19]	[-0.18]
Δ(Cum.Agg.Corp)(-2)	-0.0001	0.0002	0.0101
	[-0.70]	[0.94]	[0.32]
Adj. R2	0.007	0.097	0.006
Obs	1022		

6 Conclusion

The recent success of the microstructure approach to foreign exchange markets suggest that the assumption of standard macroeconomic models that all market participants can be modeled as having the same expectation is too strong. The FX microstructure literature argue that market participants have heterogeneous expectations due to differences in information set. Such differences can arise from the proprietary trading flows banks enjoy with their end-users. These flows are private information in the sense that they are not observed by others than the parties of the transaction. Several empirical studies have shown that order flows, transactions signed according to the action of the liquidity-consuming party, have a strong and lasting impact on exchange rates. This is consistent with a view that order flow is a vehicle for aggregating the heterogeneous information sets in the market. Furthermore, these results are inconsistent with a view that the market is characterized by homogeneous expectations. In such a world, actual transaction should have only minuscule effects, if any at all.

The view that heterogeneous expectations can be important in a market such as the foreign exchange market has, however, received some opposition. The typical argument is that foreign exchange rates are determined by macroeconomic factors that are equally well observed by all market participants. In this paper we meet this skepticism about private information in the foreign exchange rate market by studying the forecast power of the end-user flows of five major banks in the spot SEK/EUR market over the period 2001 to 2004. These end-user transactions are private in the sense that others do not observe them. As such they can not be instantaneously reflected in the exchange rate. If they contain price-relevant information it should be possible to forecast with them because this information should be reflected in the price some time down the road.

Our bank-specific out-of-sample forecast based on these end-user flows do reasonably well on several tests. This in itself suggest that there may exist private information in the foreign exchange market. Our forecasts are based on simple, non-optimal, models, and do not make any claims to the profitability of these forecasts.

The argument of the skeptics mentioned above miss an important point, namely that most macroeconomic factors are not observed until they have almost lost their relevance due to the long lags in publishing. The microstructure approach takes the view that in the mean time market makers simply have to aggregate information in order to quote regret-free prices. One of the few sources of macro-relevant information available outside of macro-announcements are the actions of the agents that together make up the macro-aggregate. Hence, producers' and consumers'transactions with banks give banks micro-signals on macro-events. As such they have a piece of the puzzle, but not the whole picture. The relevant micro-information is dispersed among the market participants. The private information of each bank is not of the insider type suggested by the equity market literature, but rather reflecting different information set. As such it is to be expected that such simple bank-specific forecasts not necessarily outperfom the forecasts of public information models, but rather complements them.

In comparison of public information based forecasts and bank-specific forecasts the bank-specific forecast do slightly better than the public information forecast, but we can not reject that a combination of forecasts are desirable. This is consistent with the hypothesis that private information is of the dispersed type, but inconsistent with views that these end-user order flow do not constitute private price-relevant information.

Since it may take time for exchange rates to reflect private information we investigate the price-relevance of the end-user flow by aggregating them across banks, and analyzing the potential long-run relationship between exchange rate level and cumulative end-user order flows in a cointegration framework.

Together we believe the results in this paper support the view that the foreign exchange market is characterized by heterogeneous information, and that an important source of such information is the end-user order flows of banks. The ability to detect this is a function of the extremely high quality of our data, covering several banks, and thereby a large part of the market, over a relatively long period.

A Forecasting results

Table 9: Public information models. Each year, 2001-2004

			(1) Interest rates		(2) FX return		(3) Equity return		(4) 1 & 2		(5) 1 & 3	
Sample	Horizon	Test	Stat.	*t*-test	Stat.	*t*-test	Stat.	*t*-test	Stat.	*t*-test	Stat.	*t*-test
2001	One day	RMSE	0.981	-2.50	1.189	0.94	1.215	0.97	0.979	-2.34	0.982	-2.25
		Sign	0.577	2.47	0.538	1.20	0.526	0.82	0.554	1.72	0.574	2.36
		Projection	0.029	2.89	0.011	1.14	0.007	0.69	0.038	3.05	0.034	2.87
	One week	RMSE	0.981	-0.67	1.000	-0.27	1.002	-0.17	0.976	-1.13	0.974	-1.15
		Sign	0.542	1.35	0.585	2.73	0.565	2.08	0.593	2.96	0.535	1.12
		Projection	0.045	1.76	0.030	2.27	0.026	1.91	0.061	2.55	0.064	2.38
	One month	RMSE	0.945	-0.69	1.043	0.13	1.063	0.31	0.962	-0.83	0.974	-0.58
		Sign	0.608	3.45	0.667	5.33	0.630	4.15	0.626	4.04	0.631	4.19
		Projection	0.117	2.25	0.048	1.05	0.039	0.97	0.159	4.95	0.171	2.79
2002	One day	RMSE	0.987	-2.48	0.984	-2.11	0.985	-1.45	0.977	-2.36	0.979	-1.88
		Sign	0.512	0.38	0.547	1.51	0.524	0.76	0.553	1.71	0.545	1.45
		Projection	0.020	2.86	0.025	2.46	0.031	2.49	0.036	2.64	0.038	3.01
	One week	RMSE	0.976	0.02	0.978	0.08	0.982	0.21	0.962	0.11	0.970	0.37
		Sign	0.512	0.38	0.539	1.26	0.500	0.00	0.577	2.47	0.542	1.33
		Projection	0.090	1.57	0.066	1.57	0.062	1.39	0.061	1.84	0.057	1.56
	One month	RMSE	0.929	-0.55	0.928	-0.86	0.974	-0.29	0.856	-1.21	0.924	-0.57
		Sign	0.480	-0.65	0.614	3.65	0.594	3.02	0.603	3.30	0.538	1.23
		Projection	0.318	3.52	0.193	3.43	0.127	2.65	0.428	5.65	0.312	3.48
2003	One day	RMSE	0.985	-1.94	0.988	-2.21	0.981	-1.91	0.978	-2.35	0.972	-2.35
		Sign	0.510	0.32	0.565	2.08	0.605	3.35	0.528	0.89	0.583	2.66
		Projection	0.028	3.25	0.024	2.49	0.037	2.84	0.043	3.28	0.055	3.60
	One week	RMSE	0.985	-0.73	0.970	-1.38	0.985	-1.27	0.963	-1.37	0.977	-1.01
		Sign	0.545	1.45	0.534	1.07	0.581	2.59	0.567	2.15	0.560	1.90
		Projection	0.060	1.84	0.070	2.26	0.040	1.82	0.088	2.67	0.066	2.10
	One month	RMSE	0.969	-0.73	0.932	-1.48	0.935	-1.98	0.897	-2.54	0.922	-1.86
		Sign	0.571	2.26	0.660	5.11	0.668	5.36	0.703	6.49	0.695	6.23
		Projection	0.101	2.46	0.228	4.86	0.151	3.44	0.272	5.34	0.170	3.45
2004	One day	RMSE	0.981	-1.84	0.983	-1.72	0.979	-1.62	0.974	-1.81	0.971	-1.84
		Sign	0.535	1.12	0.558	1.87	0.578	2.50	0.541	1.32	0.553	1.69
		Projection	0.039	2.80	0.031	2.76	0.035	2.46	0.047	3.00	0.050	2.90
	One week	RMSE	0.968	-1.17	0.939	-1.63	0.979	-0.80	0.904	-2.11	0.949	-1.56
		Sign	0.550	1.62	0.663	5.25	0.620	3.87	0.654	4.96	0.580	2.57
		Projection	0.090	2.57	0.189	4.68	0.089	2.88	0.236	4.65	0.159	3.53
	One month	RMSE	0.879	-1.51	0.990	-0.12	0.990	-0.13	0.826	-2.02	0.872	-1.56
		Sign	0.641	4.56	0.558	1.87	0.527	0.87	0.648	4.77	0.640	4.51
		Projection	0.489	4.85	0.268	3.82	0.235	3.33	0.483	5.05	0.424	4.18

Table 10: Bank-specific models (Direction of order flow). Each year, 2001-2004

			Bank A		Bank B		Bank C		Bank D		Bank E	
Sample	Horizon	Test	Stat	*t*-test	Stat	*t*-test	Stat	*t*-test	Stat	*t*-test	Stat	*t*-test
2001	One day	RMSE	0.991	-2.27	0.972	-3.39	1.015	0.88	0.974	-2.62	0.985	-1.72
		Sign	0.570	2.23	0.629	4.14	0.550	1.59	0.554	1.72	0.560	1.90
		Projection	0.025	2.56	0.045	3.98	-0.001	-0.06	0.046	3.15	0.041	2.47
	One week	RMSE	0.999	-1.02	0.964	-1.46	0.994	-0.89	0.963	-1.54	0.987	-0.99
		Sign	0.571	2.27	0.613	3.62	0.547	1.51	0.663	5.20	0.541	1.31
		Projection	0.024	2.35	0.076	3.39	0.054	1.93	0.082	3.33	0.031	2.42
	One month	RMSE	0.951	-1.01	0.825	-2.69	0.872	-1.54	0.836	-2.26	0.947	-1.54
		Sign	0.664	5.23	0.756	8.19	0.612	3.59	0.803	9.69	0.654	4.93
		Projection	0.126	2.70	0.328	5.08	0.441	3.94	0.410	5.26	0.126	3.00
2002	One day	RMSE	0.976	-2.39	0.974	-2.70	1.001	-0.09	0.972	-2.54	0.976	-2.93
		Sign	0.561	1.96	0.579	2.54	0.526	0.82	0.575	2.41	0.549	1.58
		Projection	0.048	3.82	0.046	3.01	0.029	1.55	0.058	3.34	0.040	3.64
	One week	RMSE	0.969	0.37	0.964	0.23	1.238	1.32	0.969	0.48	0.951	-0.23
		Sign	0.592	2.94	0.575	2.41	0.508	0.25	0.587	2.79	0.553	1.71
		Projection	0.043	1.95	0.056	2.21	0.039	0.78	0.038	1.54	0.086	2.68
	One month	RMSE	0.975	0.23	0.790	-2.18	1.127	0.99	0.938	-0.72	0.908	-0.96
		Sign	0.621	3.88	0.786	9.14	0.667	5.33	0.694	6.22	0.660	5.12
		Projection	0.104	1.91	0.461	5.21	0.411	3.34	0.196	3.00	0.255	3.12
2003	One day	RMSE	0.982	-2.40	0.982	-1.95	1.016	0.71	0.981	-2.21	0.978	-2.35
		Sign	0.552	1.65	0.546	1.48	0.532	1.01	0.582	2.61	0.544	1.39
		Projection	0.033	2.96	0.043	2.92	0.002	0.18	0.042	2.87	0.044	3.14
	One week	RMSE	0.961	-1.77	0.954	-1.70	1.008	0.19	0.973	-0.95	0.976	-0.81
		Sign	0.567	2.15	0.586	2.74	0.512	0.38	0.538	1.21	0.579	2.53
		Projection	0.089	2.69	0.084	2.77	0.113	2.25	0.067	2.01	0.099	2.37
	One month	RMSE	0.953	-1.11	0.772	-2.31	0.952	-1.18	0.882	-1.94	0.874	-1.74
		Sign	0.615	3.68	0.737	7.57	0.623	3.93	0.673	5.53	0.758	8.24
		Projection	0.149	3.04	0.469	8.16	0.168	2.74	0.295	5.18	0.453	5.00
2004	One day	RMSE	0.973	-2.69	0.973	-2.06	0.987	-0.74	0.965	-1.81	0.976	-2.07
		Sign	0.537	1.19	0.563	2.03	0.518	0.56	0.531	1.01	0.576	2.45
		Projection	0.039	3.40	0.051	3.21	0.040	2.73	0.076	3.29	0.038	3.09
	One week	RMSE	0.928	-1.49	0.916	-1.72	0.963	-1.36	0.932	-1.92	0.952	-1.96
		Sign	0.611	3.58	0.656	5.04	0.584	2.70	0.605	3.40	0.619	3.83
		Projection	0.184	3.49	0.274	6.00	0.159	2.74	0.178	4.02	0.109	3.29
	One month	RMSE	0.785	-2.22	0.912	-0.96	1.119	1.88	0.939	-0.71	0.949	-0.61
		Sign	0.732	7.47	0.695	6.30	0.545	1.44	0.660	5.16	0.541	1.32
		Projection	0.640	8.76	0.331	4.06	0.455	2.25	0.345	4.07	0.294	3.37

Table 11: Bank-specific models (Volume of order flow). Each year, 2001-2004

			Bank A		Bank B		Bank C		Bank D		Bank E	
Sample	Horizon	Test	Stat	t-test	Stat	t-test	Stat	t-test	Stat	t-test	Stat	t-test
2001	One day	RMSE	0.992	-2.52	0.975	-3.41	1.048	0.90	0.978	-2.38	0.981	-2.45
		Sign	0.582	2.62	0.602	3.25	0.562	1.98	0.558	1.85	0.575	2.41
		Projection	0.023	2.86	0.045	3.07	0.015	1.98	0.043	3.30	0.031	3.57
	One week	RMSE	1.000	-1.01	0.961	-1.53	0.986	-1.10	0.968	-1.39	0.973	-1.84
		Sign	0.550	1.60	0.588	2.83	0.547	1.51	0.613	3.62	0.578	2.49
		Projection	0.019	2.13	0.078	3.38	0.068	1.95	0.085	3.03	0.047	3.24
	One month	RMSE	0.991	-0.46	0.924	-1.48	3.044	0.95	0.963	-0.88	0.905	-1.21
		Sign	0.673	5.53	0.695	6.23	0.710	6.73	0.690	6.08	0.710	6.73
		Projection	0.137	2.16	0.172	4.03	0.450	2.56	0.159	3.04	0.258	4.13
2002	One day	RMSE	0.984	-2.20	0.973	-1.68	0.996	-0.45	0.981	-1.55	0.968	-2.92
		Sign	0.545	1.45	0.548	1.52	0.534	1.08	0.520	0.63	0.518	0.57
		Projection	0.031	2.47	0.075	2.20	0.024	1.80	0.047	1.99	0.056	4.21
	One week	RMSE	0.958	-0.07	0.955	-0.09	1.151	1.44	0.963	0.23	0.946	-0.43
		Sign	0.560	1.92	0.504	0.13	0.560	1.90	0.532	1.02	0.593	2.97
		Projection	0.091	2.23	0.058	2.46	0.086	1.71	0.039	1.77	0.096	3.32
	One month	RMSE	0.980	0.40	0.922	-1.15	1.027	0.38	0.899	-0.91	0.941	-0.84
		Sign	0.596	3.06	0.667	5.33	0.710	6.73	0.750	8.00	0.672	5.50
		Projection	0.110	3.21	0.183	2.59	0.770	6.09	0.307	2.81	0.202	3.22
2003	One day	RMSE	0.984	-1.87	0.983	-2.54	1.020	0.77	0.985	-2.03	0.985	-1.78
		Sign	0.544	1.39	0.544	1.41	0.524	0.76	0.578	2.48	0.540	1.27
		Projection	0.036	2.44	0.033	3.39	0.017	1.85	0.042	2.42	0.031	2.39
	One week	RMSE	0.974	-1.31	0.968	-1.34	0.969	-1.22	0.959	-1.02	0.949	-1.49
		Sign	0.496	-0.13	0.566	2.10	0.512	0.38	0.610	3.50	0.647	4.69
		Projection	0.057	2.22	0.066	1.96	0.103	2.10	0.098	2.27	0.116	3.25
	One month	RMSE	0.889	-1.99	0.875	-2.29	0.963	-0.87	0.979	-0.67	0.974	-0.63
		Sign	0.667	5.32	0.594	2.99	0.623	3.93	0.558	1.84	0.619	3.80
		Projection	0.267	4.41	0.241	5.15	0.187	3.14	0.166	2.78	0.128	2.86
2004	One day	RMSE	0.969	-2.25	0.976	-2.20	2.427	1.00	0.951	-2.47	0.964	-2.87
		Sign	0.537	1.19	0.523	0.76	0.506	0.19	0.566	2.14	0.584	2.70
		Projection	0.044	2.52	0.040	2.78	-0.078	-0.73	0.082	3.17	0.063	3.32
	One week	RMSE	0.922	-1.53	0.967	-0.97	1.158	0.90	0.954	-1.53	0.966	-1.24
		Sign	0.603	3.33	0.559	1.89	0.584	2.70	0.645	4.66	0.568	2.20
		Projection	0.224	3.38	0.150	3.29	0.203	2.13	0.171	3.84	0.133	2.78
	One month	RMSE	0.952	-0.47	0.899	-1.19	1.872	1.08	0.859	-1.70	0.934	-0.81
		Sign	0.658	5.08	0.645	4.66	0.580	2.57	0.707	6.68	0.642	4.58
		Projection	0.528	5.12	0.352	3.89	-0.037	-0.13	0.417	6.32	0.316	5.14

B Cointegration results

Table 12: Cointegration test: Corporate customers

	Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value 0.05	Prob.
No deterministic trend	None	0.0167	19.77	24.28	0.17
	At most 1	0.0025	2.53	12.32	0.90
	At most 2	0.0000	0.00	4.13	0.99
No trend, constant in CE	None *	0.0260	40.26	35.19	0.01
	At most 1	0.0106	13.37	20.26	0.33
	At most 2	0.0025	2.53	9.16	0.67
Constant in VAR (linear deterministic trend)	None *	0.0259	40.11	29.80	0.00
	At most 1	0.0105	13.26	15.49	0.11
	At most 2	0.0024	2.43	3.84	0.12
Trend in CE, constant in VAR	None *	0.0361	62.41	42.92	0.00
	At most 1	0.0166	24.83	25.87	0.07
	At most 2	0.0075	7.68	12.52	0.28
Trend in CE, constant and trend in VAR	None *	0.0361	54.91	35.01	0.00
	At most 1	0.0154	17.34	18.40	0.07
	At most 2	0.0015	1.51	3.84	0.22

Table 13: Cointegration of exchange rate and cumulative financial customer order flow

Cointegraion			
SEKEUR(-1)	1		
SPREAD-DIFF(-1)	-0.1503		
	[-1.46]		
Cum.Agg.Fin	-0.0023		
	[-3.09]		
C	-8.8450		
	[-78.57]		
VEqM			
	D(SEKEUR)	D(SPREAD-DIFF)	D(Cum.Agg.Fin)
CointEq1	-0.0225	0.0107	2.8378
	[-3.41]	[1.45]	[2.06]
D(SEKEUR(-1))	0.0409	0.0423	-17.7407
	[1.30]	[1.20]	[-2.71]
D(SEKEUR(-2))	-0.0175	0.0253	-14.7316
	[-0.55]	[0.72]	[-2.24]
D(Cum.Agg.Fin)(-1)	0.0001	0.0004	-0.0231
	[0.68]	[2.42]	[-0.74]
D(Cum.Agg.Fin)(-2)	-0.0002	0.0001	0.0021
	[-1.07]	[0.77]	[0.07]
D(SPREAD-DIFF(-1))	0.0215	-0.3236	0.9698
	[0.77]	[-10.38]	[0.17]
D(SPREAD-DIFF(-2))	0.0023	-0.1211	1.2900
	[0.08]	[-3.89]	[0.22]
Adj. R-squared	0.0091	0.0971	0.0089

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