Microstructure Order Flow: Statistical and Economic Evaluation of Nonlinear Forecasts

Mario Cerrato*, Hyunsok Kim*[1] and Ronald MacDonald*
University of Glasgow, Department of Economics, Adam Smith building.

April 17, 2014

[1]Corresponding author: Hyunsok Kim (E-mail: hyunsok.kim@pusan.ac.kr) Busan National University, Department of Economics; Mario Cerrato (E-mail: m.cerrato@lbss.gla.ac.uk) and Ronald MacDonald (E-mail: r.macdonald@lbss.gla.ac.uk) University of Glasgow, Department of Economics, Adam Smith building.

Abstract

In this paper we propose a novel extension of the standard market microstructure order flow model by incorporating non-linearities into the order flow - exchange rate relationship. This important issue has not been accounted for in the existing empirical literature. We investigate this issue using a new data set and focusing on out-of-sample forecasts. Forecasting power is measured using standard statistical tests and, additionally, using an alternative approach based on measuring the economic value of forecasts after building a portfolio of assets. While there is little statistical value in conditioning on our proposed models, its economic value is significantly high.

JEL Classification:F31; F41; G10

Keywords: microstructure, order flow, forecasting

1 Introduction

There is something of a consensus in the exchange rate literature that macro based models of the exchange rate fail to outperform a simple random walk model in an out-of- sample forecasting context (see, for example, Meese and Rogoff, 2002). Given this, many researchers have turned to a market microstructure approach to provide alternative insights into the forecasting behavior of exchange rates. For example, Evans and Lyons (2002b), Evans and Lyons (2005b) and Sager and Taylor (2008) use such an approach and provide mixed evidence that microstructure models (i.e. order flow models) can do better than a simple random walk in out-of-sample forecasts. The main conclusion of Evans and Lyons (2002b) is that order flow is a significant determinant of exchange rates and can also be used to forecast exchange rates out-of-sample. However, Sager and Taylor (2008) find little empirical evidence supporting these conclusions after employing interdealer and commercially available order flow data. This strand of the literature assumes that market participants discover information gradually (i.e. by trading in the market).

However, the strength of the relationship between order flow and exchange rates may also be dependent upon prevailing market conditions or the announcement of macroeconomic news - see for example, Love and Payne (2003). Bacchetta and Wincoop (2006),Rime et al. (2010) and many others. If this is correct then it may be that the relationship between exchange rate returns and order flow is a nonlinear type of relationship and therefore the constrasting results cited above may be due to a wrong empirical model.

For example, Bacchetta and Wincoop (2006) and Rime et al. (2010) stress the importance of information heterogeneity in the FX market. Such information are then aggregated through trading activity. The presence of asymmetric information and the liquidity imbalance in the market can generate nonlinearities (for example, we report empirical evidence suggesting that price reversal is an important issue in the foreign exchange market and consequently the relationship between exchange rate returns and order flow is likely to be nonlinear). Also the time of the release of the information and/or the quality of the information can produce nonlinearities (see Andersen et al. (2003)). These are important issues that, with a very few exceptions, have been neglected in the literature. Therefore, the modeling approach proposed in this paper is an important contribution.

In order to capture non-linearities in a microstructure framework, we suggest two novel models. The first model considers time varying parameters and the smooth transition model. We then evaluate the statistical and economic performance of our models by comparing them with a simple Random Walk and show that there is a higher economic and statistical value by conditioning on our models. This is an important result.

In addition to the contribution cited earlier, we also use a unique dataset of customer order flow obtained from UBS in London. Although our order flow data is not available to all market participants, we still believe it is very important to analyse its forecasting power.

The remainder of this paper is organized as follows. In the next section, we provide a brief literature review. Section 3 describes the link between order flow and exchange rates and our statistical evaluation methods. The forecasting setup and the investor's asset allocation problem are described in Section 4, and the results on the statistical and economic evaluation of the forecasting models that condition on order flow are reported in Section 5. The final section concludes the paper and recommends further research.

2 A brief review of exchange rate predictability issues from a microstructure perspective.

Microstructure models view order flow as a random variable which maps heterogeneous disperse information into price discovery. Thus, relative to macro based exchange rate models, order flow in the microstructural approach represents the missing link between exchange rate changes and changes in economic conditions. Consider the following (contemporaneous) order flow model,

$$\Delta s_t = \beta_1 \Delta(i_t - i_t^*) + \beta_2 X_t + \varepsilon_t \tag{1}$$

where $\Delta s_t = s_{t-1} - s_t$, with s being the logarithm of the nominal exchange rate, i and i^* are the domestic and foreign interest rates, X_t the order flow at time t, and ε_t is a white noise term.

Using the above model, Evans and Lyons (2002b) report significant explanatory power when the mark–dollar and the yen–dollar exchange rates are considered. The empirical analysis of Evans and Lyons (2002a) is extended to an additional seven exchange rates and they report explanatory power ranging from 0.00% to 68%. They also report a high out of sample power of the order flow model when compared to a simple random walk model. Killeen et al. (2006) also reports significant explanatory power of the order flow model which is consistent with the results of Evans and Lyons (2002b). Following the earlier cited studies, a number of empirical studies have confirmed a contemporaneous explanatory role for order flow in exchange rate models.

Recently Sager and Taylor (2008) investigate this issue further in a large empirical study and suggest a modification of model (1) above, the so called "publication lag" model, to take into account that public information may be impounded in prices with a delay:

$$\Delta s_t = \beta_1 \Delta(i_{t-1} - i_{t-1}^*) + \beta_2 X_{t-1} + \varepsilon_t, \tag{2}$$

They show that the (lagged) order flow model has very little (in-sample and out-of-sample) explanatory power and cannot outperform a simple random walk model. This result is consistent with the empirical evidence of Engel and West (2005).

Cerrato et al. (2009) use weekly customer order flow for nine of the most liquid currencies and investigate the in-sample and out-of-sample forecasting power of the (lagged) order flow models. Although the empirical results using disaggregate data are encouraging, overall the empirical results, using also aggregate data, are in line with Sager and Taylor (2008)[1]. Thus, empirical evidence (using lagged order flow

[1]However, the in-sample results, using the contemporaneous order flow model, strongly support

model) suggests that the predictive relationship of order flow and currency returns is rather weak. In this paper we claim that this result may be mainly due to using mispecified models. Indeed, the linearity assumption in the order flow-exchange rate returns may be too restrictive for several reasons. For example, Bacchetta and Wincoop (2006) and Rime et al. (2010) stress the importance of information heterogeneity in the FX market. Heterogeneity might induce nonlinearities which are not accounted for by the standard linear models used in the literature. Additionally, the presence of asymmetric information and the liquidity imbalance in the market can also generate nonlinearities (in the next sections we shall provide a simple example of this).

Evans and Lyons (2005a), Evans and Lyons (2008), and Love and Payne (2008) have provided empirical evidence that macro news triggers trading that reveals dispersed information, which in turn affects currency prices, and a number of papers have sought to clarify the relationship between the release of economic news and order flow. Rime et al. (2010) point out that the heterogenous interpretation of macroeconomic news may lead market makers to make inferences differently and that the order flow incorporates this information gradually. The results in Rime et al. (2010) are also consistent with theoretical models as in Bacchetta and Wincoop (2006) and Evans and Lyons (2008) and suggest that one should introduce nonlinearities in the standard microstructure models which relate order flow to exchange rate returns.

The empirical literature reviewed above reports contrasting results on the usefulness of order flow to explain exchange rate returns. Furthermore, it is important to stress that none of the above studies has clearly demonstrated that order flow can be used to forecast exchange rate returns once perfect foresight is considered. We claim in this paper that the contrasting results reported in the literature are due to the presence of nonlinearities driving the relationship between exchange rate returns and order flow.

2.1 Empirical models and evaluation

The empirical literature reviewed earlier assumes a linear relationship between order flow and the exchange rate. To the best of our knowledge only two studies Luo () and Nguyen and Shin (2011) have recognized the importance of considering nonlinearities in the relation between order flow and exchange rates returns. There might be different reasons why this relationship should be nonlinear. We shall discuss these reasons in detail in this section as well as in the next sections. In this section, we start with a simple example where we claim that nonlinearities may be due to the presence of price reversal in the forex market. Therefore, we present a simple exercise to test for the presence of price reversal. Consider the following model:

$$\Delta s_t = \alpha + \beta_1 X_t + \beta_2 X_{t-1} + \varepsilon_t$$

where X is the order flow for each group and ε_t is a white noise process.

This model can be used to test for the presence of a price reversal in the market.

such a model. In effect, with weekly data, the lagged model might be too restrictive.

Price Reversal in Forex (aggregate order flows)									
	EUR	JPY	GBP	CHF	AUD	CAD	NOK	SEK	NZD
β_1	**0.0010**	**0.0041**	**0.0024**	0.0004	**0.0123**	**0.004**	**0.0157**	-0.003	**0.0435**
	(2.26)	(4.85)	(2.96)	(0.50)	(4.93)	(1.85)	(2.05)	(-0.57)	(5.63)
β_2	**-0.0011**	-0.0001	-0.0003	0.0007	-0.0014	-0.0003	-0.0028	0.0017	-0.0034
	(-2.57)	(0.09)	(-0.48)	(0.77)	(-0.56)	(-0.15)	(-0.38)	(0.31)	(0.44)
$\mathbf{R}^2$	0.04	0.06	0.02	0.01	0.06	0.01	0.05	0.00	0.08
Prob.	0.003	0.000	0.011	0.645	0.000	0.177	0.112	0.836	0.000

Table 1: Price Reversal in Forex

A price reversal implies a positive coefficient on the contemporaneous order flow variable and a negative coefficient on the lagged order flow variable. Table 1 shows the empirical results for the data used in our study (the data sets used in our study are discussed in detail in the next section).

Table (1) shows the estimates of the coefficients, β_s and adjusted R-squared across the nine different currencies used in this study. It also shows the probability value (Prob.) for an F-test for testing the restriction that the coefficients of the model are insignificant. We can see that, for seven currencies out of nine, the coefficients have the expected sign. The F-test shows joint significance of the parameters in most cases. Following Andrade et al. (2008) we interpret this as indicating the presence of price reversal in the market [2].

Apart from price reversal, the presence of nonlinearities in the order flow - exchange rate relationship may also be due to other reasons. For example, the Evans and Lyons (2002b) models are derived under the assumption of continuous market equilibrium and that the price impact of order flow is constant over time because of unchanged liquidity condition. Evans and Lyons (2002b) recognize that these assumptions may be strong on empirical grounds. Nguyen and Shin (2011) show that the price impact of trades is different depending on different market conditions and the relationship between order flow and exchange rate returns is nonlinear.

2.2 Time-varying parameter model

The first model we use allows for time varying parameters[3]. Evans and Lyons (2002b) models assume that the informativeness of the order flow is constant under different market conditions and over time and therefore one can assume that the parameters of the model do not change. However, French and Roll (1986) for the equity market and Lyons (1996) for the forex market, find empirical evidence suggesting that the informativeness of order flow changes over time. For example French and Roll (1986) find that "informative order flow arriving at the market during non-halt-Wednesday periods causes an increase in volatility over halt-Wednesday

[2] Brunnermeir et al (2009) show that exchange rate returns are induced by carry trading activity. We are aware that this is a very simple example and that investigating the relationship between price reversal and carry trading is an interesting issue, but we leave it on the agenda for the near future as it is beyond the scope of this study.

[3] Time-varying parameter models in the FX market have also been used by Berger et al (2009).

periods when there is no such order flow"[4]. Therefore, the assumption of constant model parameters implicit in the Evans and Lyons (2002b) models could be rather restrictive. In this section we propose the following time varying parameter model:

$$\Delta s_{t+k} = \alpha + \beta_t X_{t-1} + \varepsilon_{t+k}.$$

The parameters of the model are estimated in the usual way, using the first n observations. The estimates are then updated in each subsequent observation, $s_{n+1}, s_{n+2}...s_T$. The model uses a recursive filter which is very simple to implement. [5] Thus, once the tth observation becomes available, β_t may be obtained from β_{t-1} without the matrix inversion implied by OLS (ordinary least squares).

2.3 Smooth transition model

In the example in Table 1 the price impact of the order flow changes across the different groups of customers. There are customers (for example hedge funds) which possess more (relevant) information than others (see also the discussion in Cerrato et al. (2009)) and dealers learn relevant information by the way these customers trade (Kyle (1985)). The presence of asymmetric information in the market can lead to liquidity imbalance which is only eliminated gradually[6].Additionally to that, the price imact of negative (positive) order flow can be different (see Evans and Lyons (2002b))[7].

We use a smooth transition model which can better capture the dynamics between exchange rate returns and order flow described above. We propose a non-linear model where the band of inaction caused by the presence of higher asymmetric information (lower liquidity) in the market, generates slow adjustment to the equilibrium. We employ the smooth transition function, $CMK-STAR$ recently suggested by Cerrato et al. (2010)

$$\Delta s_{t+k} = \alpha + \beta S(\theta) X_{t-1} + \varepsilon_{t+k},$$

where

$$S(\theta) = [1 + \exp\{\gamma_1 (X_{t-1} - c_1)\mathbf{I}_t - \gamma_2 (X_{t-1} - c_2)(1 - \mathbf{I}_t)\}]^{-1},$$

and θ represents parameter set to be estimated. The function $S(\theta)$ allows for both threshold effects and smooth transition movements of X_{t-1}. In the central regime, when $-c < X_{t-d} < c$, $S(X_{t-d}, \theta) = 0$. In the limiting outer regimes, when $X_{t-d} < -c$ and $c < X_{t-d}$, $S(X_{t-d}, \theta) = 1$. The specification given by $S(\theta)$ allows the transition

[4] Breedon and Ranaldo (2009) show that such a variability might be induced by seasonality.

[5] Given the basic setup

$$y_t = X_t \beta_t + \varepsilon_t$$

The relevant formulae are driven by

$$\beta_t = \beta_{t-1} + \left(X'_{t-1} X_{t-1}\right)^{-1} x_t \left(y_t - X_t \beta_{t-1}\right) / f_t$$

where $f_t = 1 + x'_t \left(X'_{t-1} X_{t-1}\right)^{-1} x_t$ and $X_t = (x_1, x_2, ..., x_t)$

[6] For example in the Kyle (1985) model, traders will split large trades into smaller ones over a longer period of time.

[7] It could also be different due to different market condition. A simple example could be the case of a carry trade strategy where asymmetric patterns could arise due to buy and sell direction.

depending on X_{t-1} and captures the asymmetry induced by upside and downside market conditions. We use this model in our forecasting exercises.

2.4 Forecast evaluation

We assess the out of sample forecasts produced by the three models above in different ways. Firstly, we use the root mean squared forecast error (RMSFE):

$$RMSFE = \sqrt{\frac{\varepsilon'_{t+k}\varepsilon_{t+k}}{T}}.$$

Additionally, we also construct a test statistic for comparing the forecasting performance of the models relative to a simple random walk (RW). Given two forecasts, the RW forecast and the forecast provided by the alternative models (hereafter AM), the ratio of RMSFE against RW can be used to evaluate the out of sample forecasts. We also support this test using the Diebold and Mariano (1995) test. This test allows us to compare the forecasting accuracy of two competing models. Defining $d_t = g(\varepsilon_{1,t}) - g(\varepsilon_{2,t})$ where $g(.)t$ is a given loss function and $t = 1, ..., n$, the Diebold-Mariano test statistic is

$$DM = \frac{\bar{d}}{\left[var\left(\bar{d}\right)\right]^{\frac{1}{2}}}$$

where $\bar{d} = n^{-1}\sum_{t=1}^{n} d_t$ and $var\left(\bar{d}\right)$ represents the asymptotic (long-run) variance of $\sqrt{T}\bar{d}$.

Diebold and Mariano (1995) shows that under the null of equal predictive accuracy, $DM \sim N(0, 1)$, and we can reject the null of equal predictive accuracy at the 5% level if

$$|DM| > 1.96.$$

We use the Diebold-Mariano test to assess the out of sample forecasts of our models with respect to a simple Random Walk model RW.

3 Economic value of exchange rate predictability

Most of the previous studies in the exchange rate micorstructural literature have focused on evaluating the statistical performance rather than the economic significance of a nonlinear approach. Here we also examine the latter and specifically examine the economic value of nonlinear models to risk-averse investors. To measure the economic value of the out-of-sample forecasts, we address the issue of whether our three models can be used practically by assessing the forecasts where a portfolio of assets is rebalanced according to a trading rule at each time t.

3.1 Portfolio weights of a mean-variance framework

In order to measure the economic performance of a portfolio it is standard to use Sharpe ratios. However, as Marquering and Verbeek (2004) and Han (2006) note, Sharpe ratios can underestimate the performance of dynamically managed portfolios. This happens because Sharpe ratios are calculated using the average standard deviation of the realized returns, which overestimates the conditional risk (standard deviation) faced by an investor at each point in time. Consequently, Sharpe ratios cannot properly quantify the economic gains of a dynamic strategy.

As an alternative measure of forecasting performance, we use a mean-variance framework and calculate the performance fee to quantify the economic gain from using the exchange rate models introduced above with respect to a simple random walk model. The framework for our analysis is straightforward. We consider an investor who uses a mean-variance optimization rule to allocate funds across assets. The investor's objective is to maximize the expected return matching a target expected volatility.

Allowing for weekly rebalancing, the solution to the investor's portfolio problem is a dynamic trading strategy that specifies the optimal asset weights. Implementing this strategy requires estimates of both the conditional expected returns and the conditional covariance matrix. If the conditional expected return and covariance are constant, the optimal portfolio weights w will be constant over time. However, when the conditional expected return and covariance are defined as recursive estimates, investors will rebalance their portfolio weights and change strategies. Thus, in terms of one-step ahead forecasts, we treat the expected returns as the conditional mean, $\mu_{t+1|t} = E_t\left[r_{t+1} \mid \mathcal{F}_t\right]$, and let the variation in the portfolio weights be driven purely by changes in the conditional covariance matrix, $\sum_{t+1|t} = E_t\left[\left(r_{t+1} - \mu_{t+1|t}\right)\left(r_{t+1} - \mu_{t+1|t}\right)' \mid \mathcal{F}_t\right]$ where $\mathcal{F}_t$ represents the current information set.

To maximize the conditional expected return, $\mu_{t+1|t}$, subject to a given level of conditional volatility, σ_p^*, investors solve the following problem at time t,

$$\begin{gathered}\max_{w_t}\left\{\mu_{p,t+1} = w_t'\mu_{t+1|t} + \left(1 - w_t'\mathbf{1}\right) r_f\right\} \\ \text{s.t. } \left(\sigma_p^*\right)^2 = w_t' \sum\nolimits_{t+1|t} w_t\end{gathered}$$

where $\mu_{p,t+1}$ and σ_p^* denote the conditional mean and variance of the portfolio return, $r_{p,t+1}$ of risky assets. In the present setting, w_t is the portfolio weights on the risky assets, and r_f is the return on the riskless asset. Among the trading strategies such as the minimum variance and maximum return, the above mean-variance analysis solves for the weight that maximizes conditional return where the portfolio variance is equal to a fixed target.

After constructing the covariance matrix of the portfolio, we determine the weights by maximizing the conditional mean of the portfolio return. The solution to this problem yields the following risky asset weights,

$$w_t = \frac{\sigma_p^*}{\sqrt{C_t}} \sum\nolimits_{t+1|t}^{-1} \left(\mu_{t+1|t} - \mathbf{1} r_f\right)$$

where $C_t = \left(\mu_{t+1|t} - \mathbf{1}r_f\right)' \sum_{t+1|t}^{-1} \left(\mu_{t+1|t} - \mathbf{1}r_f\right)$. The optimal weights will vary across the models depending on the conditional mean and volatility. That is, the trading strategy identifies the rebalanced portfolio that optimizes maximum conditional expected return subject to the conditional variance-covariance.

In our analysis, the benchmark against which we compare the model specifications is a simple RW. In other words, our objective is to evaluate whether there is any economic value in conditioning on microstructure order flow and non-linear models and, if so, which of the four specifications including RW has superior forecasting power.

3.2 Performance measures under quadratic utility

To measure the performance of a trading strategy, using a generalization of West et al. (1993)'s method, Fleming et al. (2001) suggest comparing the performance of the dynamic strategies to that of the unconditional mean-variance efficient static strategy. The latter is based on the relation between mean-variance analysis and quadratic utility. Using a second-order approximation to the investor's true utility function, the investor's realized utility is defined as

$$U(W_{t+1}) = W_{t+1} - \frac{\lambda}{2}W_{t+1}^2 = W_t R_{p,t+1} - \frac{\lambda}{2}W_t^2 R_{p,t+1}^2,$$

where W_{t+1} is the investor's wealth at $t+1$, $R_{p,t+1}$ is the gross portfolio return, equal to $1 + r_{p,t+1}$ and λ represents absolute risk preference.

In our empirical exercise we fix the value of relative risk aversion (RRA) as δ. Given the level of initial wealth, W_0, the average realized utility is then defined as

$$\bar{U}(\cdot) = W_0 \sum_{t=0}^{T-1} \left\{ R_{p,t+1} - \frac{\delta}{2(1+\delta)} R_{p,t+1}^2 \right\},$$

where δ is constant. The average realized utility ($\bar{U}$) can be used to consistently estimate the expected utility generated at the given level of initial wealth, W_0, and value of relative risk aversion (RRA), δ. If the value of RRA is assumed to be $\delta = \{2, 6\}$ and the initial wealth is fixed at $W_0 = 1$, we can standardize the investor problem of maximum conditional expected return and assess the economic value of our FX strategies in the context of asset allocation.

To measure the economic value of our FX strategies, we use the average utility and compute the performance fee as suggested in Fleming et al. (2001). The selected pairs of portfolios, RW against alternatives are evaluated by equating the average utilities. That is, if an investor is indifferent between holding a portfolio where the optimal weights have been computed using a simple RW and an alternative portfolio using a more "sophisticated" approach, then the value of Φ can be interpreted as the performance fee that the investor would be willing to pay to switch from the RW to the alternative model, such as TVP and STAR. The performance fee, Φ, is defined as:

$$\sum_{t=0}^{T-1}\left\{\left(R_{p,t+1}^{AM}-\Phi\right)-\frac{\delta}{2\left(1+\delta\right)}\left(R_{p,t+1}^{AM}-\Phi\right)^{2}\right\}=\sum_{t=0}^{T-1}\left\{R_{p,t+1}^{RW}-\frac{\delta}{2\left(1+\delta\right)}\left(R_{p,t+1}^{RW}\right)^{2}\right\},$$

where $R_{p,t+1}^{RW}$ is the gross portfolio return obtained using forecasts from the benchmark RW model, and $R_{p,t+1}^{AM}$ is the gross portfolio return constructed using the forecasts from the alternative models. Thus, the utility-based criterion measures how much the investor is willing to pay for conditioning on order flow, as in the AM strategy, for the purpose of forecasting exchange rate returns. In the context of this maximum return dynamic strategy, we can compute both the in-sample and the out-of-sample performance fee, Φ.

3.3 Transaction costs

In the literature, transaction costs are generally assumed given and not estimated. For example, Marquering and Verbeek (2004) consider three levels of transaction costs, 0.1%, 0.5%, and 1%, representing low, medium, and high costs, respectively. Our empirical models use dynamic strategies and in this context transaction costs can play a significant role in determining returns and comparative utility gains where individuals rebalance their portfolios. Thus, instead of assuming a given cost, we follow the method introduced by Han (2006), della Corte et al. (2009) and Rime et al. (2010), and calculate the break-even transaction costs,

$$\tau\sum_{j=0}^{9}\left|w_{t}^{j}-w_{t-1}^{j}\frac{1+r_{t+1}^{j}}{R_{p,t+1}}\right|,$$

which make the investors indifferent between the dynamic and buy-and-hold strategies in terms of utility. In the present setting, the break-even transaction cost, τ, is the minimum proportional cost that cancels out the utility advantage of a given strategy.

Using the above mean-variance quadratic-utility framework, we design a global strategy consisting of an US investor holding a portfolio of 10 currencies: one domestic (United States), and nine foreign currencies. The investor is exposed to currency risk. We employ each of the 4 models to forecast the one step ahead period of the exchange rate returns. Thereafter, we dynamically rebalance our portfolio by computing the new optimal weights for the maximum return strategy conditioned on the forecasts of each model. In the analysis, the yields of the riskless bonds are proxied by the LIBOR rates.

We report the performance fees for the combinations corresponding to the following cases: (1) three sets of target annualized portfolio volatilities $\sigma_p^* = \{8\%, 10\%, 12\%\}$; (2) all pairs of 3 models against RW; and (3) degrees of RRA $\delta = \{2, 6\}$. We report our estimates of Φ and break-even transaction cost, τ as annualized fees expressed in basis points.

Linearity test for the STAR model					
	aggregate	disaggregate			
		AM	CO	HF	PC
EUR/dollar	10.198†	4.022	1.713	4.794†	0.161
JPY/dollar	4.393	2.022	1.002	10.517†	11.476†
GBP/dollar	13.046†	32.893†	6.698†	1.518	3.789
CHF/dollar	10.885†	5.943†	17.234†	5.669†	0.073
AUD/dollar	3.725	9.074†	64.932†	2.875	23.236†
CAD/dollar	3.939	13.249†	1.689	4.705†	5.471†
NOK/dollar	22.766†	1.818	2.147	0.645	17.980†
SEK/dollar	15.545†	8.687†	13.278†	0.083	3.802
NZD/dollar	36.289†	7.843†	32.099†	18.601†	3.631

Table 2: Linearity test to the aggregate and disaggregate order flows

4 Estimation and empirical results

4.1 Data and preliminary test

In this study we use the order flow data set used in Cerrato et al. (2009). The data set consists of customer (weekly frequency) order flows from UBS and covers the period November, 02 2001 - November, 23 2007 for nine of the most liquid currencies. This is a new and interesting customer order flow data set. It is aggregated across currency pairs with customers split into 4 classifications: asset managers, hedge funds, corporate and private clients. The currencies considered are the Canadian Dollar (CAD), the Swiss Franc (CHF), the Euro (EUR), the Australian Dollar (AUD), the New Zealand Dollar (NZD), the UK Pound (GBP), the Japanese Yen (JPY), the Norwegian Krone (NOK) and the Swedish Krone (SEK). We use the three month LIBOR rate collected from Bloomberg to approximate the risk-free rate.

Since all rates are foreign currency per US dollar, a positive coefficient indicates dollar buying (foreign currency selling), the rate will increase as the foreign currency weakens. Conversly, a decline in this rate represents a strengthening of the foreign currency relative to the US dollar. Descriptive statistics for this data set are reported in Cerrato et al. (2009). Since exchange rates are found to be $I(1)$, we employ log differenced rates.

Linearity tests against STAR nonlinearity for the order flow are reported in Table (2). We use the approach as suggested in Harvey and Leybourne (2007). To implement this test, we select the AR order in the regression using a general-to-specific methodology and a 10%-significance level of 4.605, with a maximum permitted AR order of four and a minimum order of two. We find evidence of nonlinearity for six aggregate order flows and more than half the disaggregate order flows. Thus, more than half of the series analyzed exhibit evidence of nonlinearity and this suggests that nonlinear models may be appropriate. This is an important result which further confirms our modeling choice.

4.2 Customer order flow data: out of sample forecasts

4.2.1 Aggregate order flow

The out-of-sample predictions are reported in Table[8] (3). The out-of-sample exercise involves two steps: (1) the initial parameter estimation for the first 267 observations, and (2) sequential weekly updating of the parameter estimates for the rest of the out-of-sample period. In other words, the forecasts at any given week are constructed according to a recursive procedure that is conditional only upon information up to the date of the forecast. The model is then successively re-estimated as the date on which forecasts are conditioned moves through the data set. Hence the design of the out-of-sample exercise is computationally intensive.

Generally, at all of the horizons the RMSFE statistics are lower than those associated with the random walk forecasts. However, the Diebold-Mariano test statistic shows that in very few cases there is a evidence (at the 5% level) that our proposed models do better than a Random Walk model. Overall the results using aggregate data is in line with most of the empirical papers in the area and suggest there is very little statistical value from using order flow to forecast exchange rate returs in the short-run.

4.2.2 Disaggregate order flow

Evans and Lyons (2005b) argue that the lack of success in generating significant results is generally supportive of the core hypotheses of the market microstructure literature may be due to using aggregate customer order flow data. For example, the heterogeneities in the customer segment of the foreign exchange market imply that different customers may react to news in different ways. Sager and Taylor (2008) point out that knowledge of the types of customers prevalent in the market at any given time, and of the ways in which they trade and interact with the wider market, should help understanding of the behavior of an exchange rate at that time.

In this section, following Evans and Lyons (2005b), Sager and Taylor (2008) and Cerrato et al. (2009), we test whether the predictive performance of the order flow model can be improved using disaggregate customer data.

Unfortunately the results are not encouraging. We only find evidence against the Random Walk model in very few cases[9].

4.3 Economic evaluation

Although an empirical model might be statistically valid, it could not be appropriate when viewed from the standpoint of whether investors or corporate treasurers can use it in practice. In this and the following sections we follow Della Corte et al

[8] Note that all the empirical results presented in this and the following sections, unless we do not specify the opposite, have been obtained with the inclusion of interest rate differentials in the microstructure equation(s) presented earlier. We have also done the same analysis after dropping interest rate differential from the equation and results were qualitatively unchanged. These results are available upon request.

[9] To save space we only report results for the Asset Manager group although very similar results have also been obtained for Corporate Clients, Hedge Fund and Private Client.

Out of sample prediction results: forecasts of lagged models using aggregate order flow

			$y_{t+k} - y_t = \alpha + \beta_t X_t$			$y_{t+k} - y_t = \alpha + \beta S(.) X_t$		
		RW	TVP	TVP/RW	DM	STAR	STAR/RW	DM
EUR/dollar	k =1	0.8251	0.7705	0.9337	0.66	0.8036	0.9738	0.94
	2	1.1888	1.1433	0.9618	0.45	1.1180	0.9405	1.55
	3	1.5593	1.3907	0.8919	1.29	1.3673	0.8769	$2.54^{\ddagger}$
	4	1.9177	1.6496	0.8602	1.57	1.6888	0.8807	$2.44^{\ddagger}$
JPY/dollar	k =1	1.4158	1.3557	0.9473	0.30	1.4372	1.0151	0.92
	2	1.6339	1.5897	0.9623	0.36	1.6440	1.0061	1.85
	3	2.0933	1.9511	0.9216	0.62	2.1870	1.0448	-1.07
	4	2.5297	2.5317	0.9894	0.08	2.6450	1.0456	-1.15
GBP/dollar	k =1	0.9075	0.9710	1.0700	-0.41	0.9193	1.0130	0.28
	2	1.1965	1.2563	1.0499	-0.25	1.2979	1.0847	-0.99
	3	1.2499	1.5925	1.2741	-0.92	1.3441	1.0753	-0.71
	4	1.4430	1.3897	0.9631	0.33	1.4872	1.0306	-0.11
CHF/dollar	k =1	0.9753	0.9583	0.9825	0.18	0.9744	0.9990	0.67
	2	1.3205	1.3134	0.9946	0.14	1.2974	0.9825	0.89
	3	1.7454	1.6346	0.9365	0.87	1.6723	0.9581	1.18
	4	2.0218	1.8593	0.9196	0.78	1.9006	0.9401	1.88
AUD/dollar	k =1	1.7140	1.5930	0.9195	0.51	1.7273	1.0078	0.98
	2	2.4420	2.2989	0.9311	0.47	2.4273	0.9940	1.42
	3	3.0105	2.7978	0.9189	0.92	2.9562	0.9819	1.65
	4	3.6174	3.4043	0.9303	0.47	3.5103	0.9704	1.97
CAD/dollar	k =1	1.1734	1.0998	0.9273	0.46	1.1549	0.9842	1.78
	2	1.9397	1.7557	0.8953	0.95	1.8898	0.9743	2.07
	3	2.4604	2.1121	0.8488	1.43	2.3263	0.9455	3.47
	4	2.8834	2.5251	0.8657	1.49	2.6150	0.9069	4.28
NOK/dollar	k =1	1.2942	1.2681	0.9799	0.23	1.2924	0.9986	1.18
	2	1.8547	1.7153	0.9249	0.83	1.8513	0.9982	0.81
	3	2.3427	2.1602	0.9221	0.93	2.3246	0.9923	0.93
	4	2.8701	2.6324	0.9172	0.87	2.6784	0.9332	$2.49^{\ddagger}$
SEK/dollar	k =1	1.0968	1.1198	1.0210	-0.07	1.1087	1.0109	0.43
	2	1.7057	1.7482	1.0249	-0.12	1.6950	0.9938	0.97
	3	2.2680	2.2576	0.9954	0.15	2.2116	0.9751	1.67
	4	2.7126	2.6869	0.9905	0.20	2.5885	0.9543	$1.98^{\ddagger}$
NZD/dollar	k =1	2.0884	2.1966	1.0518	-0.24	2.0764	0.9942	$2.31^{\ddagger}$
	2	2.9435	3.3655	1.1434	-0.83	2.9299	0.9954	1.04
	3	3.6272	3.6422	1.0041	0.06	3.5782	0.9865	1.04
	4	4.4060	4.3904	0.9965	0.11	4.3427	0.9856	0.66

Table 3: Estimated Results for TVP and STAR with Aggregate Order Flow

Out of sample prediction results: forecasts of lagged models using disaggregate data (AM asset manager)

			$y_{t+k} - y_t = \alpha + \beta_t X_t$			$y_{t+k} - y_t = \alpha + \beta S(.) X_t$		
		RW	TVP	TVP/RW	DM	STAR	STAR/RW	DM
EUR/dollar	k =1	0.8251	0.7785	0.9333	0.54	0.8039	0.9743	1.25
	2	1.1888	1.1595	0.9647	0.30	1.1619	0.9774	0.91
	3	1.5593	1.3972	0.8861	1.24	1.4064	0.9020	2.14
	4	1.9177	1.6988	0.8757	1.22	1.6824	0.8773	2.32
JPY/dollar	k =1	1.4158	1.3556	0.9472	0.30	1.4158	1.0000	2.01
	2	1.6339	1.6045	0.9712	0.27	1.6527	1.0115	0.71
	3	2.0933	1.9561	0.9240	0.56	2.1446	1.0245	-0.05
	4	2.5297	2.5202	0.9849	0.11	2.6080	1.0310	-0.72
GBP/dollar	k =1	0.9075	0.9250	1.0192	-0.06	0.9023	0.9943	0.76
	2	1.1965	1.2236	1.0227	-0.08	1.2847	1.0738	-0.84
	3	1.2499	1.2225	0.9781	0.29	1.3623	1.0899	-0.83
	4	1.4430	1.4022	0.9717	0.27	1.5529	1.0761	-0.63
CHF/dollar	k =1	0.9753	0.9464	0.9703	0.25	0.9750	0.9996	1.17
	2	1.3205	1.2454	0.9431	0.62	1.3036	0.9872	1.29
	3	1.7454	1.5927	0.9125	1.18	1.6934	0.9702	1.64
	4	2.0218	1.8287	0.9045	0.92	1.9167	0.9480	1.89
AUD/dollar	k =1	1.7140	1.7088	0.9970	0.08	1.7234	1.0055	1.17
	2	2.4420	2.3896	0.9785	0.23	2.4087	0.9864	1.04
	3	3.0105	2.8320	0.9407	0.80	2.9690	0.9862	1.18
	4	3.6174	3.3228	0.9186	0.65	3.5535	0.9824	1.29
CAD/dollar	k =1	1.1734	1.2018	1.0243	-0.08	1.1476	0.9781	$1.97^{\ddagger}$
	2	1.9397	2.4407	1.2583	-0.84	1.8518	0.9547	$2.48^{\ddagger}$
	3	2.4604	3.7873	1.5393	-1.05	2.2423	0.9113	$3.85^{\ddagger}$
	4	2.8834	3.9927	1.3847	-1.01	2.6023	0.9025	$3.80^{\ddagger}$
NOK/dollar	k =1	1.2942	1.2357	0.9446	0.44	1.3203	1.0202	0.06
	2	1.8547	1.7585	0.9378	0.50	1.8412	0.9928	0.91
	3	2.3427	2.1920	0.9252	0.80	2.2949	0.9796	1.21
	4	2.8701	2.6341	0.9073	0.95	2.6952	0.9391	2.59
SEK/dollar	k =1	1.0968	1.1279	1.0284	-0.13	1.1010	1.0039	0.74
	2	1.7057	1.7667	1.0358	-0.21	1.6791	0.9844	1.17
	3	2.2680	2.2506	0.9923	0.17	2.2048	0.9721	1.64
	4	2.7126	2.6887	0.9912	0.17	2.6016	0.9591	1.72
NZD/dollar	k =1	2.0884	2.1326	1.0211	-0.06	2.1144	1.0124	0.81
	2	2.9435	3.0504	1.0363	-0.15	2.9745	1.0105	0.43
	3	3.6272	3.6731	1.0127	-0.01	3.6371	1.0027	0.61
	4	4.4060	4.3788	0.9938	0.11	4.3906	0.9965	0.83

Table 4: Estimated Results for TVP and STAR with Disaggregate Order Flow - AM asset managers

(2009) and build a portfolio of currencies and measure the out-of-sample forecasting performance using the mean variance approach introduced in the previous sections. We build an efficient portfolio by investing in the daily return of two currencies and use the two exchange rates to convert the portfolio return into US dollars. The maximum return strategies are evaluated at three target portfolio return volatilities, 8%, 10%, and 12%. We report the out-of-sample performance fees, Φ, and the break-even transaction costs, τ^{BE}. The fees denote the amount an investor with quadratic utility and a degree of relative risk aversion equal to 2 and 6 would be willing to pay for switching from the RW model to an alternative model. The target portfolio volatilities are set at 8%, 10%, and 12%. τ^{BE} is defined as the minimum proportional cost that cancels out the utility advantage of a strategy. The fees are expressed in annual basis points.

4.3.1 Aggregate and disaggregate customer order flows

Table (5) reports the empirical results[10]. We estimate the fees assuming different degrees of relative risk aversion, specifically $\delta = 2$ and $\delta = 6$.

We start with the out-of-sample performance fees which are displayed in Table (5). Overall performance fees are all positive which implies that there is economic value by conditioning on our proposed models. This is a new and important result since the vast majority of studies in this area have focused on linear models. Furthermore, our result is in contrast to the seminal contribution of Meese and Rogoff (1983). As an example, with $\sigma_p^* = 10\%$ and $\delta = 2$, the performance fees for switching from RW to an alternative model are 1793 bps for TVP and 1951 bps for $STAR$, when aggregate order flow is used. Based on performance fees the STAR model is the best performer model[11].

If transaction costs are sufficiently high, the period-by-period fluctuations in the dynamic weights of an optimal strategy will render the strategy too costly to implement relative to the static random walk model. We address this concern by computing the break-even transaction cost, τ, as the minimum proportional cost that cancels out the utility advantage of a given strategy. In comparing a dynamic strategy with the static random walk strategy, an investor who pays a transaction cost lower than τ will prefer the dynamic strategy.

The out-of-sample break-even transaction costs are reported in Table (5). Generally, transaction costs are reasonably high. They tend to be higher than 50 bps. Marquering and Verbeek (2004) argue that, at the reasonably high transaction cost of 50 bps, there is still significant out-of-sample economic value in empirical models that condition on the microstructure order flows, especially under nonlinear specification. Therefore, the out-of-sample economic value we have reported is robust to reasonably high transaction costs. The Asset Manager group is the best performer followed by Corporate Client. Surprisingly, the Hedge Fund group is only the third

[10]In this table we report the results using the microstructure model presented earlier but omitting the interest rate differential.

[11]The performance fees reported, which one could charge for the trading strategy based on customer order flow forecasts, are very profitable probably due to the fact that the strategy used is not a publicly available strategy.

	Performance fee for out-of-sample forecasts							
	Aggregate							
	TVP				STAR			
σ_p^*	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	1556.7	104.6	1557.2	104.6	1686.1	172.9	1686.6	172.9
10%	1793.6	96.4	1794.1	96.4	1951.8	159.9	1952.2	160.0
12%	2030.3	90.9	2030.8	90.9	2216.8	151.2	2217.3	151.2
	AM(Asset Manager)							
	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	2031.2	9.1	2031.7	9.1	1619.1	18.5	1619.7	18.5
10%	2387.9	8.5	2388.4	8.5	1872.8	17.1	1873.3	17.1
12%	2744.6	8.2	2745.1	8.2	2126.5	16.2	2127.0	16.2
	CO(Corporate Client)							
	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	1525.7	50.7	1526.2	50.8	1345.8	84.1	1346.3	84.2
10%	1756.0	46.7	1756.5	46.7	1531.1	76.6	1531.6	76.6
12%	1986.4	44.0	1986.9	44.0	1716.5	71.5	1717.0	71.6
	HF(Hedge Fund)							
	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	1409.9	34.1	1410.4	34.1	1250.7	22.2	1251.2	22.3
10%	1611.3	31.1	1611.8	31.1	1412.3	20.1	1412.8	20.1
12%	1812.6	29.2	1813.1	29.2	2273.8	98.6	2274.3	98.7
	PC (Private Client)							
	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	1324.8	33.7	1325.3	33.7	1293.3	27.5	1293.8	27.5
10%	1504.9	30.6	1505.4	30.6	1465.4	24.9	1465.9	24.9
12%	1684.9	28.5	1685.4	28.6	1637.5	23.2	1638.0	23.2

Table 5: Economic Value for the TVP and STAR Forecasts with Order Flows

	Performance fee for out-of-sample forecasts with interest rate differentials							
	Aggregate							
	TVP				STAR			
σ_p^*	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	1711.91	164.74	1712.41	164.79	2416.61	140.24	2417.07	140.26
10%	1984.42	152.69	1984.90	152.73	2851.97	132.27	2852.42	132.29
12%	2256.42	144.62	2256.89	144.65	3285.68	126.88	3286.11	126.90
	AM(Asset Manager)							
	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	1813.3	89.04	1813.79	89.06	1415.12	112.01	1415.64	112.05
10%	2115.53	83.10	2116.00	83.12	1617.76	102.44	1618.26	102.47
12%	2417.75	79.14	2418.20	79.15	1820.40	96.05	1820.89	96.08
	CO(Corporate Client)							
	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	1624.78	113.68	1625.27	113.72	1349.32	85.21	1349.86	85.24
10%	1879.83	105.22	1880.31	105.24	1535.44	77.56	1535.96	77.59
12%	2134.88	99.58	2135.36	99.60	1721.55	72.47	1722.06	72.49
	HF(Hedge Fund)							
	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	1574.79	68.96	1575.29	68.99	1361.94	11.60	1362.47	11.60
10%	1817.19	63.66	1817.68	63.68	1551.28	10.57	1551.79	10.57
12%	2059.57	60.13	2060.05	60.14	1740.60	9.88	1741.11	9.88
	PC (Private Client)							
	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}	Φ_2	τ_2^{BE}	Φ_6	τ_6^{BE}
8%	1518.76	72.06	1519.18	72.10	1138.06	54.00	1138.48	34.03
10%	1221.36	60.70	1221.78	60.72	1753.89	75.06	1754.31	55.08
12%	1922.17	53.00	1922.57	53.02	1868.49	89.04	1868.90	89.05

Table 6: Economic Value for the TVP and STAR Forecasts with Interest Rate Differetials and Order Flows

best performer[12]. More important, the various performance measures reported indicates that the best results are typically obtained using aggregated order flow rather than the disaggregated ones. This result contasts with Cerrato et al (2009) and Evans and Lyons (2005b).

We now estimate the microstructure model once again but we also include an interest rate differential. We hope in this way to disentangle the contribution of the interest rate differential to the forecasting performance generated by our models. Results are reported in Table 6. Overall the results reported in Table 6 are in line with the previous results and confirm that the best results are obtained when aggregate data are used. Both the performance fees and the transaction costs reported in Table 6 are much higher than the ones reported in Table 5. For example, if we consider aggregate data, the difference (in basis points) between the performance fees before and after including interest rate differentials raise by an impressive 190bp (minimum), 900bp (maximum). The same happens with the break even transaction costs, -28bp (min), 57bp (max)[13]. Therefore, the contribution of interest rate differentials to forecasting estimates seems to be very relevant.

5 Robustness

In this section we conduct some robustness tests to check that our results are not driven by a specific model specification. Table (7) compares Sharpe Ratios for a simple Random Walk (RW) model and the two models described earlier. We use aggregate and disaggregate order flow. Sharpe Ratios from the time varying and nonlinear models are always higher that the ones from the simple Random Walk model. This result confirms the results reported in the previous table. Generally, conditioning on STAR models generates the highest Sharpe Ratios. This result is also in line with what presented in Table 6. Finally, in line with the results in Table 6, Sharpe Ratios from aggregated data are higher than the Sarpe Ratios using disaggregated data. Overall these empirical results are in line with the ones reported in the previous section.

The order flow models we have used in all the tables above did not contain an interest rates differential. As an additional check, we have also repeated all the empirical applications as above using the same approaches but using the interest rates differential as an additional regressor. The empirical results are in line with what is already reported and therefore not given here to save space[14].

6 Conclusion

This paper makes several contributions to the literature on exchange rates forecasting. We focus on the initiating customer trades and extend the order flow model to account for nonlinearities. In a microstructure context, Gradojevic and Yang (2006)

[12]Cerrato et al (2011) show that the order flow from the financial group (i.e. Hedge Fund and Asset Manager) contain relevant information which can be exploited for trading.

[13]Note that from the results in Table 6 this spread is generally positive.

[14]These empirical results are available upon request.

Sharpe Ratios for Out of Sample Forecasts				
		Aggregate		
		Sharpe Ratio		
		RW	TVP	STAR
Aggregate	σ_p^*	0.1886	4.6449	1.7699
	8%	1.0437	1.1295	1.1319
	10%	0.8350	0.8956	0.8996
	12%	0.6958	0.7464	0.7447
		Disaggregate		
AM(Asset Manager)	σ_p^*		3.5678	2.9737
	8%		1.1231	1.1311
	10%		0.8985	0.9049
	12%		0.7487	0.7541
CO(Corporate Client)	σ_p^*		1.3858	1.2759
	8%		1.1218	1.1209
	10%		0.8924	0.8967
	12%		0.7479	0.7403
HF(Hedge Fund)	σ_p^*		3.3544	1.8675
	8%		1.1228	1.1246
	10%		0.8900	0.8997
	12%		0.7446	0.7417
PC (Private Client)	σ_p^*		1.7673	2.1585
	8%		1.1295	1.1342
	10%		0.9036	0.8974
	12%		0.7330	0.7561

Table 7: Sharpe Ratios for TVP and STAR models

highlights the necessity of embodying information in a nonlinear way. In contrast to the recent empirical literature in this area, our empirical results show that order flow, which is related to the economic fundamentals, has good forecasting power to forecast exchange rate returns when forecasts are evaluated using a battery of economic measures. This result is even stronger when aggregate order flow data are used. This result is in contrast with Cerrato et al (2009) and Evans and Lyons (2005b).

We find that i) the predictive ability of the microstructure order flow has substantial economic value in a dynamic portfolio allocation context and that nonlinear models outperform the naive RW model; ii) that customer order flow data contain more relevant information when aggregate data is used; iii) in the out-of-sample exercises, an interest rate differential appears to be an important element which should not be neglected from the model. We believe these are new and important results which have not been previously documented.

References

Andersen, T. G., T. Bollerslev, F. X. Diebold, and C. Vega (2003). Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American Economic Review 93*, 38–62.

Andrade, S. C., C. Chang, and M. S. Seasholes (2008). Trading imbalances, predictable reversals, and cross-stock price pressure. *Journal of Financial Economics 88*, 406–423.

Bacchetta, P. and E. V. Wincoop (2006). Can information heterogeneity explain the exchange rate determination puzzle? *American Economic Review 96*, 552–576.

Breedon, F. and A. Ranaldo (2009). Intraday patterns in FX returns and order flow. *Swiss National Bank*.

Breedon, F., D. Rime, and P. Vitale (2010). A transaction data study of the forward bias puzzle. *CEPR Discussion Paper 7991*.

Brunnermeier, M. K., S. Nagel, and L. H. Pedersen (2008). Carry trades and currency crashes. *NBER Macroeconomics Annual 2008 23*, 313–347.

Cerrato, M., H. Kim, and R. MacDonald (2010). Three-regime asymmetric STAR modeling and exchange rate reversion. *Journal of Money Credit and Banking 42*(7), 1447–1467.

Cerrato, M., N. Sarantis, and A. Saunders (2009). An investigation of customer order flow in the foreign exchange market. *University of Glasgow Dept. of Economics Discussion Papers 2009-25.*

della Corte, P., L. Sarno, and I. Tsiakas (2009). An economic evaluation of empirical exchange rate models. *Review of Financial Studies 22*, 3491–3530.

Diebold, F. X. and R. S. Mariano (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics 13*, 253–263.

Engel, C. and K. D. West (2005). Exchange rates and fundamentals. *Journal of Political Economy 113*, 486–517.

Evans, M. D. D. and R. K. Lyons (2002a). Informational integration and FX trading. *Journal of International Money and Finance 21*, 807–831.

Evans, M. D. D. and R. K. Lyons (2002b). Order flow and exchange rate dynamics. *Journal of Political Economy 110*, 170–180.

Evans, M. D. D. and R. K. Lyons (2005a). Do currency markets absorb news quickly? *Journal of International Money and Finance 24*, 197–217.

Evans, M. D. D. and R. K. Lyons (2005b). Meese-rogoff redux: Micro-based exchange-rate forecasting. *American Economic Review Papers and Proceedings 95*, 405–414.

Evans, M. D. D. and R. K. Lyons (2008). How is macro news trasmitted to exchange rates? *Journal of Financial Economics 88*, 26–50.

Fleming, J., C. Kirby, and B. Ostdiek (2001). The economic value of volatility timing. *The Journal of Finance LVI*, 329–352.

French, K. R. and R. Roll (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics 17*, 5–26.

Gradojevic, N. and J. Yang (2006). Non-linear, non-parametric, nonfundamental exchange rate forecasting. *Journal of Forecasting 25*, 227–245.

Han, Y. (2006). Asset allocation with a high dimensional latent factor stochastic volatility model. *The Review of Financial Studies 19*, 237–271.

Harvey, D. I. and S. J. Leybourne (2007). Testing for time series linearity. *Econometrics Journal 10*, 149–65.

Killeen, W. P., R. K. Lyons, and M. J. Moore (2006). Fixed versus flexible: Lessons from EMS order flow. *Fixed versus flexible: Lessons from EMS order flow 25*, 551–579.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica 53*, 1315–1335.

Love, R. and R. Payne (2003). Macroeconomic news, order flows and exchange rates. *Financial Markets Group Working Papers*.

Love, R. and R. Payne (2008). Macroeconomic news, order flows, and exchange rates. *Journal of Financial and Quantitave Analysis 43*, 467–488.

Luo, J. Market conditions, order flow and exchange rates determination. *London School of Economics Mimeo*.

Lyons, R. K. (1996). Optimal transparency in a dealership market with an application to foreign exchange. *Journal of Financial Intermediation 5*, 225–254.

Marquering, W. and M. Verbeek (2004). The economic value of predicting stock index returns and volatility. *Journal of Financial and Quantitative Analysis 39*, 407–429.

Meese, R. A. and K. Rogoff (1983). Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of International Economics 14*, 3–24.

Nguyen, V. H. and Y. Shin (2011). Asymmetric price impacts of order flow on exchange rate dynamics. *University of Leeds working paper series*.

Rime, D., L. Sarno, and E. Sojli (2010). Exchange rate forecasting, order flow and macroeconomic information. *Journal of International Economics 80*, 72–88.

Sager, M. and M. P. Taylor (2008). Commercially available order flow data and exchange rate movements: Caveat emptor. *Journal of Money, Credit and Banking 40*, 583–625.

West, K. D., H. J. Edison, and D. Cho (1993). A utility-based comparison of some models of exchange rate volatility. *Journal of International Economics 35*, 23–45.