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EXCHANGE RATE FORECASTING WITH INFORMATION FLOW APPROACH

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Abstract. The purpose of this article is to assess exchange rate forecasting possibilities with an information flow approach model. In the model the three types of information flows are distinguished: fundamental analysis information flow through particular macroeconomic determinants, microstructure approach information flow through dealer clients' positioning data, technical analysis information flow through technical indicators. By using regression analysis it is shown that the composed model can forecast the exchange rate, the most significant information flows are distinguished. The results lead to further development of the information flow approach as a tool to forecast exchange rate fluctuations.

Keywords: foreign exchange market, information flow approach, microstructure approach, fundamental models, technical analysis.

JEL Classification: F31, E47.

Introduction

Foreign exchange market is the largest financial market with its rapidly increasing turnover. According to the latest data from Bank for International Settlements (BIS 2013), in April 2013 the daily turnover was 5.505 trln. USD, which is 33.49% more than in April 2010. Cerrato *et al.* (2011), King *et al.* (2013, 2010) divide market participants into two main groups: market makers (dealers) and their clients. The clients can be financial clients, corporate clients and retail clients. Financial clients are the investment managers (real money investors, who buy and sell currencies to gain exposure to a particular asset), hedge funds, proprietary trading firms, which usually use leverage to trade in the foreign exchange market. Corporate clients are the importers and exporters of goods and services. Retail clients are small companies and people who buy currency in relatively small quantities. Central banks can be distinguished as a separate foreign exchange market participant group. Every group of these market participants has different purpose to be in the foreign exchange market, their investment horizon is different as well. Increasing amount of participants in the market and increasing international trade turnovers lead to great demand for exchange rate forecasts. On the other hand, the amount of factors which influence the fluctuations of exchange rates, the heterogeneity of market participants, the amount of financial instruments which allow to gain exposure to a particular currency and the organizational form (over the counter system) of the market complicate the process of generating exchange rate forecasts.

In the second part of 20th century there were many exchange rate forecasting models introduced. Rasekhi, Rostamzadeh (2011) classify the models to fundamental and technical. Fundamental models try to predict the exchange rate based on the fundamental factors with the purpose to distinguish the intrinsic value of the two currencies, while technical models forecast the exchange rate based on the price fluctuations from the past. It is argued that fundamental exchange rate forecasting models cannot predict the exchange rates for short term period. Even in nowaday research a paper of Meese, Rogoff (1983) is often quoted, where the two authors show that standard fundamental exchange rate forecasting models fail to predict the

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exchange rate better than random walk for time periods shorter that 1 year. Therefore in the short term the exchange rate disconnect puzzle exists while Bailliu and King (2005) state, that the short term exchange rate forecasts are important for market participants who need to take investment, savings and risk management decisions.

Technical exchange rate forecasting models provide better forecasting results, although Schulmeister (2008) and Zwart *et al.* (2009) summarize, that the profitability of technical analysis trading is decreasing significantly since late 1980s. Kaiser, Kube (2009) argue, that, compared to the popularity of technical analysis in practice, there are still relatively few studies that investigate the value of this source.

Recently another, microstructure approach to exchange rate determination, was introduced. In this approach it is believed that there is a relationship between exchange rate returns and the market praticipants' order flow. Lyons (2001) states that this approach was developed by researchers spending time with currency traders and examining what information do the traders use. Bailiu and King (2005) say that this approach can provide promising results, although more research on the model has to be done (Sager, Taylor 2008; Vitale 2007; Rime *et al.* 2007).

Gehrig, Menkoff (2004) after making a survey of FX dealers and fund managers show that there are three sources of information which were used by the respondents to determine future exchange rates: fundamental analysis, technical analysis and order flow analysis. Zwart *et al.* (2009) after combining technical and fundamental analysis tools for forecasting the returns of emerging market currencies add, that flow analysis information could increase economic value of emerging markets currency investments. This leads to a suggestion that all three above stated approaches have to be combined for determining fluctuations in exchange rates. Therefore, the *problem* arises: how to forecast the exchange rate with information flow approach? The *aim* of the research: to assess exchange rate forecasting possibilities with information flow approach, *tasks*: to provide the theoretical background of exchange rate forecasting with fundamental approach, technical approach, microstructure approach models, to compose a model for exchange rate forecasting with information flow approach, to evaluate how the exchange rate can be forecasted with the composed model. *Methods* used for the research: analysis and synthesis, comparative analysis to distinguish the appropriate information flows for the exchange rate forecasting, linear regression – to make the calculations of the model.

The remainder of the paper is organized as follows: in Section 1 previous research in separate fields of fundamental models, technical analysis models, microstructure approach models are discussed, in Section 2 the research model is composed and the data for the research is chosen, in Section 3 the results are discussed, last section concludes.

1. Previous research in exchange rate determination field

There is no agreement on which fundamental models can predict the exchange rate most accurately. Haidar (2011) discusses that there are some research where purchasing power parity models can predict the exchange rate, while Simpson and Grossman (2010) argue that purchasing power parity can determine the exchange rate only in the long run. Boschen and Smith (2012) prove that interest rate parity models can determine the exchange rate in the shorter term because of the structural changes in the foreign exchange market (increasing turnover and increasing amount of participants), Chinn and Liang (2009) show that with using longer term interest rate the forecasting results are more accurate than with the shorter term interest rate. Rasekhi, Rostamzadeh (2011) used sticky price monetary model to determine the exchange rate, although they make a conclusion that the model cannot outperform the random walk. There were also attempts to combine various fundamental exchange rate determination models. Hsing (2010a) used uncovered interest rate parity, purchasing power parity, flexible price monetary and Mundell Fleming models to determine USD/AUD exchange rate. It was found that uncovered interest rate parity model reflects exchange rate movements the best. The same author made an analogous research to determine RON/USD exchange rate, where it was also shown that uncovered interest rate parity model is the best among the chosen ones to reflect the exchange rate movements (Hsing 2010b). Rasekhi and Rostamzadeh (2011) tried to determine EUR/USD exchange rate by creating a genetic algorithm. The largest part of the algorithm was composed of the portfolio balance model which means that in this case this model determined the exchange rate the best. The worst model for predictions was the purchasing power parity model. Therefore there is no agreement on which fundamental model is the most suitable to predict the exchange rates. On the other hand, it was found that interest rates might predict exchange rate fluctuations better in the future because of the structural changes in the foreign exchange market. For further discussion on advantages and drawbacks of fundamental exchange rate forecasting models see Mačerinskienė, Balčiūnas (2013).

According to Lyons and Moore (2009), fundamental models are based on international trade flows, which compose approximately 6% of the turnover in the foreign exchange market, while microstructure approach focuses on the part where currencies are also bought to gain exposure to other assets or as a separate asset. Therefore application of microstructure approach should lead to better exchange rate determination results. In these models order flow data can be used together with fundamental determinants. Evans and Lyons (2002) in the model used interest rates and they show that only interest rates cannot determine exchange rate, where determination coefficient is lower than 1% and is statistically insignificant. But when order flow is included, the determination coefficient increases to 60% and is statistically significant.. Rime *et al.* (2007) show that the interest rate variable is statistically insignificant, while order flow data can determine from 18% to 42% of the changes in exchange rates. Mokoena *et al.* (2009) use order flow data, commodity price index and a proxy for country risk through the difference between South Africa bond index and the combined bond index of the world. They make a conclusion that the exchange rate depends on order flow data and the difference between interest rates. Gradojevic (2007) uses crude oil prices and interest rate difference between the U.S. and Canada. Cerrato *et al.* (2011) add sticky price monetary model, Evans, Lyons (2005) use only order flow data. Therefore microstructure approach models can be combined with fundamental models although it is concluded that order flow data can determine exchange rate fluctuations better than macroeconomic variables.

While there are doubts on the forecasting possibilities of fundamental exchange rate models, Park, Irwin (2007) summarize 95 studies of application of technical analysis to trading in foreign exchange market. The authors find that 56 studies showed positive returns of technical trading (chartist) strategies, in 20 studies the returns of the strategies were negative, and the rest of the researches showed mixed results (see Menkoff, Taylor 2007 for another extensive research). Schulmeister (2008) use 1024 technical models for trading strategies in the DM (euro)/USD market. There were two types of models used: momentum models and models based on moving averages. The author shows that all of the models in the period between 1973 and 1999 provided positive returns. In the out of sample period between 2000 and 2004 91.7% of the models remained profitable. The profits were led by exploitation of persistent trends in exchange rates. Krishnan, Menon (2009) analyse technical trading strategies for currency pairs EUR/USD, GBP/USD, USD/CHF, USD/JPY and by analysing profitability, maximum drawdown, time in position, dealt lots and commission fees show that trading in EUR/USD is more profitable compared to trading in the other pairs. They also show that there is no difference in profits while using different timeframes for trading, although trading in short term timeframes leads to greater risk. Zafeiriou, Kalles (2013) create an artificial neural network of different period moving average indicators, price oscillator, stochastic oscillator and a relative strenght index. While it was shown that the price oscillator led to the greatest success in directional trend forecasting, the system of the above mentioned indicators generated more entry points compared to the entry points generated by the separate indicators. Bask (2007) combines Dornbush sticky price monetary model with moving averages and shows that currencies tend to overshoot more than it is stated in the Dornbusch model. Zwart *et al.* (2009) make a research on forecasting emerging markets exchange rates with combining fundamental and technical trading strategies. For fundamental strategy real interest rates and GDP growth were used, in the technical trading strategy price resistance levels and short term – long term moving averages were used. The results show that a combined strategy provides more stable returns than separate fundamental and technical strategies.

Figure 1 summarizes how the models were combined in the previuos researches:

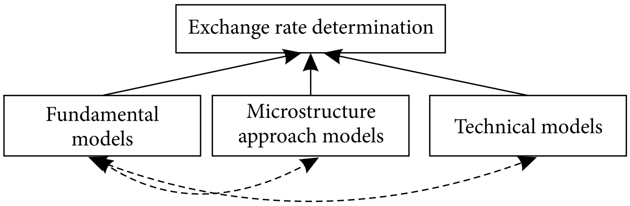

Fig. 1. Exchange rate determination models
(source: composed by the authors)

The dotted arrow lines in Figure 1 show which models were used together in the previous researches.

While there are many researches of separate fundamental, technical and microstructure approach models, we were unsuccessful to find any research where all three approaches were applied together. There were papers which composed fundamental and technical approach strategies, some authors used microstructure approach with fundamental variables. It is shown that combination of different approaches lead to more stable returns.

2. Data, research methods and information flow approach model

The results of the previous studies show that there is a lack of research where all three information sources would be combined for the purpose of determining the exchange rates. In this part particular variables of each information flow will be chosen and the model for the research will be composed. The research will be done on the three mostly traded exchange rates: EUR/USD, USD/JPY, GBP/USD. BIS (2013) states that these currency pairs composed 24.1%, 18.3% and 8.8% respectively of the overall foreign exchange market turnover in April 2013. Based on three types of exchange rate forecasting models summarized in Figure 1, the model of information flow approach is composed:

$$p = f + o + t, \tag{1}$$

where: p – change in the exchange rate, f – change in the fundamental variable(s), o – change in the microstructure approach variable (order flow), t – change in the technical analysis variable (technical indicator).

Interest rates are widely used as a fundamental variable for exchange rate determination and in some cases they are used in microstructure approach models as well. Moreover Boschen, Smith (2012) conclude that because of the structural changes in the foreign exchange market, uncovered interest parity might hold better in the future. Therefore for this research interest rates of USD, EUR, JPY and GBP will be used. The interest rates will be calculated based on 3 months Libor contracts, as it was done in Boschen and Smith (2012). The daily changes of 3 month USD, EUR, JPY and GBP contracts were obtained from St. Luis FED database.

In the microstructure approach model trading is done in two levels. The participants of the first level are the clients of the market makers who analyze exchange rate fluctuations and buy or sell the currency based on their analysis results. In the second level the market makers trade between each other. They observe the order flow of the first segment and adjust their present positions respectively. The greater emphasis is put on the order flow of the first segment, because these market participants might have more information about possible changes in the investment environment in the future. Rime *et al*. (2007) use client order flow and make a conclusion that order flow of this segment can determine the fluctuations in exchange rates. Evans and Lyons (2002) use market maker's order flow. Menkoff *et al.* (2013) show that asset managers' order flows are associated with permanent shifts in future exchange rates, while hedge funds' order flow impact future exchange rate less, corporate customers' and private clients' order flows represent uninformed trading. Gradojevic (2007) uses order flow data to explain the drop in Canadian dollar (CAD) between 1994 and 1998. He distinguishes commercial clients order flow (Canadian residents and non-residents), order flow of financial institutions based in Canada (non- FX dealers), order flow of foreign institutions (including FX dealers), interbank order flows. The conclusion is made that CAD/USD exchange rate fell because of the bets of foreign institutions on the drop in Canadian dollar. Various order flow data is used in microstructure approach research while the greatest emphasis is put on client order flow (Lovcha, Perez-Laborda 2010).

Chinn, Moore (2011), Jalil, Feridun (2010), Sager, Taylor (2008) argue that main drawback of the microstructure approach models is the access of the order flow data. Because foreign exchange market is organized as an OTC market, we were unable to find any research where the order flow data would be composed of all the transactions in the wholesale market. Lovcha, Perez-Laborda (2010), Gradojevic (2007), Jalil, Feridun (2010), Onur (2008) used central banks' data in their studies, also data from trading Reuters, EBS trading platforms are used. Table 1 shows which part in transaction turnover belongs to the EBS trading platform.

Table 1. EBS share in market turnover (source: Breedon *et al.* 2010)

	Currency Pair		
	EUR/USD	USD/JPY	GBP/USD
EBS share of electronic	81%	95%	7%
Electronic share of total	54%	50%	54%
EBS share of total	44%	48%	4%
Average trade size	\$4.49 mln.	\$3.87 mln.	\$3.57 mln.
Average Bid-Ask Spread	0.017%	0.018%	0.056%

Sager, Taylor (2008) use client order flow indexes, composed by banks JP Morgan and RBS, Evans and Lyons (2002) in their research use Citibank data. Table 2 shows the part of the banks in the overall FX turnover.

Table 2. Market share of the largest participants in the foreign exchange market 2011 (source: Euromoney 2013)

Bank	Market share 2011
Deutsche Bank	14.57%
Citi	12.26%
Barclays	10.95%
UBS	10.48%
HSBC	6.72%
JPMorgan	6.60%
RBS	5.86%
Credit Suisse	4.68%
Morgan Stanley	3.52%
Goldman Sachs	3.12%

While it is popular to use the order flow data provided by some banks, none of the banks' turnover is greater than 15%. Mutafoglu, 2010 for his research uses speculator positioning data obtained from Chicago Mercantile Group, while the turnover of this exchange in October 2013 was \$80 bln. Nolte, I., Nolte, S. (2012) used foreign exchange dealer's Oanda retail clients' positioning data. Table 3 shows the largest retail Forex platforms.

Dealer's Oanda daily turnover in 2011 was \$6.8 bn. According to King, Rime 2010, in 2010 retail segment composed 8–10% of the overall spot market daily turnover, that is \$125–150 per day. Therefore the dealer's turnover composes 4.51–5.44% of the spot retail market. This is the largest dealer for the moment which provides publicly accessible clients' positioning data which can be used for the calculations. The broker FXCM allows their clients to access their clients' positioning data, although in their dataset there were some periods when the positioning data was not collected.

Table 3. The largest foreign exchange retail market dealers and brokers, 2011 (source: Finance Magnates 2011[1])

No.	Dealer/ Broker	Monthly turnover ($ bln.)	Daily turnover ($ bln.)
1	FXCM	321	14.6
2	Saxo Bank	232	10.5
3	GFT	200	9.1
4	Alpari	192	8.7
5	Gain Capital	161	7.3
6	IG Group	160	7.3
7	Oanda	150	6.8
8	FXDD	100	4.5
9	FXPro	98	4.5
10	Forex Club	80	3.6

Therefore the dealer Oanda was chosen as a provider of daily client positioning ratio for this research.

Various methods for microstructure approach model calculations are used in the research. Evans, Lyons (2005), Rime *et al.* (2007) use linear regression, Gradojevic, Yang (2006), Lovcha, Perez-Laborda (2010) use genetic algorithms. Rime *et al.* (2007) compose an investment strategy and evaluate it with economically with Sharpe ratio.

In technical analysis research various technical indicators are used, although Bask (2007), Zwart *et al.* (2009) conclude that moving averages (MAs) are the most commonly used indicators for combining the trading strategies. The authors distinguish two different types moving averages (MAs): the short period moving average and the long period moving average, while the short period can be between 1–8 periods (Schulmeister 2008), long period term MA can be between 10–30 periods, where 1 period MA is the current exchange rate. Zwart *et al.* (2009) as a short term period MA use 1–20 day MAs and 15–200 day MAs for the long term period. When a short term period MA crosses the long term period MA from below, a buying signal is created, when short term period MA crosses the long term period MA from the above, a selling signal is created. Therefore in this research two MAs will be chosen: 5 day period as a short term MA and 30 day period as a long term MA.

Based on the three sources of information which are used by market participants, the information flow model is specified (Fig. 2).

In the model the exchange rate is determined by fundamental information, which in this research is represented by the daily changes in 3 month Libor interest rates, daily changes in dealer's Oanda client positioning ratio is used as a proxy for order flow data, 5 day period and 30 day period moving averages are used as a proxy for technical information flow. The retail traders' positioning data was available for 1 year, therefore the study covers period from 12.2.2013 to 10.9.2014 (the data from 10.22.2013 to 12.22.2013 was used to calculate the 30 MA). The linear regression model was composed to see which information flow is the most significant and what is the determination coefficient of the model.

3. Results, discussion and limitations

The study shows that the determination coefficients for EUR/USD, USD/JPY and GBP/USD are 0.593, 0.353 and 0.372 respectively. They are similar to the ones provided by Rime *at al.*(2007) and Evans, Lyons (2002) who used order flow data and the interest rates to determine the fluctuations in exchange rates. The rest of the model's results are presented in Table 4.

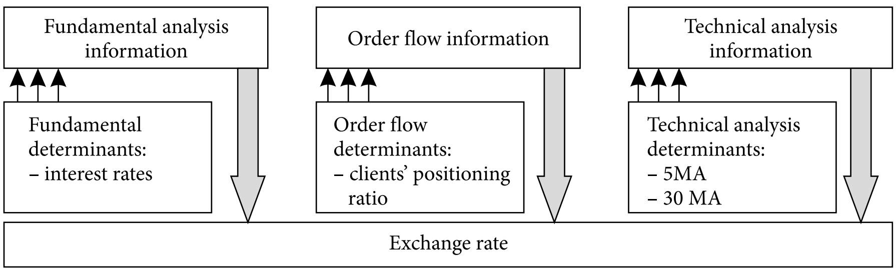

Fig. 2. Information flow approach to exchange rate determination (source: composed by the authors)

Table 4. Results of the information flow model (source: composed by the authors)

	IR USD	sig.	IR EUR	sig.	IR JPY	sig.	IR GBP	sig.	Posit. Ratio	sig.	MA 5	sig.	MA 30	sig.
E_U	–0.001	0.957	–0.01	0.081					–0.023	0.000	0.646	0.000	0.529	0.044
U_J	0.069	0.057			0.033	0.255			–0.035	0.000	0.466	0.002	0.490	0.092
G_U	–0.011	0.701					0.020	0.702	–0.160	0.000	0.720	0.000	0.148	0.633

[1] For further discussion see http://forexmagnates.com/forex-magnates-q3-2011-retail-forex-volume-survey-fxcm-worlds-largest-forex-broker

Table 4 shows the coefficients of the independent variables (USD, EUR, JPY, GBP Libor interest rates, client positioning ratio, MA5 and MA30), and their statistical significance levels. It is noticeable that the interest rate variables are statistically insignificant for all three exchange rates (as in Evans, Lyons 2002), MA30 variable is statistically significant only in EUR/USD pair. The coefficients of client positioning ratio are negative, which means that retail traders tend to position against the present direction in the price. The difference between long and short MA, and the difference between the interest rates were also used for the calculations, although the coefficients were statistically insignificant.

Although the determination coefficients fall in between the results of studies performed by other researchers in microstructure approach field, the data in this study was used for one year, since it was the longest time period for which it was possible to obtain the clients positioning ratio from dealer Oanda. Also more variations of the moving averages, more technical indicators for future research can be used. The information from fundamental analysis could be expanded to other variables – shorter and/or longer period interest rates could be used for the calculations. Moreover, there could be various trading strategies composed to economically assess the profitability of the information flow approach.

Conclusions

Microstructure approach to exchange rate determination emerged between fundamental and technical analysis models recently. While there are many doubts on the possibility for the fundamental models to determine the exchange rate in the short term, uncovered interest rate parity starts to hold more often, which means that interest rates could determine the exchange rate better in the future. It can be attributed to the structural changes in the foreign exchange market. On the other hand, order flow data can determine the exchange rate better than the interest rates in the models where the two variables are used. There are various trading systems composed out of the technical indicators and it is showed that the systems can be profitable, on the other hand their profitability has been decreasing since 1980s.

In some studies fundamental models are combined with microstructure approach or with technical indicators. But there was no research found were the microstructure approach models would be combined with technical models. Some authors conclude that the performance of the investing strategies could lead to better results if order flow element would be included. Moreover, survey of market participants shows that three information sources are used for the analysis in the industry: fundamental variables, technical analysis and order flow analysis. This proves that there is a demand for a model where all three information sources would be combined.

An information flow approach model in the research was composed. Based on the analysis of previous researches, interest rates were chosen as a proxy for fundamental information flow, retail clients' positioning ratio was used as order flow information, technical indicators MA 5 and MA 30 were chosen as a proxy for technical indicator information flow. It is showed that the created information flow approach model can determine 59.3%, 35.3% and 37.2% of the fluctuations in EUR/USD, USD/JPY and GBP/USD respectively. The results are similar to the findings of other researches where the microstructure approach was combined with the interest rate variable. Since the model can determine 59.3% of the EUR/USD exchange rate fluctuations, it can be used to forecast the exchange rate.

For the three exchange rates client positioning ratio and 5 periods MA were statistically significant determinants. Interest rates were not statistically significant. This finding agrees with previous research, where microstructure approach was combined with fundamental variables.

The composed information flow approach model can be applied for further researches where data of longer time period, more technical indicators and more fundamental determinants would be used. It would also be interesting to compose investment strategies with information flow approach and to evaluate them economically with the purpose of comparing the results with previously performed analysis of various technical indicators.

We were not successful in finding any similar research where all three sources of information flows would be combined for exchange rate determination. Further development of this model would lead to greater success in exchange rate forecasting, especially in shorter term periods.

Disclosure statement

None of the authors have any competing financial, professional, or personal interests from other parties.

References

BIS. 2013. *Triennial Central Bank survey. Foreign exchange turnover in April 2013: preliminary global results* [online]. Bank for International Settlements [cited 2 October 2014]. Available from Internet http://www.bis.org/publ/rpfx13fx.pdf

Bailliu, J.; King, M. R. 2005. What drives movements in exchange rates?, *Bank of Canada Review* Autumn: 3–16 [online], [cited 15 September 2014]. Available from Internet: http://faculty.haas.berkeley.edu/lyons/Bailliu_King_what%20drives%20movements.pdf

Bask, M. 2007. Chartism and exchange rate volatility, *International Journal of Finance and Economics* 12: 301–316. http://dx.doi.org/10.1002/ijfe.315

Boschen, J. F.; Smith, K. J. 2012. The uncovered interest rate parity anomaly and foreign exchange market turnover, *International Business & Economics Research Journal* 11: 299–306. http://dx.doi.org/10.19030/iber.v11i3.6862

Breedon, F., *et al.* 2010. *A transaction data study of the forward bias puzzle* [online]. Federal Reserve Bank of New York. 36 p. [cited 15 September 2014]. Available from Internet: http://newyorkfed.org/research/conference/2010/cb/Breedon_Rime_Vitale.pdf

Cerrato, M.; Sarantis, N.; Saunders, A. 2011. An investigation of customer order flow in the foreign exchange market, *Journal of Banking & Finance* 35: 1892–1906. http://dx.doi.org/10.1016/j.jbankfin.2010.12.003

Chinn, M. D.; Moore, M. 2011. Order flow and the monetary model of exchange rates: evidence from a novel data set, *Journal of Money, Credit & Banking* 43: 1599–1624. http://dx.doi.org/10.1111/j.1538-4616.2011.00460.x

Chinn, C.; Liang, H. 2009. The long-run uncovered interest rate parity in view of a trading strategy, *Applied Economics* 41: 2927–2739. http://dx.doi.org/10.1080/00036840701320225

Evans, D.; Lyons, R. K. 2002. Order flow and exchange rate dynamics, *Journal of Political Economy* 110: 170–180. http://dx.doi.org/10.3386/w7317

Evans, M. D. D.; Lyons, R. K. 2005. Meese-Rogoff redux: micro-based exchange rate forecasting, *American Economic Review* 95: 405–414. http://dx.doi.org/10.3386/w11042

Euromoney. 2013. *FX survey 2013: Methodology* [online]. Euromoney [cited 15 September 2014]. Available from Internet: http://www.euromoney.com/Article/3196819/FX-survey-2013-Methodology.html

Finance Magnates. 2011. *Forex Magnates Q3 2011 Retail Forex Volume Survey – FXCM world's largest forex broker* [online]. Finance Magnates [cited 15 September 2014]. Available from Internet: http://www.financemagnates.com/forex/brokers/forex-magnates-q3-2011-retail-forex-volume-survey-fxcm-worlds-largest-forex-broker/

Gehrig, T.; Menkoff, L. 2004. The use of analysis in foreign exchange: explanatory evidence, *Journal of International Money and Finance* 23: 573–594. http://dx.doi.org/10.1016/j.jimonfin.2003.12.006

Gradojevic, N. 2007. A market mircorstructure analysis of the Canadian dollar depreciation episodes in the 1990s, *Applied Financial Economics* 17: 1377–1387. http://dx.doi.org/10.1080/09603100601018807

Gradojevic, N.; Yang, J. 2006. Non-Linear, non-parametric, non-fundamental exchange rate forecasting, *Journal of Forecasting* 25: 227–245. http://dx.doi.org/10.1002/for.986

Haidar, J. I. 2011. Currency valuation and purchasing power parity, *World Economics* 12: 1–12. http://dx.doi.org/10.2139/ssrn.1864343

Hsing, Y. 2010a. Analysis of movements in the AUD/USD exchange rate: comparison of four major models, *Applied Economics Letters* 17: 575–580. http://dx.doi.org/10.1080/13504850802047003

Hsing, Y. 2010b. Analysis of the behavior of the RON/USD exchange rate: a comparison of major models, *International Review of Applied Financial Issues & Economics* 2: 272–284.

Jalil, A.; Feridun, M. 2010. Explaining exchange rate movements: an application of the market microstructure approach on the Pakistani foreign exchange market, *Journal of Developing Areas* 44: 255–265. http://dx.doi.org/10.1353/jda.0.0083

Kaiser, J.; Kube, S. 2009. Behavioral finance models experimental macroeconomics: on the determinants of currency trade decisions, *The Journal of Behavioral Finance* 10: 44–54. http://dx.doi.org/10.1080/15427560902728969

King, M. R.; Osler, C. L.; Rime, D. 2013. The market microstructure approach to foreign exchange: looking back and looking forward, *Journal of International Money and Finance* 38: 95–119. http://dx.doi.org/10.1016/j.jimonfin.2013.05.004

King, M. R.; Sarno, L.; Sojli, E. 2010. Timing exchange rates using order flow: the case of the Loonie, *Journal of Banking & Finance* 34: 2917–2928. http://dx.doi.org/10.1016/j.jbankfin.2010.02.016

King, M. R.; Rime, D. 2010. The $4 trillion question: what explains FX growth since the 2007 survey?, *BIS Quarterly Review* December: 27–42 [online], [cited 15 September 2014]. Available from Internet: http://www.bis.org/publ/qtrpdf/r_qt1012e.htm

Krishnan, R.; Menon, S. S. 2009. Impact of currency pairs, time frames and technical indicators on trading profit in forex spot market, *International Journal of Business Insights and Transformation* 2(2): 34–51.

Lovcha, Y.; Perez-Laborda, A. 2010. Is exchange rate – customer order flow relationship linear? Evidence from the Hungarian FX market, *Journal of International Money and Finance* 35: 20–35. http://dx.doi.org/10.1016/j.jimonfin.2013.01.002

Lyons, R. K. 2001. *The microstructure approach to exchange rates*. Cambridge: MIT Press. 333 p.

Lyons, R. K.; Moore, M. J. 2009. An information approach to international currencies, *Journal of International Economics* 79: 211–221. http://dx.doi.org/10.1016/j.jinteco.2009.08.003

Mačerinskienė, I.; Balčiūnas, A. 2013. Theoretical advantages and drawbacks of fundamental exchange rate forecasting models, in *Whither our Economies – 2013: 3rd International Scientific Conference*, 24–25 October 2013, Vilnius, Lithuania [online], [cited 15 September 2014]. Available from Internet: http://woe.mruni.eu/wp-content/uploads/2013/11/WOE-2013-ONLINE.pdf

Meese, R. A.; Rogoff, K. 1983. Empirical exchange rate models of the seventies. Do they fit out of sample?, *Journal of International Economics* 14: 3–24. http://dx.doi.org/10.1016/0022-1996(83)90017-X

Menkoff, S.; Sarno, L.; Schmeling, M.; Schrimpf, A. 2013. Information flows in dark markets: dissecting customer currency trades, *Journal of Finance*, Forthcoming. http://dx.doi.org/10.2139/ssrn.2062257

Menkoff, L.; Taylor, M. P. 2007. The obstinate passion of foreign exchange professionals: technical analysis, *Journal of Economic Literature* 45: 936–972. http://dx.doi.org/10.1257/jel.45.4.936

Mokoena, T.; Gupta, R.; Van Eyden, R. K. 2009. Market microstructure approach to the exchange rate determination puzzle, *IUP Journal of Monetary Economics* 7: 101–115 [online], [cited 15 September 2014]. Available from Internet: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1461321

Mutafoglu, T. H. 2010. Position of non-commercial traders in foreign currency futures and spot exchange rates in the long run, *Global Journal of Finance & Banking Issues* 4: 32–40 [online], [cited 15 September 2014]. Available from Internet: http://globip.com/articles/globalfinance-vol4-article3.pdf

Nolte, I.; Nolte, S. 2012. How do individual investors trade?, *European Journal of Finance* 18: 921–947. http://dx.doi.org/10.2139/ssrn.1538760

Onur, E. 2008. The role or asymmetric information among investors in the foreign exchange market, *International Journal of Finance & Economics* 13: 368–385. http://dx.doi.org/10.1002/ijfe.367

Park, C.; Irwin, S. H. 2007. What do we know about the profitability of technical analysis?, *Journal of Economic Surveys* 21: 786–826. http://dx.doi.org/10.1111/j.1467-6419.2007.00519.x

Rasekhi, S.; Rostamzadeh, M. 2011. Fundamental modeling exchange rate using genetic algorithm: a case study of European countries, *Journal of Economics & Behavioral Studies* 3: 352–359 [online], [cited 15 September 2014]. Available from Internet: http://connection.ebscohost.com/c/case-studies/74607707/fundamental-modeling-exchange-rate-using-genetic-algorithm-case-study-european-countries

Rime, D.; Samo, L.; Sojli, E. 2007. *Exchange rate forecasting, order flow and macroeconomic information*, Norges Bank Working papers, 1–39 [online], [cited 15 September 2014]. Available from Internet: http://www.norges-bank.no/Upload/60866/arb-2007-02.pdf

Sager, M.; Taylor, M. P. 2008. Commercially available order flow data and exchange rate movements: caveat emptor, *Journal of Money, Credit & Banking* 40: 583–625. http://dx.doi.org/10.1111/j.1538-4616.2008.00129.x

Schulmeister, S. 2008. Components of the profidability of technical currency trading, *Applied Financial Economics* 18: 917–930. http://dx.doi.org/10.1080/09603100701335416

Simpson, M. W.; Grossman, A. 2010. Can a relative purchasing power parity-based model outperform a random walk in forecasting short-term exchange rates?, *International Journal of Finance and Economics* 16: 375–392. http://dx.doi.org/10.1002/ijfe.435

Vitale, P. 2007. A guided tour of the market microstructure approach to exchange rate determination, *Journal of Economic Surveys* 21: 903–934. http://dx.doi.org/10.1111/j.1467-6419.2007.00524.x

Zafeiriou, T.; Kalles, D. 2013. Short term trend prediction of foreign exchange rates with a neural-network based ensemble of financial technical indicators, *International Journal on Artificial Intelligence Tools* 22(3): 13. http://dx.doi.org/10.1142/S0218213013500164

Zwart, G.; Markwat, T.; Swinkels, L.; van Dijk, D. 2009. The economic value of fundamental and technical information in emerging currency markets, *Journal of International Money and Finance* 28: 581–604. http://dx.doi.org/10.1016/j.jimonfin.2009.01.004

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