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EXCHANGE RATES: PREDICTABLE BUT NOT EXPLAINABLE? DATA MINING WITH LEADING INDICATORS AND TECHNICAL TRADING RULES

Abstract. This paper presents a data mining approach to forecasting exchange rates. It is assumed that exchange rates are determined by both fundamental and technical factors. The balance of fundamental and technical factors varies for each exchange rate and frequency. It is difficult for forecasters to establish the relative relevance of different kinds of factors given this mixture; therefore the utilization of data mining algorithms is advantageous. The approach applied uses a genetic algorithm and neural networks. Out-of-sample forecasting results are illustrated for five exchange rates on different frequencies and it is shown that data mining is able to produce forecasts that perform well.

Keywords: exchange rates, data mining, artificial neural networks, genetic algorithms.
JEL Classification: C45, C53, F31.

1. INTRODUCTION

This paper examines the extent to which leading indicators, technical trading rules and financial market indicators improve exchange rate forecasts, and can thus be combined in forecast models on different frequencies. Attempts at forecasting exchange rates are usually categorized into fundamental attempts and technical attempts. The underlying assumption of fundamental attempts is that fundamentals do matter and the structure of forecast models can be described by economic theory. Technical attempts, on the other hand, assume that psychological dynamics in the foreign exchange market are of importance and such dynamics can be captured by technical indicators. In this paper both categories are seen as complementary and useful in providing information on future exchange rate movements, and

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thus also for the generation of forecast models. The problem, however, is that relatively less is known about the interrelationships between the two categories and how these two categories can be combined. Especially as relatively less is known about it and the interrelationships are complex, data mining appears to be effective in combining the two approaches. The data mining approach presented consists of two stages. The first step is the model selection for which a genetic algorithm (GA) is applied. The GA investigates various combinations of fundamental variables and technical variables and measures their ability to forecast exchange rates. As an unlimited number of such combinations are conceivable an automated optimisation process (like that provided by GA) is effective. The second step in the data mining approach consists of an artificial neural network (ANN). The reason for this approach is that non-linearity may be exploited. The hypothesis that the behavior of exchange rates is, to some extent, non-linear has been examined by several authors and an ANN therefore may improve forecast accuracy. However, the presented data mining approach is unique in the relevant literature (not only in forecasting exchange rates) and presents itself as a method for combining different philosophies (categories) of forecasting exchange rates.

Sections 1–4 are dedicated to the relationship between fundamentals and technical indicators on the foreign exchange market. The fundamentals and technical indicators that are observed, i.e. considered in the data mining search space, will be discussed. As data mining allows the consideration of a large number of fundamentals, as well as traditional fundamentals, fundamentals such as in particular leading indicators are also used. This part will therefore focus on the question of which fundamentals and technical indicators are worth consideration. In Sections 5 and 6 we consider the methods applied and we present the data mining process. As will be shown, data mining is a powerful tool for finding good combinations of explanatory variables on future exchange rate movements. However, the issue of causality in particular will be sketched, as selection in data mining is based on statistical not logical criteria. Empirical results on a daily, weekly and monthly frequency show that data mining is effective in finding combinations of fundamentals and technical indicators, but raises the problem of how these results can be interpreted or explained (Section 7). It will be shown that even though effective and successful combination of variables can be detected, these combinations are hard to describe so the question can be raised as to whether exchange rates are predictable but not explainable (Section 8).

The seminal works of Meese and Rogoff (1983a, 1983b) showed that fundamental forecasting is relatively unsuccessful in comparison to the naïve forecast. Their names and work rank amongst the most cited when it comes to discussions on exchange rate forecasting because they documented the failure of popular fundamental exchange rate models. However, exchange rates are highly volatile, i.e., movements in nominal exchange rates are larger than movements in macroeconomic fundamentals. As it is documented in the literature, many foreign exchange dealers view fundamental and technical analysis as complementary forms of analysis, and thus as effective for deals. It has been found that the relative importance of fundamental versus technical analysis depends on the extent of the horizon focused on. For shorter horizons, more weight is given to technical analysis, and more weight is given to fundamental analysis for longer horizons (e.g. Taylor and Allen 1992) Cheung and Chinn 2001. Cheung and Wong 2000). In response to the fact that on the foreign exchange market there exist participants who base their decisions on technical as well as on fundamental information, Frankel and Froot (1988) developed a model that uses two approaches to forecasting exchange rates. These consist of the fundamentalist approach, which bases the forecast on economic fundamentals, and the technical approach, which bases the forecast on the past behavior of the exchange rate. This was, in fact, a new methodology in economics, as only the fundamentalist approach had been applied before. Nevertheless their theoretical work provides only little assistance for practical forecasts therefore in some sense this work may narrow the gap between theory and applied forecasting literature.

2. TRADING INFORMATION ON THE FOREIGN EXCHANGE MARKET

Some economists say that exchange rates are driven by psychological factors and other market dynamics, rather than by economic fundamentals. As surveys of participants in the foreign exchange market show, there is a large group of currency traders who base their decisions regarding long and short positions not on fundamentals or theoretical economic relationships but on technical trading rules (for recent surveys e.g. Cheung and Chinn 2001, Cheung and Wong 2000). These market participants are trying to chase trends and feel that by observing past price changes, enough information can be collected to predict future price movements. This means nothing more than that they believe that patterns can be found in past exchange rate behavior that are likely to recur. It is no surprise that currency traders turn away from fundamental analysis and embrace technical analysis. One reason is that traditional (fundamental) approaches were often out-performed in forecasting future exchange rate fluctuations. There is much evidence in the literature that simple technical trading rules are profitable (cf. Sweeney 1986, Taylor 1992, Neely et al. 1996, LeBaron 1999, Schulmeister 2001). However, there is more in favor of the technical approach. Exchange rate theories which assume that market participants form rational expectations based on complete information, struggled in explaining which relevant economic fundamentals could have prompted actual exchange rate movements. Therefore, economic theory was on the defensive and was in some sense forced to consider alternative approaches. Also, as the share of currency traders basing their expectations and decisions on "non-fundamental" information rapidly grew, traditional exchange rate literature was increasingly occupied with this topic. Frankel and Froot (1990) have carried out pioneering work in the field of investigating the interactions of chartists and fundamentalists on the foreign exchange market and the consequential impact on exchange rate behavior. More recent work has been carried out by Menkhoff (1998) who investigated the impact of the existence of noise traders on the foreign exchange market and the consequences for fundamental approaches of exchange rate determination.

3. TECHNICAL SOURCES OF INFORMATION ON FUTURE EXCHANGE RATE MOVEMENTS

Methods and techniques for gaining extra profits have been known of for a long time. Especially for the prediction of stock prices, numerous "technical" techniques and trading rules have been developed (e.g. King 1932 and Roos 1955). Most studies on the profitability of technical trading focus on moving average rules. One reason for this focus is the fact that moving average rules are easy to express algebraically, whereas, foreign exchange market participants use various other techniques like bar charts, gaps, islands, key reversals (which define price objectives and form gaps and patterns on bar charts), candle charts and candle patterns, point and figure charts (construction, scale, box reversal, objective counting) graphical methods (head and shoulders, flags, triangles, diamonds, broadening patterns, pennants and wedges etc.), and momentum indicators and oscillators (rate of change, stochastics, moving average convergence divergence, parabolics, etc.). Even though a variety of technical rules are evident in this paper, in most of the literature on the interrelation between fundamentals and technical rules moving average rules are employed. The moving average is $m_t(n)$ defined as

(1) $$m_t(n) = \frac{1}{n}\sum_{i=1}^{n-1} S_{t-i}$$

where S_t is the nominal exchange rate and n is the length of the moving average. Simple (but commonly applied) technical trading rules consider the signal $\Phi(n_1, n_2)$ to be defined by $\Phi(n_1, n_2) = m_t(n_1) - m_t(n_2)$, whereas $n_1 < n_2$ and n_1 and n_2 are the short and long moving averages. However, if $\Phi(n_1, n_2)$ exceeds zero, the short-term moving average exceeds the long-term moving average to a certain extent. As a consequence, a signal for buying is obtained. In case that $\Phi(n_1, n_2)$ is negative, a signal for selling is generated. In this paper several such moving average rules are observable and are thus integrated in the data mining search space. Depending on the frequency considered (daily, weekly and monthly) different moving average rules are constructed ranging from [1, 20], [1, 25], [1, 30] to [1, 100] and [2, 20], [2, 25] and so on, to [10, 100] and beyond. The first number of such pairs denotes the short period and the second number denotes the long periods.

4. FUNDAMENTAL SOURCES OF INFLUENCE ON FUTURE EXCHANGE RATE MOVEMENTS

Even though technical trading rules are popular, the effectiveness of such rules is the subject of debate in the literature. As mentioned before, there exists literature which stresses the profitability of technical treading rules. Nevertheless, some economists are skeptical about the profitability of technical trading rules (e.g. Malkiel 1990). One reason for this skeptical point of view is the view that the price of money must somehow be related to fundamentals. There are numerous fundamentals that are worth being considered, but these may actually rather problematically conceal whatever information they may contain on exchange rate behavior. Other than technical sources of influence, all other variables are labeled as fundamentals. This definition is comprised of a monthly frequency traditional series such as industrial production (final products, materials and more), capacity utilization rate (different sectors), purchasing managers indices, personal income (with spreads etc.), employment (unemployment, civilian labor force, etc.), average weekly hours of production (different sectors), real retail, manufacturing and trade (non-durable goods, durable goods, merchant wholesalers, etc.), consumption, housing starts and sales (non-farm, private housing units etc.), real inventories and inventory-sales ratios, orders and unfilled orders (various sectors), money and credit quantity aggregates (M1, M2, M3, M4, commercial and industrial loans outstanding, etc.), price indexes (commodity price index, producer price index, consumer price index, etc.), average hourly earnings (different sectors), interest rates (with spreads) and especially on higher frequencies, for example financial market data (exchange rates, bonds, stock prices, sector indexes, etc.).

5. ON THE USE OF FINANCIAL MARKET DATA

As well as "traditional" fundamentals and technical indicators, financial market data has been added to the search space. The categorization of financial market series summarizes a bulk of data such as stock market indices (sector indices, country indices), bonds (government bonds and corporate bonds) as well as swaps, forward and future rates (on them). Thus, there is a pool of series on financial assets, and asset prices and derivatives respectively. However, the reason for the consideration of such data in the data mining search space is twofold. Firstly, there is a simple reason for the availability of other fundamental series, such as series for economic growth and inflation. Financial market data can be used to proxy fundamental influences. The second, and probably more important, reason for the presence of financial market series in the forecast models is that financial market data reflects international flows of capital, which in turn can influence exchange rates. From a theoretical point of view the causality between, for example, stock prices and exchange rates is in two directions. This means that a change in exchange rates may change stock prices as variations in exchange rates alter companies' profits and this in turn affects stock prices. More interesting for the purpose of this paper is the other direction, which means that an increase in domestic stock prices creates an increase in domestic wealth and will therefore lead to an increase in the demand for money, so that interest rates will also increase. Thus, higher interest rates are likely to cause capital inflows that result in an appreciation of the domestic currency! It has to be stressed that the use of financial market data is obvious, as currency traders also base their expectations of the future behavior of exchange rates and thus their decisions on such financial market data. In this sense, such series could also be labeled as fundamentals. In addition to this argument there is a more simple reason why currency traders base their actions on such fundamentals, namely because besides chart analysis there is nothing else left to consider on higher frequencies. The arguments regarding the advantages of using financial market data to construct forecast models on high frequencies are therefore quite strong. Thus, the fundamental influences on exchange rate fluctuations in the short-term can certainly be sought in the sphere of the financial world.

6. THE DATA MINING APPROACH

Data mining is applied for the purpose of finding an optimal mixture of fundamentals and technical indicators, and thus for finding optimal forecast models. The two methods used in the data mining approach are ANN and GA. Depending on the frequency, the search space of fundamentals and technical indicators consists of some thousand variables to be examined, taking also into consideration various forms of data transformations and lags. The use of ANN and GA in the field of finance now has a tradition of many years behind it and these methods recently spilled over into the field of economics. The specific combination and coordination of ANN and GA in this work is unique. In this paper a GA is applied as a tool for model selection. This means that the ANN is provided by information which has been sorted out by a GA (in a previous step). GA are powerful instruments for finding solutions for optimization problems in poorly understood large spaces and can be quite effective in solving large-scale combinatorial optimization problems (like the problem of finding a well-performing mixture of fundamental and technical sources of influences on exchange rates). It is therefore no surprise that GA have become more and more popular not only in applied forecasting literature, but (e.g. Arifovic 2001) also regarding the theoretical issues on exchange rates. For exchange rate forecasting the utilization of GA is manifold (e.g. Allen and Karjalainen 1999) on the application of GA to find technical forecasting rules). However, the GA maintains a so-called population of solution candidates for the given problem. Elements are selected out of this population randomly and are allowed to reproduce. In the GA literature, the term reproduction is frequently heard, although it means nothing more than a combination of some aspects of two parent solutions.

For this paper this means that fundamentals and technical information (aspects) of forecast models (solutions) are combined. The criteria for the allowance of reproduction are called *fitness*, but this is nothing more than a function of the cost of the solution it represents. In this work the fitness is measured by the R^2 and by the hitrate (direction of change) in *out-of-sample evaluations*. Fitness is crucial because elements which do not meet a specific fitness level die. This means they are taken from the population and replaced by offspring that are more successful. This means nothing more than that forecast models that are more successful than others are replacing less successful forecast models. As can be seen, this basic idea is very simple and appealing for the large search space (universe of possibly influencing variables on future exchange rate fluctuations) focused on in this work. Nevertheless, for specific tasks, such as finding optimal combinations of input-time series (fundamentals, technical trading rules and financial market series) in this paper, the application of a GA has some advantages in comparison to other optimization tools such as for example the hill climbing methods (e.g. Michalewicz 1996 for a more detailed discussion on hill climbing methods and GA). Experience has shown that the use of various forms of GA beat other optimization techniques by far for finding well-performing forecast models, when considering aspects of calculation time. The use of new technologies such as GA and ANN in a sophisticated data mining approach possibly allows the detection of temporary inefficiencies, which firstly economists can not observe or describe and secondly, are seen earlier than other market participants. This is a fundamental advantage of the approach presented in this paper, and in general for data mining. One disadvantage of such data mining is that it is hard to distinguish between "real" relationships and spurious causality in (limited) results, so that the risk is quite high to be blinded by the goodness of the achieved results. However, in general for the purpose of forecasting it is not necessarily important to distinguish between "real" causalities and spurious causalities if (and only if) forecast performance over time does not suffer, which means that seemingly spurious causalities are stable and provide well-performing forecast results. As will be shown in the discussion on the results, the appearance of variables in the forecast models are sometimes hard to describe (from a theoretical perspective) but are producing well-performing forecasts. This means that those "machine driven found" variables are predicting exchange rates with a considerably good performance rate, but are not explaining exchange rates in the sense that they are delivering causal relationships such as relationships from economic theory. Moreover, the explanatory variables in the forecast models appear to be case specific and time dependent.

7. RESULTS

The success of the applied approach is evaluated in out-of-sample tests. On a monthly frequency, a period of (the last) 30 months was chosen to measure the performance, on a weekly frequency (the last) 60 weeks and on a daily frequency (the last) 100 days. As mentioned, the results are out-of-sample forecasts and for every time step t, the weights of the ANN are trained to new information available at time $t-1$! To describe the data used in this work it can be summarized that the entire data set covers 128 periods (02.28.1991 – 09.28.2001) on a monthly frequency, 274 periods (08.02.1996 – 10.26.2001) on a weekly frequency and 860 periods (07.15.1998 – 10.30.2001) on a daily frequency. The success of the applied data mining approach in constructing forecast models is mixed (see the Appendix 1 for details on the empirical results and Appendix 2 for the variables included by the data mining approach). One main characteristic of the applied approach is that technical indicators were not selected (included in forecast models), i.e. are seen as not informative for future exchange rate behavior (even at higher frequencies). At a monthly frequency success is most promising, as for most exchange rates relatively stable performances can be stated and as the inputs (explanatory variables) selected by data mining are reasonable (in particular cf. Table 1 and 4). At the weekly and daily frequency (in particular cf. Table 2, 3 and 4) the applied data mining approach sometimes resulted in a loose combination of input time series to explain future exchange rates (cf. Appendix 2). The concern for the latter frequencies is that most of the forecast models found by data mining may be ill-fitted and/or the result of data snooping. Moreover, the composition of the data mining forecast models at a daily and weekly frequency allows almost no profound statements about found economic structures, dependencies and relationships to be made! The selection of input variables appears to be chaotic as series frequently are included which are from outside the underlying bilateral exchange rate (currency) relation. In contrast to the forecast models at a daily and weekly frequency, at the monthly frequency a common structure is observable which is to say that nearly all models selected by data mining include variables to explain relative economic growth. Leading indicators in particular, such as new car sales and registrations, housing starts and more have been chosen by data mining in modeling the growth differential to explain future exchange rate fluctuation.

8. CONCLUSIONS

In this paper an attempt was made to find exchange rate forecast models on different frequencies on the basis of a broad and large data base (search space) which included fundamentals, technical indicators and financial market series. Therefore a data mining approach which is based on a GA for model selection and an ANN for the generation of forecasts was applied, whereas data mining included no technical indicators in forecast models.

This is surprising, as on higher frequencies (daily and weekly) foreign exchange market participants base their trading decision on such technical indicators. On the other hand, on higher frequencies financial market data has been included and proved to be effective in out-of-sample evaluations. On a low forecasting frequency (monthly), more macroeconomic data was available for the construction of forecast models and data mining resulted in the inclusion of various macroeconomic variables, especially regarding leading indicators which are associated with relative economic growth. All this suggests, that fundamentals can be informative for future exchange rate movements also on higher frequencies. Nevertheless, from a strict theoretical perspective data mining results may be judged as a loose combination of explanatory variables. This result is not surprising as the criteria for data mining are exclusively statistical and not theoretical plausibility. This leads to the conclusion that exchange rates may be predictable using data mining techniques but their movements are hard to describe and explain by economic theory.

APPENDIX 1: Forecasting Results (Performance)

Table 1. Forecasting results on a monthly frequency

Monthly Frequency	Euro/US dollar	Pound/US dollar	Yen/US dollar	Euro/Pound	Euro/Yen
Correlation (Target, Forecast)	0.3880	0.2714	0.3588	0.3552	0.3946
Stdev (Target)	0.0305	0.0200	0.0339	0.0232	0.0406
Stdev (Forecast)	0.0106	0.0098	0.0157	0.0098	0.0128
Stdev (Residual)	0.0281	0.0197	0.0319	0.0217	0.0374
R^2	0.1505	0.0737	0.1287	0.1262	0.1557
Hitrate	60%	60%	67%	67%	63%

Table 2. Forecasting results on a weekly frequency

Weekly Frequency	Euro/US dollar	Pound/US dollar	Yen/US dollar	Euro/Pound	Euro/Yen
Correlation (Target, Forecast)	0.4863	0.3086	0.4406	0.3250	0.3581
Stdev (Target)	0.0170	0.0138	0.0132	0.0120	0.0191
Stdev (Forecast)	0.0077	0.0043	0.0096	0.0041	0.0085
Stdev (Residual)	0.0148	0.0131	0.0124	0.0114	0.0179
R^2	0.2365	0.0952	0.1941	0.1057	0.1282
Hitrate	73%	72%	70%	75%	72%

Table 3. Forecasting results on a daily frequency

Daily Frequency	Euro/US dollar	Pound/US dollar	Yen/US dollar	Euro/Pound	Euro/Yen
Correlation (Target, Forecast)	0.0259	0.0943	0.0500	-0.0611	0.1221
Stdev (Target)	0.0067	0.0050	0.0062	0.0055	0.0063
Stdev (Forecast)	0.0017	0.0012	0.0019	0.0006	0.0024
Stdev (Residual)	0.0069	0.0050	0.0064	0.0056	0.0065
R^2	0.0007	0.0089	0.0025	0.0037	0.0149
Hitrate	54%	58%	55%	60%	52%

Table 4. Forecast errors of the data mining models

Evaluation Period	Exchange rate	ME	MAE	MSE	MPE	MAPE
30 months	Euro/US dollar	-0.0036	0.0199	0.0007	-0.4070	2.1408
30 months	Pound/US dollar	-0.0045	0.0248	0.0009	-0.2932	1.6376
30 months	Yen/US dollar	0.1067	2.8760	13.0058	0.0516	2.5127
30 months	Euro/Pound	-0.0030	0.0103	0.0002	-0.4913	1.6649
30 months	Euro/Yen	-0.3497	2.9167	14.8819	-0.3991	2.7826
60 weeks	Euro/US dollar	0.0014	0.0098	0.0002	0.1527	1.0977
60 weeks	Pound/US dollar	-0.0008	0.0139	0.0003	-0.0613	0.9654
60 weeks	Yen/US dollar	0.1832	1.1985	2.1612	0.1581	1.0118
60 weeks	Euro/Pound	0.0007	0.0052	0.0000	0.1113	0.8396
60 weeks	Euro/Yen	0.2417	1.4840	3.4281	0.2212	1.4182
100 days	Euro/US dollar	0.0016	0.0047	0.0000	0.1729	0.5273
100 days	Pound/US dollar	0.0007	0.0054	0.0001	0.0463	0.3722
100 days	Yen/US dollar	-0.0037	0.5843	0.5952	-0.0051	0.4808
100 days	Euro/Pound	0.0000	0.0028	0.0000	-0.0023	0.4483
100 days	Euro/Yen	0.1035	0.5697	0.4910	0.0944	0.5274

Note: mean error (ME) $= \frac{\sum_{i=1}^{n}(A_t - F_t)}{n}$, mean absolute error (MAE) $= \frac{\sum_{i=1}^{n}|A_t - F_t|}{n}$, mean squared error (MSE) $= \frac{\sum_{i=1}^{n}(A_t - F_t)^2}{n}$, mean percentage error (MPE) $= \frac{\sum_{i=1}^{n}\left(\frac{A_t - F_t}{A_t}\right)\cdot 100}{n}$, mean absolute percentage error (MAPE) $= \frac{\sum_{i=1}^{n}\left(\left|\frac{A_t - F_t}{A_t}\right|\right)\cdot 100}{n}$, with F denoting forecasts and A denoting actual (realized) values.

APPENDIX 2: Description of the Forecast Models

Forecast models on a monthly frequency:

$$EUR_{t+1} = ((\Delta EUIP_{t-2} - \Delta USIP_{t-2}), \Delta EUIP_{t-2}, \Delta USNCAR_{t-3}, \Delta DEGDP_{t-2})$$

$$GBP_{t+1} = ((\Delta LIGBP3MD_t - \Delta LIGBP1YD_t), (\Delta US3MT_t - \Delta US30YT_t), \Delta SPC_t, \Delta FTSE_t, (\Delta USCPI_{t-1} - \Delta GBCPI_{t-1}))$$

$$JPY_{t+1} = ((\Delta USNCAR_{t-1} - \Delta JPNCAR_{t-1}), \Delta USM1_{t-1}, \Delta FGBLc1_t, \Delta TYc1_t, \Delta SPc1_t, \Delta JPIP_{t-2}, \Delta USNCAR_{t-2}, \Delta JPY_{t-1})),$$

$$EURGBP_{t+1} = \begin{pmatrix} (\Delta DEGDP_{t-6} - \Delta GBGDP_{t-6}), (\Delta DEGDP_{t-6} - \Delta USGDP_{t-6}), (\Delta DEHSTART_{t-3} - \Delta GBHSTART_{t-3}) \\ (\Delta EUIP_{t-3} - \Delta USIP_{t-3}), \Delta USNCAR_{t-3}, \Delta DENCAR_{t-2} \end{pmatrix}$$

$$EURJPY_{t+1} = (\Delta JPIP_{t-5}, \Delta USNCAR_{t-5}, \Delta DECPI_{t-2}, \Delta FDXc1_{t-1})$$

Forecast models on a weekly frequency:

$$EUR_{t+1} = \begin{pmatrix} \Delta USD1X10F_t, \Delta LIGBP3MD_t, \Delta LIGBP1YD_{t-1}, \Delta JPY_{t-2}, \\ \Delta EURJPY_{t-2}, \Delta USD12X18F_t, \Delta JPY1MZ_t, \Delta USJOBC_{t-2} \end{pmatrix}$$

$$GBP_{t+1} = (\Delta FTSE_{t-4}, \Delta USD7X10F_t, \Delta GBP9X12F_t, \Delta JP1YT_{t-9}, \Delta GB30YT_{t-9}, \Delta JPY10YZ_{t-3})$$

$$JPY_{t+1} = (\Delta N225_t, \Delta SPC_t, \Delta GDAXI_t, \Delta LIGBP1MD_t, \Delta GB30YT_{t-3}, \Delta GB3MT_{t-3})$$

$$EURGBP_{t+1} = (\Delta USJOBC_{t-2}, \Delta USD7X10F_t, \Delta USD3X9F_t, \Delta JPY_{t-6}, \Delta SPC_t, GREX10_{t-2}, EURGBP_{t-3})$$

$$EURJPY_{t+1} = (\Delta JP20YT_t, \Delta JPY9YZ_t, \Delta US30YT_{t-5}, \Delta FLGc1_{t-5}, \Delta JPY1MZ_{t-5}, GBP6X12F_{t-9}, DJI_t)$$

Forecast models on a daily frequency:

$$EUR_{t+1} = (\Delta FTSE_{t-3}, \Delta GREX5_t, \Delta GREX10_t, \Delta DJI_t, \Delta LIUSD1MD_t, \Delta SPC_t, LIJPY1MD_{t-3}, FDBc1_t, \Delta SPc1_t, \Delta JNIc1_t)$$

$$GBP_{t+1} = (\Delta FDBc1_t, \Delta USc1_t, \Delta SPc1_t, \Delta TYc1_t, \Delta JNIc1_t, LIUSD1YD_{t-3}, GREX10_t, GB3MT_{t-3})$$

$$JPY_{t+1} = \begin{pmatrix} \Delta FGBMc1_t, \Delta JNIc1_t, \Delta SPC_t, \Delta FDXc1_t, \Delta GDAXI_t, \Delta GREX5_t, N225_t, \\ EURJPY_t, \Delta AORD_t, \Delta EU1YT_t, \Delta EU30YT_t, \Delta TYc15_t, FGBLc1_t \end{pmatrix}$$

$$EURGBP_{t+1} = \begin{pmatrix} \Delta EURJPY_t, \Delta JPY_t, \Delta GREX1_t, \Delta STOXX50E_t, \Delta GB10YT_t, \Delta GB1MT_t, US10YT_t, JP1YT_t \\ FDXc1_t, \Delta JNIc1_t, \Delta FDBc1_t, \Delta US10YT_t, \Delta GB1MT_t, \Delta JP3MT_t, US30YT_t \end{pmatrix}$$

$$EURJPY_{t+1} = (\Delta IXIC_t, \Delta EURJPY_t, \Delta FTSE_t, \Delta N225_t, \Delta RTX_t, SSMI_t, FRc1_t)$$

Abbreviation	Variable name	Abbreviation	Variable name
AORD	Australia all orders index	*JP3MT*	Japan 3 month government bond
DECPI	Germany consumer price index	*JPIP*	Japan industrial production
DEGDP	Germany gross domestic product	*JPNCAR*	Japan car sales
DEHSTART	Germany housing starts	*JPY10YZ*	Japan 10 year zerobond
DENCAR	Germany car sales	*JPY1MZ*	Japan 1 month zerobond
DJI	Dow Jones industrial index	*JPY9YZ*	Japan 9 year zerobond
EU1YT	European Union 1 year government bond	*LIGBP1MD*	Great Britain LIBOR 1 month
EU30YT	European Union 30 year government bond	*LIGBP1YD*	Great Britain LIBOR 1 year
EUIP	European Union industrial production	*LIGBP3MD*	Great Britain LIBOR 3 month
*FDBc*1	LIFFE gilt future	*LIUSD1MD*	United States LIBOR 1 month
*FDXc*1	German DAX future	*LIUSD1YD*	United States LIBOR 1 Year
*FGBLc*1	Bund future	*N225*	Nikkei 225 index
*FGBMc*1	Great Britain bond future	*RTX*	Russian traded index
*FLGc*1	LIFFE long gilt future	*SPC*	Standard and Poor's 500 index
*FRc*1	French Franc/US dollar future	*SPc*1	Standard and Poor's future
FTSE	FTSE index	*SSMI*	Swiss market index
GB10YT	Great Britain 10 year government bond	*STOXX50E*	Eurostoxx 50 index
GB1MT	Great Britain 1 month government Bond	*TYc*1	United States T-note future
GB30YT	Great Britain 30 year government bond	*US10YT*	United States 10 year government bond
GB3MT	Great Britain 3 month government bond	*US30YT*	United States 30 year government bond
GBCPI	Great Britain consumer price index	*US3MT*	United States 3 month government bond
GBGDP	Great Britain gross domestic product	*USc*1	United States bond future
GBHSTART	Great Britain housing starts	*USCPI*	United States consumer price index
GBP6X12F	Great Britain 6M-12M swap	*USD12X18F*	United States 12M-18M swap
GBP9X12F	Great Britain 9M-12M swap	*USD1X10F*	United States 1M-10M swap
GDAXI	German DAX	*USD3X9F*	United States 3M-9M swap
*GREX*1	German rent index 1 year	*USD7X10F*	United States 7M-10M swap
*GREX*10	German rent index 10 year	*USGDP*	United States gross domestic product
*GREX*5	German rent index 5 year	*USIP*	United States industrial production
IXIC	Nasdaq composite index	*USJOBC*	United States jobless claims
*JNIc*1	Japan Nikkei 225 index future	*USM*1	United States money supply (M1)
JP1YT	Japan 1 year government bond	*USNCAR*	United States car sales
JP20YT	Japan 20 year government bond		

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MOŻLIWOŚCI MODELOWANIA I PROGNOZOWANIA KURSÓW WALUTOWYCH: WSKAŹNIKI WYPRZEDZAJĄCE I ANALIZA TECHNICZNA

(Streszczenie)

W artykule przedstawiono proces eksploracji danych statystycznych w prognozowaniu kursów walutowych. Zakładamy, że kursy walutowe pozostają pod wpływem zarówno czynników o charakterze fundamentalnym, jak i czynników pozaekonomicznych. Równowaga pomiędzy tymi czynnikami różni się w zależności od rodzaju kursu walutowego i częstotliwości jego pomiaru.

Prognostykom trudno jest ustalić względną siłę wpływu różnych czynników, stąd analiza polegająca na eksploracji danych ma określone zalety. W proponowanym podejściu wykorzystano algorytmy genetyczne i sztuczne sieci neuronowe. Przedstawiliśmy wyniki eksperymentów prognostycznych poza próbą statystyczną w odniesieniu do pięciu kursów walutowych, obserwowanych z różną częstotliwością. Pokazaliśmy, że metoda eksploracji danych może stanowić skuteczne narzędzie prognostyczne.