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# Master Thesis

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**Faculty of Economics and Business Administration, Tilburg University**

**Finance Department**

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# “Forecast Accuracy and Biases in Professional FX Rate Predictions”

Graduate Master Thesis.

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# Abstract

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This master thesis examines professional FX rate forecasts for major dollar exchange rates (EUR/USD, GBP/USD and USD/JPY). The results indicate that financial professionals do not comply with the rational expectation hypothesis as well as they tend to succumb to biased FX rate predictions. The extrapolative stabilizing expectations and adaptive expectations represent our key findings among biases in currency markets. Moreover, the topically oriented trend adjustment documents pervasive influence of current exchange rate on the FX rate forecasts. This study offers a behavioral explanation for biased professional FX rate forecasts suggesting that informativeness of FX rate predictions that can be achieved also by flawed FX rate predictions might be equally important to forecast accuracy.

Key words: Forecast accuracy, Biases in FX rate predictions, Rational expectation hypothesis, Topically oriented trend adjustment (TOTA), Miscalibration, Accuracy-informativeness tradeoff

# Foreword

Presented graduate master thesis has an ambition to examine the theory of behavioral finance and combine its recent research results and developments with the theory of forecasting. In particular, a close attention has been paid to the forecast accuracy and biases in professional FX rate predictions. Besides introducing a deep theoretical knowledge and background for forecast accuracy, expectation biases and relevant behavioral theories, the presented thesis offers an exhausting application of theoretical knowledge to real-life data in its empirical part. The selection of this topic for the master thesis results from my combined interest in behavioral finance and FX rate forecasts.

I believe that this master thesis can positively contribute to the field of university research by its wide literature overview about forecasting FX rates as well as by its practical application to the most recent data on exchange rates.

I hereby declare that I wrote this master thesis on my own and that I mentioned all references that I used.

I would like to thank professor Jenke R. ter Horst for his valuable remarks and patience.

I would like to devote this master thesis to Branislav Sopira, who I will always remember as a good friend and a wonderful father.

Tomas Car, Tilburg, June 2007

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# 1. Introduction

## *1.1 Motivation*

Exchange rate predictions play a key role in open-economy macroeconomic models. Undoubtedly, predicting FX rates belongs to crucial features of governments' or central banks' macroeconomic policies that should secure a sustainable economic development as well as stable monetary and fiscal policy. Önkal et all. (2003) argue on the example of Turkey that predicting of FX rates is of special importance especially for those countries that undergo rapid and volatile economic changes. Moreover, FX forecasting is vital to financial institutions that provide various financial products as well as to investors who want to make use of a range of financial instruments. Essentially, the exploitation of professional FX rate forecasts can be twofold. First, clients of the banks or portfolio and asset managers can benefit from professional FX rate predictions by incorporating them into the possible future scenarios and thus get prepared for the future. On the other hand, banks utilize FX rate predictions, especially, in eliminating possible risks that occur practically everywhere. In particular, banks supply the market with many guaranteed products (i.e. click funds) that represent a relatively safe investment. Such products are often sought after because of their comprehensibility to investors. They represent, however, a tough task for banks' specialists and financial engineers who often need to use i.e. a variety of currency barrier options to construct such products. At this point, predicting FX rates is of enormous importance, as forecasters are required to project FX rates in a long run or set an estimate for a certain date in future. FX forecasting is though interesting also for the other side of financial markets – professional and individual investors or exporting and importing firms whose profits are substantially affected by exchange rate volatility. Specifically, investors can utilize their forecasting abilities when entering currency forwards and futures markets.

On the other hand, it is often argued that it is futile to try to predict exchange rates, because the FX market is considered to be an efficient market (Goodman, 1978; Frankel and Rose, 1995). Already Mussa (1979) claims in his work that the natural logarithm of major dollar exchange rates follows more or less a random walk and is convinced about the unpredictability of these exchange rates. The market is efficient when market participants have access to all available information and at the same time this information is already incorporated in the price (strong efficiency hypothesis). In other words, the historical record of exchange rates encompasses no information which can be exploited by market participants to accurately predict future spot rates (weak efficiency hypothesis). According to strong efficiency hypothesis exchange rate expectations are formed rationally – it is believed that forecasters are able to obtain all available information and process it in optimal way, i.e. by using an ideal forecasting model. If this approach is correct then, following strong efficiency hypothesis, prediction errors are random caused only by unexpected news.

However, real life evidence suggests that market participants do not always behave fully rationally and in line with theoretical concept of efficient markets and this fact led to creation of new concept of Behavioral finance that has gained a decent respect among economic theories in recent years. We do believe that Statman's view on market participants as normal (behavioral) people is more plausible and applicable to practice than the idea of purely rational market participants maximizing their utility. An empirical result meets the criteria for an anomaly if it is not sufficient to use only rational reasoning or if implausible assumptions are needed to explain it within the paradigm. The existence of many anomalies confirms the intuition that although rational behavior is in the best interest of an individual, investors' behavior is often biased and irrational. We find this paradox very interesting and would like to elaborate more on it. In particular, we can accept the fact that non-professional investors who frequently lack essential knowledge of finance are susceptible to behave not in line with rational expectations. Moreover, they tend to be easily influenced by their emotions which usually lead them to losses. But, is this also true for professional investors that are believed to be better informed and equipped with just right financial knowledge?

A straightforward approach to answer this question is, in case of exchange rate forecasting, an analysis of predictions that are done by professional forecasters (financial experts and researchers). Such professionals should be able to mimic rational expectations and come as close as possible to unbiased predictions, because they are supposed to be the best forecasters, as they have been chosen by banks due to their comparative advantage in the area of financial and currency markets. Several studies were devoted to the research of rational expectations based on survey data (Bofinger and Schmidt, 2004; Stadtmann and Audretsch, 2005). Overall, these studies have come to the conclusion that rational expectation hypothesis does not hold for the exchange rate forecasting and thus not only individual amateur investors, but also financial professionals are prone to biased predictions and irrational behavior in financial markets.

Our study evaluates the performance of financial professionals predicting FX rates. The professional forecasts are provided by Reuters and we compare them to the main benchmark of simple forecasting model following random walk. Moreover, in our study we compare FX predictions to forward rates testing another hypothesis, which of those models used better estimates future spot rate. We also measure forecast accuracy across different currencies and time horizons which allows us to conclude about predictability of currencies and time horizons. In line with former research our results suggest that professional forecasters perform rather poor and their FX predictions are not compatible with rational expectation hypothesis. It also appears that highly paid financial professionals with their big research teams are in their FX predictions defeated by forecasting models following random walk or no change, which is still a forecasting model guaranteeing far from perfect FX predictions and therefore should be taken cautiously by investors.

Behavioral finance literature might offer possible explanations to our results. In general, limitations in information processing might lead forecasters to use simple rules of thumb, so-called heuristics. Previous research suggests that anchoring heuristic might be highly responsible for biased FX forecasts in a way that current FX rate serves as an anchor and has a too strong impact on the forecasts. Another behavioral explanation suggests that fear of losing a good reputation forces a financial professional to follow a herd rather than stick out. In our study we investigate biases in professional forecasts and relate them to behavioral theory. In particular, we examine FX rate predictions for their biased extrapolative, adaptive and regressive expectations. We also tackle the issue of overconfidence, a typical psychological trait among experts and according to Glaser, Nöth and Weber (2007)[1], the most studied bias in the theoretical and empirical behavioral finance literature. We believe that behavioral finance, as relevant theory, can be helpful by using its insights into understanding market participants' behavior. In this way, behavioral finance can contribute to improvement of the design of financial products and services and discounting for investors' irrational preferences.

## *1.2 Overview and contribution of the Thesis*

The principal task of this thesis is to find out whether financial professionals are susceptible to irrational behavior and to offer an explanation of their behavior. We believe that finding behavioristic patterns in actions of professionals will confirm the relevance of behavioral finance and its validity in explaining decision making in financial markets. Moreover, the contribution of our research can be also seen in a detailed comparison of

[1] Published in D.J. Köhler and N. Harvey: Blackwell Handbook of Judgment and Decision Making – Chapter 26

FX rates predictions among three currency pairs (EUR/USD, USD/GBP and USD/JPY), as the most of scholar articles focus only on examining of EUR/USD exchange rate. Using recent Reuters data from 1999 to 2007 adds to our research a topical flavour.

Chapter 2 presents a wide literature overview about currency markets. In particular, we tackle the issue of forecasting of uncertain events such as predicting FX rates with judgmental and statistical forecasting models. The chapter discusses numerous empirical studies that examine forecast accuracy and forecast methods as well as insights from behavioral finance that help us clarify behavior of professionals in currency markets.

Chapter 3 introduces and describes analyzed dataset collected from Reuters database and Reuters FX polls. Reuters asks professionals from prominent international banks about their predictions (point estimates) of major dollar exchange rates on a monthly basis. These point predictions are recorded in a database and allow us to compare the performance of individual banks as well as to analyze and compare forecast accuracy of the market consensus among different currency pairs.

In Chapter 4 we address the issue of forecast accuracy where we compare forecast errors across different time horizons and this enables us to make a conclusion about the predictability of the exchange rates with respect to the length of time horizon. Moreover, in this chapter we compare forecasting ability of professionals to two simple forecasting models (forward rate and random walk or no change prediction as the estimates of future spot rate) Results in this chapter might be perceived as proof of the idea of financial professionals' rather poor forecasting ability.

In Chapter 5 we test the rational expectation hypothesis by regression analysis and we find evidence for support of the assumption about professional forecasters' irrational expectations. This finding represents a pillar premise of the thesis and is further supported by the examination of biases in expectations.

Chapter 6 scrutinizes biases in the expectation formation process and using regression analysis examines extrapolative, adaptive and regressive expectations. In addition, in this chapter we offer behavioral explanations for biased predictions of financial professionals through the topically oriented trend adjustment. Moreover, in this chapter we apply an interesting research on miscalibration, a key representative of overconfidence, in the form of accuracy-informativeness trade-off as well as the better than average effect.

Chapter 7 offers a conclusion summarising our results and sketches some paths of further research.

# 2. Related literature

## *2.1 Introduction to forecasting*

Forecasting is, at best, an imperfect science finding its place only where uncertainty occurs, which is typical of currency markets. According to Armstrong (2001), forecasting represents one of the key decision-making instruments and in a simple definition forecasting stands for analyzing historical and current data to determine future events. Basically, we differentiate between two forecasting methods – ***statistical*** (quantitative) and ***judgmental***. Both of them can bring advantages to the process of forecasting. Therefore, it is natural that researchers and practitioners try to integrate these methods in a way where both methods can positively contribute to and affect forecasting. Adjusting statistical method based on judgment might represent one way of combining these methods. However, Hogarth (1978) points out that judgmental forecasts can be often biased, and they can, therefore, easily damage the accuracy of forecasts for example by optimism, lack of consistency or political manipulation. Conversely, statistical forecasts always produce objective and unbiased results, but their absolute dependence on underlying data makes this method vulnerable as well. Following the fact that both methods have relative advantages, it seems reasonable to integrate them, which is a usual approach used in currency forecasting. Webby and O'Connor (1996) caution against focusing purely on statistical (objective) methods and propose utilizing judgmental (subjective) methods as well. Contextual information is likely to be the prime determinant of judgmental superiority over statistical models, especially if highly unstable time series, which is a perfect characteristic of foreign exchange rate development, is examined. All in all, a proper choice of statistical method is crucial to the defensibility, objectivity and precision of the forecast. However, a composite approach that would combine benefits of mechanical approaches with advantages of judgmental interpretation of soft contextual information seems to be the best solution. We do believe that such synthesis is the best assumption for the most accurate forecasts.

A proper choice of forecasting method is vital to success of a forecaster – an accurate prediction. Forecast accuracy that could be defined as *"the optimist's term for forecast errors"*[2] represents the difference between the forecasted and actual value. Armstrong and Collopy (1992) analyze different types of error measures, judge their reliability and recommend absolute percentage error (APE) as a better and more reliable

[2] http://armstrong.wharton.upenn.edu/dictionary/ (15.5.2007)

measure compared to mean squared error (MSE), which is vulnerable in its strong dependence on a scale of time series. We follow their advice and analyze in Chapter 4 accuracy of professional forecasts using not only commonly used MSE, but also APE.

Forecast accuracy studies have examined the performance of quantitative and judgmental forecasting and came to contrary conclusions. On the one hand Lawrence and O'Connor (1992) have found out that quantitative forecasting achieves better accuracy when dealing with artificial data. On the other hand, real-life data with its non-stationary character prefer the subjective to the quantitative methods that are based on a stationarity assumption (Lawrence et. all 1985).

In addition to choosing the right method and supporting forecasting techniques, forecasters should also assess uncertainty. Forecasts are often articulated as single numbers, called ***point forecasts***, which give no information about their likely accuracy. They might seem more adequate and easier to follow for decision makers who prefer setting clear objectives and unambiguous goals. In fact, it is often difficult to describe the reality with a single value due to uncertainty and it is always advisable to count with several options when predicting the future. Therefore to assess future uncertainty, it is usually important to support point forecasts by computing ***interval forecasts***. Interval forecasts, also called as forecast regions, confidence intervals or prediction intervals, are used to express predictions as a range of numbers in which future values are believed to lie. In practice it is common that FX forecasters predict point estimates, however, this information is often supplemented, especially by technical analysts, by lower and upper limit (so-called support and resistance levels).

## *2.2 Forecasting in currency markets*

### 2.2.1 Introduction

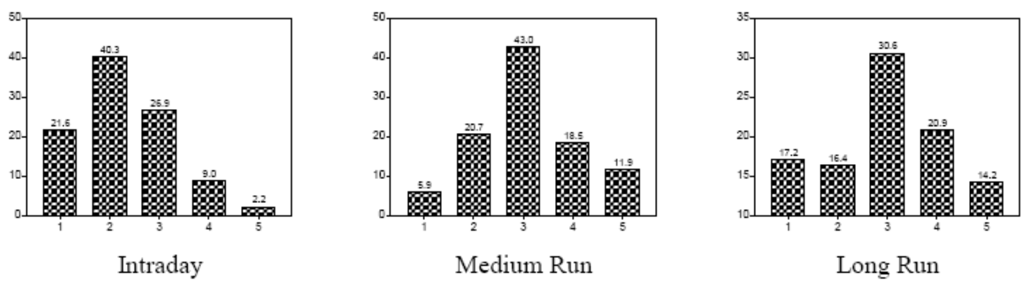
Human judgment plays a significant role in currency forecasting where quantitative models are used to provide initial estimates that are subsequently updated by the judgment of the forecaster. In some cases, the forecaster relies only on judgment alone to forecast future values. Wilkie and Pollock (1996) point out that despite its substantial and frequent usage in practice there is little academic research dealing with its evaluation. Contrary to the well documented and scrutinized statistical models, judgmental models in currency forecasting appear to be neglected. In order to evaluate them the authors propose use of probabilistic forecasting – adding a percentage value to a point estimate (strong forecast) or direction of movement (weak forecast) representing a degree of certainty.

They believe that this could help reveal biases in professional forecasts such as overconfidence and propose a practical framework that could be used when evaluating a judgmental forecasting model.

There are many scholar articles on predicting exchange rates using structural or time series models and most of them detect difficulties, if not pointless efforts, in predicting future exchange rates (Meese and Rogoff 1983; Backus, 1984 or Cheung et. all, 2002). Early studies from Meese and Rogoff (1983) represent pioneering efforts to analyze macroeconomic models designed to predict exchange rates. In their aforementioned study they try to forecast monthly or 3-months FX rates with macroeconomic fundamentals utilizing monetary and portfolio-balance models. Their final conclusion is that a rather little explanatory power is observed, and the models show no outperformance in forecasting ability compared to simple alternatives. If there are any positive results suggesting explanatory power, they are very fragile and not stable over time, which leads to an overall doubt of the authors about the use of macroeconomic models in time-series modelling of FX rates.

Cheung and Chinn (2000) base their study on previous research that claims that predicting of FX rates is pointless and try to inspect the predictability of exchange rates with respect to the time horizon. They survey FX traders with presumably the best information set rather than econometricians who have access only to limited macro data. They ask traders to rate the degree of predictability for three horizons – intraday, medium run (up to 6 months) and long run (more than 6 months) in Figure 1.

**Figure 1 Predictability of foreign exchange rates (1-no, 5-perfect predictability)**




**Source: Cheung, Y. and Chinn, M.D. (2000)**

Not surprisingly, the answers depicted in the Figure 1 show that intraday exchange rates are viewed as virtually unpredictable and that traders practically do not differentiate between medium run and long run when assessing predictability of exchange rates. Moreover, their results support the common belief that short-run exchange rates do not follow fundamentals, whereas medium-run and long-run do reflect fundamental values. We directly relate and compare our results about forecasting accuracy in Chapter 4 to Cheung and Chinn (2000) survey.

### 2.2.2 Forecasting models

For many years standard macroeconomic exchange rate models have been striving to describe or forecast real exchange rate movements, but we have to say that their accuracy is still insufficient. Bofinger and Schmid (2003, 2004) imply that this poor result might represent a main reason why financial professionals still have serious problems with predicting future FX spot rates. The canonical empirical study from Meese and Rogoff (1983) examines various macroeconomic exchange rate models from which some of them depend on flexible price monetary model, interest differentials or purchasing power parity. Last two decades were marked by exhaustive empirical research about the predictive power of the forecasting models and its empirical findings could be summed up into two major points:

*1. Short- and medium-term forecasts.* When pursuing forecast accuracy, the macroeconomic forecast models seem to lag behind forecast models that are not based on macroeconomic fundamentals at all. Meese and Rogoff (1983) commence portraying the underperformance of macroeconomic FX models compared to random walk models in the short-run (1-2 years), which has not changed over past 20 years (Rogoff, 2001). Moreover, Oberlechner and Osler (2003) argue that approximation through random walk with zero drift fits well major dollar exchange rates over short horizons. This is in line with the theory of efficient markets and is widely supported by extensive econometric evidence. Put it differently, fundamental analysis might be useless for short-term forecasts. This might explain the boom in using technical analysis in 1980s (a method of predicting price development by studying charts or historical market action), when most of currency traders reported its utilizing especially for short-term predictions (Taylor and Allen, 1992).

*2. Long-term forecasts.* There seems to be some explanatory power of structural exchange rate models when predicting longer horizons (3-5 years). Chinn and Meese (1995) provide evidence that fundamentally based models predict future FX rates in long horizon substantially better than random walk models.

As Bofinger et. all (2004) mention, there are also sceptical views criticizing two abovementioned principles, however, the crucial challenge (or impossible task) for forecasters still appears to be defeating simple random walk model in forecasting and that is also a reason why we choose random walk (or no-change) model as our benchmark model, to which we compare forecasts of financial professionals.

Additionally, we compare the accuracy of professional FX predictions to the forward rates that represent our secondary comparative model. The forward exchange rate used to be considered as a relevant and unbiased predictor of the future spot rate. Under the forward rate hypothesis, the interest differential between two currencies represents an estimate of the future FX rate. Therefore, a currency with a higher interest rate is supposed to depreciate over time in order to reduce the effect of the advantageous interest rate. *"Forward exchange rates, however, fundamentally reflect the total demand and supply for a currency in both the spot and forward markets, linked by interest rate parity, not simply the net demand for open positions in a currency based on speculator's expectations about future spot rates."*[3] Empirical work (Goodman, 1978; Froot and Thaler 1990) has reliably refused forward rate hypothesis and at the same time points at the anomaly of forward rate bias, a phenomenon that was discovered by behavioral economists in 1980s. Cavaglia et. all (1994) scrutinize forward rates covering many currencies, find forward bias and identify its two key reasons – irrational expectations and risk premium. The forward rate bias anomaly is nowadays popular amongst many hedge funds that seek to take advantage of arbitrary opportunities in currency markets – they are able to earn on interest rate differential and, additionally, on the appreciation/depreciation of the high/low yield currencies. In the empirical part of the thesis we compare professional FX rate forecasts to random walk and forward models. We assume that financial professionals will not beat random walk model and are curious if they are able to outperform at least a naive model of forward rate.

### 2.2.3 Professionals vs. amateurs

Professionals and their FX rate predictions are in the centre of our attention. In particular, we try to find out if they are able to predict unbiased values and behave rationally. Andersson (2004) points out that financial professionals are often perceived as authorities capable of superior performance and take it for granted that they are financial experts not considering their performance or expertise. Generally, myriad studies (Camerer and Johnson, 1991; Hilton, 2003; or Russo and Schoemaker, 1992) have illustrated that experts in diverse areas are not able to produce consistently superior predictions compared to trained novices or even to unknowledgeable people. Shapira and Venezia (2000) provide a clear evidence for behavioral biases also among professionally

[3] Goodman (1978), p. 416

managed investors. They focus on disposition effect (selling winners earlier than losers) and try to explain its presence among professionally managed investors by overconfidence which leads them to excessive trading. Although they deny the idealistic view on financial professionals as unbiased professional market participants, they provide evidence that disposition effect is more pervasive among individual (amateur) investors. Hence, they conclude that professional investors compared to amateur investors are likely to achieve superior results despite succumbing to behavioral heuristics.

Hartzmark (1991) challenges the forecasting ability of professionals and suggest that not forecasting expertise but luck plays a key role in forecasting process. He analyzes traders' positions in US future markets and his research implies that returns earned by futures traders are randomly generated and depend on luck rather than on traders' abilities. The author supports his conclusion by forecast coefficients that are either uniformly distributed (equal amount of traders with superior or inferior skills) or culminate at zero (there are more traders with no ability than it would be expected in random world). Hartzmark tries to find an explanation for the latter case of distribution. He suggests that this phenomenon might be explained by the fact that many traders use similar trading tactics or the same source of information. When examining traders who showed in first period superior skills, he finds out that in the subsequent period they demonstrated no or average skills. Traders that showed inferior skills in the first period improved their results slightly in following period. These results represent a strong piece of evidence in favor of luck hypothesis.

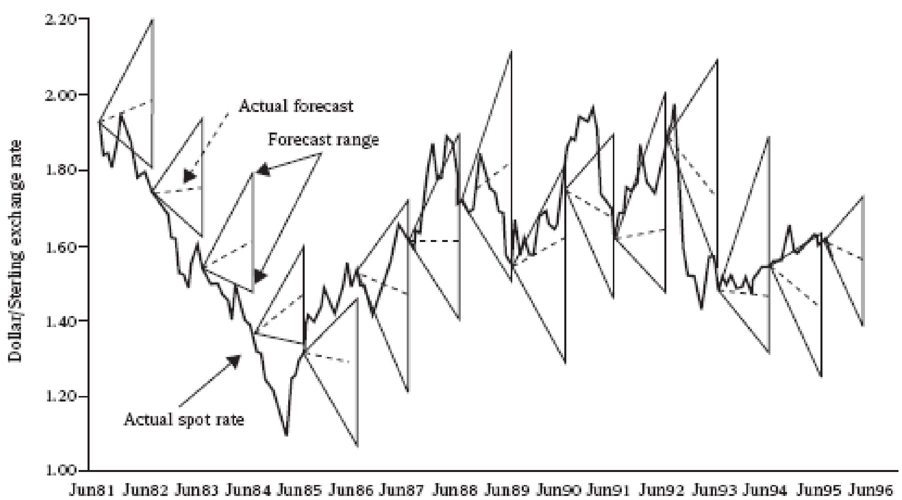
Dreger and Stadtmann (2006) analyse exchange rate expectations of financial professionals and they support findings from previous research (i.e. Frankel and Froot, 1987) about the heterogeneity of professional forecasts. One would expect financial professionals (if they are all rational) to have similar or at least insignificantly different expectations. However, homogeneous expectations are rather rare in actual currency markets and this fact leads Dreger and Stadtmann to implication that using contrary principles of technical and fundamental analyses might be the main reason of substantial variation of FX predictions. When comparing forecasts among professionals we find so-called star performers whose predictions appear to be above the average. What is more important is to examine these star performers, if they are able to maintain their position of superior forecasters for a longer period. If we find clear and supporting evidence for this, we could then claim that the forecasting skill of professionals is responsible for their superior forecasting performance (Hilton, 2003). The opposite opinion to the belief in above-the-average forecasting ability says that market players are better than average simply through chance and only for a short period of time.

Önkal et all. (2003) observe forecast accuracy of FX rates among professionals and amateurs in Turkish currency markets. They differentiate between three types of forecasts – point, directional and interval forecasts and conclude that when assessing professionals' superiority it matters how forecasters are asked for their FX predictions. In other words, professionals show a sign of inconsistency in their forecasts as they are asked to predict the same event several times but they have to use a different type of forecast each time. Moreover, they compare the professional forecasts to the ones of amateurs and find a superior accuracy of professionals when placing point or directional forecasts, although there are some amateur forecasters that dominate professionals in forecasting. When using interval forecasts the general underperformance of amateurs disappears. All in all, the authors conclude that there is a higher probability that professional forecasts will be more accurate, but then there are still many amateurs that are able to outperform professionals, so they warn against blind trust to services of financial professionals.

### 2.2.4 Forecast FX polls

Hilton (2003) provides a comprehensive illustration of the pervasive inaccuracy of expert forecasts in finance through data collected by Euromoney and Record Treasury

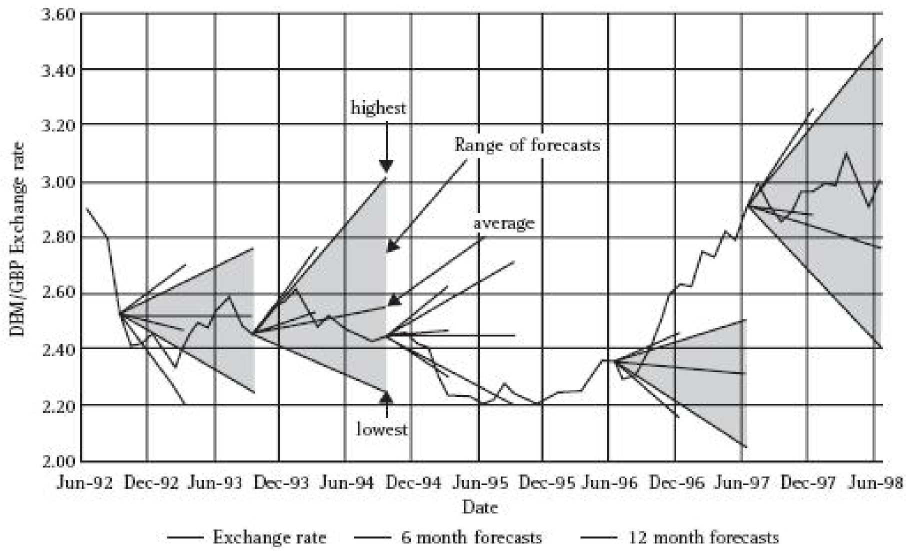
**Figure 2 Forecasts of the $/£ spot rate at a 12-month horizon from 40 top FX forecasters during 1981-96 (courtesy of Record Treasury Management).**




**Source: Hilton (2003)**

Management on financial experts' and corporate treasurers' forecasts about £/$ and £/DM. A detailed inspection of the data in both Figures 2 and 3 shows that real exchange rates rarely fall in the middle of the interval created by taking the highest and the lowest forecast made by 40 experts, and indeed often fall outside this interval.

**Figure 3 6-month and 1-year forecasts of $/£ spot rate by the UK corporate treasurers in 1990-98 (courtesy of Record Treasury Management)**




**Source: Hilton (2003)**

Cheung and Chinn (2000) address scepticism of some economists about the validity of survey methods. One might think that financial professionals (currency traders) are likely to twist their answers – FX rate predictions in order to benefit or gain an advantageous position when bargaining with a client. However, the framework of their survey provides a little incentive for the participants to distort information intentionally in order to get a competitive advantage. Moreover, they defend the use of survey data, as it represents a reliable way to illustrate market heterogeneity or diversity in professionals' expectations.

Stadtmann and Audretsch (2005) examine data from Wall Street Journal poll on FX predictions. They are primarily concerned with the question if professional forecasters form rational expectations and if they are able to beat a random walk forecasting model. They find strong evidence against rational expectations among professionals in currency markets and support it by the finding that professional predictions are not able to outperform a naive random walk benchmark model. Moreover, they scrutinize data for three kinds of biases in the expectation formation process that were thoroughly described by Frankel and Froot (1987). Specifically, they examine professional forecasts if they are affected by the recent trend of the FX rate and form so-called ***extrapolative expectations***.

They continue with investigating on ***adaptive expectations*** that represent the influence of forecast error on the change in FX rate prediction. Finally, they focus on ***regressive expectations*** that are based on the assumption that the FX rate returns back to an equilibrium level that has to be settled in advance. Stadtmann and Audretsch conclude that only about 1/3 of all professionals do not yield to biased expectations, whereas the rest of financial professionals use models based at least on one of those expectations. Moreover, the authors are able to divide forecasters based on their FX predictions into several groups, which serves as strong evidence for a heterogeneous character of the group of forecasters.

Bofinger and Schmidt (2004) compare in their study FX rate forecasts of EUR/USD among Reuters, Consensus Economics and ZEW (Zentrum für Europäische Wirtschaftsforschung, Mannheim). In line with previous research they support the hypothesis about irrational expectations, as for all market predictions their results suggest that the hypothesis about unbiasedness ought to be rejected. Again they find evidence of an inferior accuracy of professional forecasts compared to a naive random walk forecasting model. The authors sum up their study claiming that forecasting exchange rates is an enormous complex task with a high degree of uncertainty and suggest the anchoring heuristics as a possible explanation for biasedness of professional forecasts.

Bofinger , Leitner and Schmidt (2004) scrutinize FX predictions collected from Reuters database and, again, find results suggesting an inconsistency with rational expectations hypothesis. Moreover, they provide an interesting extension to a data analysis in a form of experiment, where they asked novices to predict FX rates and, surprisingly, professionals possessing exchange rate expertise perform worse in forecasting than unknowledgeable subjects. They suggest anchoring and other heuristics to be responsible for their unexpected results.

## *2.3 Insights from Behavioral finance*

### 2.3.1 Introduction

Concrete evidence from abovementioned research suggesting that financial professionals are also “only” normal people (Statman, 2005) with irrational preferences and expectations has stimulated behavioral scholars in their strive to explain irrational behavior of professionals.

Prast (2004) points out that reputational models are designed to explain the behavior of financial professionals in financial markets. Her insights into the behavior of financial professionals are based on a former research of Scharfstein and Stein (1990).

They believe that investment managers may sometimes have incentives to follow the herd rather than their private information. Although from a global point of view such financial professionals show signs of irrational behavior, from the point of view of individual managers such behavior can be rational, if managers are concerned about their reputation. The logic behind this is best expressed in the quote by J.M. Keynes from more than 70 years ago, *"Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally."* Investment managers following this utility would always prefer to tilt to the decision of others, because they are afraid of losing their reputation, if they turn out to be the only ones who are wrong. Therefore, when examining predictions of financial professionals it has to be taken into account that professionals' performance is often judged and rewarded relatively within the group (benchmarking).

As we discussed earlier, development of exchange rates seems to be well approximated by random walk, which implies accepting randomness and poor predictability of FX rates. However, day-to-day experience supported by evidence from research suggests that people have generally problems with that. O'Connor and Lawrence (1992) address in their study the ability of people to understand and perceive the randomness and imply that it is deficient. Authors imply that people have difficulty in spotting signal and in recognising and comprehending noise (randomness) which leads into the incapability of separating randomness from signal. It seems as though people were afraid to accept randomness and seek causal explanations everywhere. Hilton (2003) upgrades research about perceiving randomness into illusory correlations, an inherent part of the business world. Illusory correlations stand for mistaken beliefs which incorrectly suppose that there is a relation between a particular action and an effect. Braas and Bralver (1990) argue that traders typically overattribute profits to themselves and fail to recognize other sources of profits (i.e. bid-offer spread). They quote a head fixed-income trader for a US bank to illustrate this type of mistaken belief, *"Any trader I put in the 5- to 7-year chair makes a lot of money for us; each of them thinks that he is making the money with his smart calls. But it's really the chair that makes the money."* We find the invisible correlation between the profits and the chair (instead of traders) intriguing and we might take it as another proof of the fact that forecasting (or trading, or another) ability cannot fully determine the results of professionals in markets and that other circumstances have to be also taken into account.

### 2.3.2 Anchoring

Results from former FX polls and research suggest that financial professionals are significantly affected in their predictions either by current trend - movement in an exchange rate or by perceived fundamentals.

Behavioral finance offers a simple rule of thumb, the anchoring heuristics that could plausibly explain this not fully rational expectation. It stands for a biased quantitative judgment towards an initial anchor that has been set by a decision maker explicitly or implicitly, but is often totally irrelevant to deciding process. Theory of behavioral finance classifies this heuristics as a cognitive dissonance, in other words, it represents a mental shortcut that brain uses in order to simplify acquiring or processing of information. Tversky and Kahneman (1974) argue that such heuristics could sometimes lead to severe and systematic errors, because people are unable to make sufficient adjustments and avoid biased estimates. They illustrate this phenomenon on an example where they asked two groups of respondents the same question about the percentage of African countries in the United Nations (UN) that should be answered and compared to a given arbitrary number that was different for both groups – 10% and 65% respectively. They show that these arbitrary numbers embody anchors for both groups as their median answers are 25% and 45% respectively. Furthermore, they provide empirical evidence that anchoring arises not only when the starting point is provided, but also when the estimates are based on some incomplete calculations.

Jacowitz and Kahneman (1995) provide additional findings that anchoring is affected by the degree of uncertainty – the higher uncertainty, the more probably biased estimate towards the anchor occur. Moreover, they propose measures through which they are able to quantify the anchoring effect and conclude that people take the anchor as informative measure and make insufficient adjustments to diminish the anchoring effect.

To our surprise, already Keynes (1936) describes a human expectation process from financial perspective and his concept is very similar to the phenomenon of anchoring heuristics: "*It would be foolish, in forming our expectations, to attach great weight to matters which are very uncertain. It is reasonable, therefore, to be guided to a considerable degree by the facts about which we feel somewhat confident, even though they may be less decisively relevant to the issue than other facts about which our knowledge is vague and scanty. For this reason the facts of existing situation enter, in a sense disproportionately, into the formation of our long-term expectations; our usual* *practice being to take the existing situation and to project it into the future, modified only to the extent that we have more or less definite reasons for expecting a change."*[4]

### 2.3.3 Overconfidence

Overconfidence, one of the most robust findings in the psychology of judgment claiming that people are typically overconfident in their judgment and predictions, can be defined *"as a systematic overestimation of the accuracy of one's decisions and the precision of one's knowledge."* (Dittrich, Güth, Maciejovsky, 2005). Put it in other words, overconfidence represents an underestimation of the variance of information signals (Glaser and Weber 2004). Overconfidence belongs to one of the most prominent biases and heuristics in the field of behavioral finance and manifests itself in three main forms:

*1. Better than average effect* – people tend to believe that their abilities are above the average, which comes from the observation that more than 50% of population seems to think that they have better-than-average driving skills. Theory suggests that overconfidence is more prevalent in a feedback-infrequent and -ambiguous environment (Fischhoff, Slovic and Lichtenstein, 1977). This idea seems to sound fairly plausible when applied to financial sector where feedback is, sometimes, more than ambiguous. To give a specific example, when the market rises following positive news, it is said to be responding to the news; when it falls, it is explained by the market that has already incorporated the good news. Angner (2006) shows that economists as experts work in an environment that literally invites ambiguity and vagueness, as there are no effective institutional constraints and penalties for expressing extreme confidence in economists' judgments. He provides further evidence for his finding that the overconfidence is endemic in the experts' environment. Klayman et al. (1999) introduce a hard-easy effect implying that overconfidence disappears with easy tasks, where people, in contrary, tend to underestimate their knowledge or precision.

*2. Illusion of control and unrealistic optimism* – those prone to the illusion of control naively believe that they can control random tasks and events such as avoiding accidents, winning lotteries, buying winning stocks or avoiding losing stocks (Langer, 1975). The illusion of control automatically transforms into unrealistic optimism showing unreasonably high confidence about the future.

*3. Miscalibration* – a tendency to overestimate the precision of one's information or prediction. Studies that analyze the assessment of uncertainty usually find that people's probability distributions are too tight (Lichtenstein, Fischhoff and Phillips, 1982 or Glaser,

[4] Keynes (1936), p. 148

Weber, 2004). While miscalibration can be associated with the better than average effect, it is conceptually different: Overestimation the quality of one's knowledge does not necessarily lead to his or her believing to be better than others (Biais et al., 2002). Unlike the previous two measures of overconfidence, miscalibration is easier to quantify by an interval production task where people are asked to state a 90 percent confidence interval for several uncertain events. A well-calibrated person should correctly assess uncertain situations and only 10 percent of his or her answers should fall outside the confidence interval. However, extensive research on this topic suggests a dramatic disparity between expected 10 percent and observed outliers, leading to a conclusion that people, usually, significantly overestimate their precision. Russo and Schoemaker (1992), for instance, find percentage of surprises (the percentage of true values that fall outside the confidence interval) ranging from 42% to 64% (compare to 10%). Deaves, Lüders and Schröder (2005) carry out a survey where they use miscalibration as a proxy for overconfidence and in their conclusion support the view of overconfidence as not only a pervasive phenomenon, but also as one that is difficult to eliminate.

Yaniv and Foster (1997) present an appealing upgrade of miscalibration as the main proxy for overconfidence. They agree with other scholars who claim that people (financial experts are no exception) are prone to place too narrow subjective confidence intervals and, so, they exclude the correct answer far too often. However, in their study Yaniv and Foster challenge probabilistic calibration as a normative standard for accuracy. Rather than that they propose a different normative approach that could be applied in the interval judgment appraisal. They base this approach on the assumption that forecasts of future (unknown and uncertain) variables are often done with the aim of making a decision. Therefore, it is inevitable to take into account the communicative interactions between those who produce the judgments and ones who receive or use them when deciding. Both authors are convinced that a proper forecast should be indeed accurate, but informative as well. They illustrate their opinion on the following example of predicting future inflation rates. Forecaster, under uncertainty, might guess (A) 3%, (B) 2-4% or (C) 1-10%. Obviously, coarser prediction (C) has a higher chance of being confirmed, but on the other hand, it may not be appreciated by recipients who require properly informative as well as accurate predictions. Yaniv and Foster (1995) examine recipients' preferences about forecasts proving the intuition that informativeness is with respect to accuracy at least equally requested parameter of a prediction. One of their examples demonstrates this clearly – respondents were asked to choose one of the estimates of the number of United Nation member countries (in 1987) and at the same time they were given the correct answer 159 member states. The first estimate (A) 140-150 does not cover the correct answer, which is not the case of the second estimate (B) 50-300. The results were astonishing – most of the respondents (90%) preferred estimate A to B, although only B was technically correct. *"Thus respondents were willing to accept some error in order to obtain more informative judgments."*[5] Both authors portray forecasting as an accuracy-informativeness trade-off. They stress the necessity of balance between those two most important characteristics and add that timing of the rewards for forecasters highlights the need for the latter characteristic. Rewards for being informative are immediate, as recipients judge the informativeness of a prediction as soon as they get it. Rewards for being accurate usually need more time to be evaluated as the relevant feedback has to come up. This timing issue might work as a strong incentive for the forecasters to provide highly informative predictions.

[5] Yaniv and Foster (1997)

# 3. Data description

## *3.1 Background Information*

Generally, EUR/USD represents with a 28% share of the global turnover the most traded currency pair, followed by the USD/JPY with 17% and USD/GBP with 14%.[6] These three currency pairs cover together roughly 60% of the global turnover which underlines their dominance and we believe that the analysis of three most important exchange rates is of extreme importance. Furthermore, we are convinced that the results found out in the thesis might be used to imply hypotheses about currency markets in general, in other words, we believe that those three (most traded) currency pairs represent a strong proxy for the whole currency market. Our dataset comprises point forecasts of FX rates of three major dollar exchange rates – EUR/USD, GBP/USD and JPY/USD obtained from Reuters - the leading global provider of financial information.

Analysts and researchers from major international banks contribute on a monthly basis to Reuters FX polls their FX rate predictions on major dollar exchange rates. As we discussed earlier, some sceptics could argue that professional forecasters would be tempted to distort prediction in order to gain a competitive advantage. However, our counterarguments are twofold. First, our analysis examining Reuters FX poll data is not precedential, as it was already used for standard research before (Bofinger and Schmidt; 2003 or Bofinger, Leitner and Schmidt; 2004). Moreover, similar analyses using Wall Street Journal (WSJ) survey data set were conducted by Stadtmann (2004) or Dreger and Stadtmann (2006). Second, Reuters provides for professional forecasters incentives to be accurate, as each month the most accurate banks are presented and in the end of the year the most accurate bank is being rewarded[7]. Reuters examines the accurateness of contributors, based on how close are their one-month FX rate (EUR/USD, GBP/USD and JPY/USD) predictions compared to the last trading day of each month. Undoubtedly, belonging to a group of the most accurate banks will also positively affect the reputation of a bank, which is another powerful argument for the belief that professional forecasters try to do their best and strive to be as accurate as possible. Then, observing these data, we are able to examine FX rate predictions and draw a conclusion about the rational expectations assumption. Based on results of former research we expect to find evidence for support of irrational expectations, whereas other results would be surprising.

[6] Bank for International Settlements – Triennial Central Bank Survey (March 2005) downloaded from http://www.bis.org/publ/rpfx05t.pdf (28.5.2007)
[7] See Appendix 1 – Reuters FX Accuracy League

### *3.2 Reuters data*

Professional forecasters participate in Reuters FX polls on a monthly basis. We illustrate on an individual example of Barclays Capital[8] that the professional forecasters are requested to predict major dollar FX rates for four different time horizons.

Table 1 summarizes the number of predictions within the observed time period (January 1, 1999 – May 31, 2007), where each of time series ends with an FX rate forecast for May 31, 2007. As we can see, the length of time series is maximal since the Euro introduction in January 1999 where each of time series includes at least 90 forecasts, which is already a sufficient number for analyzing time series data. Bofinger and Schmidt (2003) and Bofinger et. all (2004) scrutinize Reuters data between 1999 and 2003, while Stadtmann (2004) and Stadtmann and Dreger (2006) examine WSJ semi-annual data between 1989 and 2005 (around 30 periods). Our thesis compared to just mentioned studies analyses either a longer time period or a higher number of FX forecasts, which makes our results at least as important as those found in the referred studies.

**Table 1 Forecast data**

| EUR, GBP and JPY predictions updated monthly | | | |
|---|---|---|---|
| **Horizon** | **From** | **Until** | **No. of prediction** |
| 1M | Jan-1-1999 | May-1-2007 | 101 |
| 3M | Jan-1-1999 | Mar-1-2007 | 99 |
| 6M | Jan-1-1999 | Dec-1-2006 | 96 |
| 1Y | Jan-1-1999 | Jun-1-2006 | 90 |

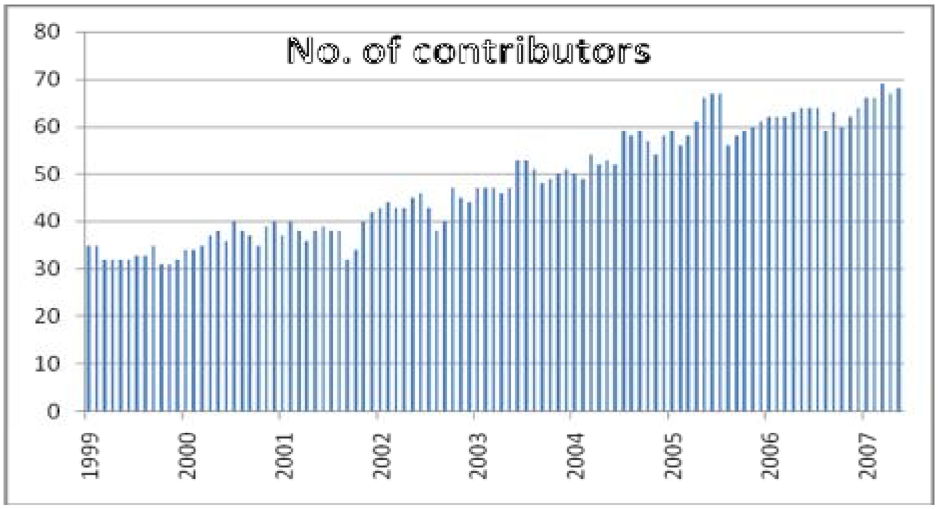
Overall during the observed period, Reuters has asked 90 major international banks to contribute their FX rate predictions. Figure 4 on the next page illustrates the development of the number of the participants between 1999 and 2007 (based on the most common 3-month EUR/USD prediction). The number of professional forecasters began at 35, it increased to a maximum of 69 and moved around 61 for the past three years. Further examination of individual FX forecasts within the observed period implies that only one bank has contributed all of the FX predictions but, what is positive, 50 banks have contributed more than 50% of all predictions.

Reuters provides for each of three currency pairs and for each of four time horizons a median forecast that is presented as a market consensus. Market consensus is hence protected against biases from extreme values (Hilary and Menzly, 2006), as it is not calculated as the mean, but rather as the median. So, in our empirical part we examine twelve market consensuses for their accuracy, rational expectations and biases and

[8] See Appendix 2 – Barclays Capital individual FX predictions

compare them to two simple forecasting models (a random walk or no change forecasting model and a forward rate model). To be able to compare median forecasts to just mentioned forecasting models, we include in our database historic time series of actual exchange rates and forward rates for three currency pairs (EUR/USD, GBP/USD and JPY/USD) from January 1999 to May 2007.

**Figure 4 Number of contributors (1999 – 2007; based on EUR/USD 3-month FX forecast)**




Appendix 3 encompasses six graphs illustrating comparison between an actual exchange rate and an FX rate prediction (market consensus) for three different currency pairs (EUR/USD, GBP/USD and JPY/USD) and for four different time horizons (1 month, 3 months, 6 months and 1 year) during the observed period. The first glimpse on the graphs is already informative, as we can clearly see that the forecast error (F-A) rises in the forecasted time period. The first descriptive statistics thus might support the intuition that the longer forecasted period, the less accurate forecasts are.

# 4. Forecast accuracy

## *4.1 Forecast error comparisons*

To judge forecast accuracy of different forecast models we follow Armstrong and Collopy (1992) and compare their forecast errors. First, we calculate for each of 12 time series Root Mean Squared Error (RMSE), Mean and Median Absolute Percentage Error (MAPE, MdAPE),

$$RMSE = \sqrt{MSE} = \sqrt{\frac{\sum_{s=1}^{S}(F-A)^2}{S}} \tag{1}$$

$$\text{MAPE} = \frac{\sum_{s-1}^{S} APE}{S} * 100 \quad \text{where APE} = \left|\frac{F-A}{A}\right| \tag{2}$$

$$\text{MdAPE} \begin{cases} = \text{ observation (S+1)/2 if S is odd or} \\ = \text{ the mean of S/2 and S/2+1 if S is even,} \\ \text{where the observations are rank-ordered by APE} \end{cases} \tag{3}$$

where F denotes professional forecast (market consensus), A stands for the actual value of the exchange rate and S represents the number of series being summarized. Table 2 summarizes three different types of forecast errors for different currencies, time horizons and forecasting models (market consensus, a random walk with zero drift and forw.

**Table 2 Forecast errors in major dollar exchange rate predictions (1999 – 2007)**

| | **EUR** | | | **GBP** | | | **JPY** | | |
|---|---|---|---|---|---|---|---|---|---|
| **RMSE** | CON | RW | FWD | CON | RW | FWD | CON | RW | FWD |
| EUR1M | 0.0310 | 0.0284 | 0.0287 | 0.0352 | 0.0361 | 0.0364 | 3.0867 | 3.0419 | 3.0887 |
| EUR3M | 0.0619 | 0.0541 | 0.0556 | 0.0607 | 0.0585 | 0.0606 | 6.2559 | 5.3666 | 5.5833 |
| EUR6M | 0.0867 | 0.0757 | 0.0795 | 0.0883 | 0.0897 | 0.0951 | 9.4034 | 7.7223 | 8.3025 |
| EUR1Y | 0.1334 | 0.1182 | 0.1271 | 0.1289 | 0.1354 | 0.1490 | 12.5379 | 9.8146 | 11.7183 |
| **MdAPE** | | | | | | | | | |
| EUR1M | 0.0182 | 0.0166 | 0.0160 | 0.0147 | 0.0160 | 0.0163 | 0.0179 | 0.0170 | 0.0181 |
| EUR3M | 0.0458 | 0.0393 | 0.0406 | 0.0247 | 0.0221 | 0.0207 | 0.0386 | 0.0298 | 0.0331 |
| EUR6M | 0.0622 | 0.0522 | 0.0574 | 0.0433 | 0.0428 | 0.0457 | 0.0572 | 0.0491 | 0.0576 |
| EUR1Y | 0.0929 | 0.0902 | 0.0884 | 0.0677 | 0.0718 | 0.0798 | 0.1014 | 0.0748 | 0.0741 |
| **MAPE** | | | | | | | | | |
| EUR1M | 0.0231 | 0.0209 | 0.0213 | 0.0172 | 0.0177 | 0.0178 | 0.0217 | 0.0210 | 0.0213 |
| EUR3M | 0.0477 | 0.0414 | 0.0425 | 0.0295 | 0.0274 | 0.0280 | 0.0434 | 0.0365 | 0.0388 |
| EUR6M | 0.0691 | 0.0582 | 0.0616 | 0.0445 | 0.0434 | 0.0463 | 0.0665 | 0.0537 | 0.0589 |
| EUR1Y | 0.1083 | 0.0944 | 0.1017 | 0.0681 | 0.0685 | 0.0754 | 0.0951 | 0.0706 | 0.0820 |

Next, we compare the forecast errors across currencies and time horizons and if we find statistically significant differences we will be able to conclude about the predictability of various time horizons or currencies and reliability of professional forecasts compared to naive forecasting models.

### 4.1.1 Accuracy across time horizons

We compare MSE of different time horizon FX predictions within the same currency and run a paired t test to verify if there are statistically significant differences.[9] The results of our analysis in Table 3 support the intuition that the accuracy decreases in the forecasted horizon and, as we can see, it is true and statistically significant[10] for all horizons and currencies. Although Cheung and Chinn (2000) suggest that longer horizons should reflect fundamental data and, hence, be easier to predict, our results are strongly in favour of the premise that the length of forecasted horizon has a deteriorating effect on the accuracy. Moreover, in their study they find out that currency traders do not virtually differentiate between forecasting medium and long horizons. Our results suggest that professional forecasts are more accurate when predicting medium horizons compared to forecasting long horizons.

**Table 3 MSE Differences across time horizons ( period Jan1999 – May2007)**

| Forecasted horizons | **EUR** | | **GBP** | | **JPY** | |
|---|---|---|---|---|---|---|
| | Difference | t-stat | difference | t-stat | difference | t-stat |
| 1M vs 3M | -0.03085*** | [-6.55] | -0.02547*** | [-5.45] | -3.16918*** | [-5.65] |
| 3M vs 6M | -0.02479*** | [-4.57] | -0.02763*** | [-4.96] | -3.14748*** | [-5.06] |
| 6M vs 1Y | -0.04674*** | [-5.94] | -0.04057*** | [-5.72] | -3.13444*** | [-5.59] |

### 4.1.2 Professionals vs. naive forecasting models

We are also curious if financial professionals are able to dominate naive forecasting models in accuracy. Again, we compare MSE[11] for different FX rate predictions to be able to judge the accuracy and superior performance of one of the forecasting models. We run paired t-test[12] to check if the differences between professional forecasts and two naive forecasting models (random walk or no change and forward estimate) are statistically significant.

[9] We test the normality of MSE differences by Kolmogorov-Smirnov and Shapiro-Wilk tests, where both of them do not reject the hypothesis about their normal distribution with $\alpha=0.05$

[10] Additionally to the paired t-test, we run non-parametric Wilcoxon signed ranks test yielding the same results – differences are statistically significant for all horizons and currencies

[11] (R)MSE vulnerability to the scale of time series is irrelevant, as we always compare MSE within the same currency

[12] We test the normality of MSE differences for all 24 pairs by Kolmogorov-Smirnov and Shapiro-Wilk tests, where both tests do not reject the hypothesis about the normal distribution for every pair with $\alpha=0.05$

**Table 4 MSE comparison of a market consensus to simple forecast models (Jan1999 – May2007)**

| | vs NO CHANGE | | vs FORWARD | |
|---|---|---|---|---|
| | difference | t-stat | difference | t-stat |
| **EUR1MP** | 0.0026**[13] | [2.163] | 0.0023* | [1.971] |
| **EUR3MP** | 0.0077*** | [3.421] | 0.0063*** | [2.984] |
| **EUR6MP** | 0.011*** | [2.679] | 0.0071* | [1.91] |
| **EUR1YP** | 0.0152** | [2.221] | 0.0063 | [1.054] |
| **GBP1MP** | -0.0009 | [-0.77] | -0.0012 | [-1.05] |
| **GBP3MP** | 0.0021 | [1.33] | 0.00004 | [0.022] |
| **GBP6MP** | -0.0014 | [-0.488] | -0.0068* | [-1.955] |
| **GBP1YP** | -0.0065* | [-1.726] | -0.0201*** | [-4.213] |
| **JPY1MP** | 0.0449 | [0.386] | -0.002 | [-0.015] |
| **JPY3MP** | 0.8893*** | [3.519] | 0.6726** | [2.179] |
| **JPY6MP** | 1.6811*** | [4.471] | 1.1009** | [2.371] |
| **JPY1YP** | 2.7232*** | [6.938] | 0.8195 | [1.411] |

The results in Table 4 indicate some interesting facts. Professional forecasts of EUR/USD and USD/JPY FX rates seem to be fully in line with the theoretical concept claiming that professionals are not able to beat a naive forecasting model based on a random walk with a zero drift. What is more, our results suggest that besides the absolute inability of professionals to beat a random walk in EUR/USD predictions they underperform also a forward model statistically significantly in 3 out of 4 predictions. Similarly, professional forecasters predicting JPY/USD significantly underperform a random walk in 3 out of 4 cases and a forward model in 2 out of 4 cases. Professional forecasts of GBP/USD FX rates seem to be an exception, as our data indicate that there is no evidence for professional forecasts' underperformance. In contrary, 2 out of 4 cases show no statistically significant difference between professional forecasts and the naive models and, to our surprise, professional forecasters compared to both competing models show a superior forecasting ability in one-year GBP/USD FX rate predictions.

### 4.1.3 Accuracy across currencies

After examining forecasting abilities of professionals we try to find out if there is a currency pair that professional forecasters are able to predict better and with greater accuracy. To compare the forecast accuracy across three different currency pairs, we need to avoid using RMSE due to its exposure to the scale of time series and hence use MAPE and MdAPE[14] that are relative measures resistant to the scale bias.

[13] ***, ** and * denote significance at the 1%, 5% respectively 10% level

[14] Statistical significance tested by paired t-test (MAPE) and Wilcoxon signed ranks test (MdAPE); the APE differences (12 pairs) were tested for normal distribution by Kolmogorov-Smirnov and Shapiro-Wilk tests with α=0.05; both tests do not reject the hypot. about the normal distribution for every pair

**Table 5 APE differences across currencies ( period Jan1999 – May2007)**

| Time horizon | | MAPE | | | MdAPE | | |
|---|---|---|---|---|---|---|---|
| | | EUR-GBP | GBP-JPY | EUR-JPY | EUR-GBP | GBP-JPY | EUR-JPY |
| **1M** | diff | 0.0059*** | -0.0045** | 0.0014 | 0.0035*** | -0.0032** | 0.0003 |
| | t-stat | [4.043] | [-2.559] | [0.713] | [-3.786] | [-2.156] | [-0.836] |
| **3M** | diff | 0.0182*** | -0.0139*** | 0.0043 | 0.0211*** | -0.0139*** | 0.0072 |
| | t-stat | [5.916] | [-3.594] | [0.87] | [-4.852] | [-3.281] | [-0.806] |
| **6M** | diff | 0.0246*** | -0.0220*** | 0.0027 | 0.0189*** | -0.0139*** | 0.0050 |
| | t-stat | [5.39] | [-3.606] | [0.356] | [-4.623] | [-3.344] | [-0.044] |
| **1Y** | diff | 0.0402*** | -0.0270*** | 0.0132 | 0.0252*** | -0.0337*** | -0.0085 |
| | t-stat | [5.124] | [-3.856] | [1.459] | [-4.472] | [-3.676] | [-0.606] |

Our results in Table 5 unanimously suggest that there is no significant difference in accuracy between professionals' predicting EUR/USD and USD/JPY FX rates. However, professional forecasters seem to have more accurate GBP/USD FX rate predictions compared to both EUR/USD and USD/JPY forecasts. What is interesting, this is true and statistically significant across all forecasted horizons and taken a fairly long observed time period (January, 1999 – May 2007) into consideration it makes our findings robust as well as surprising.

## *4.2 Advanced measures of comparison*

In this section we apply commonly used quantitative measures of forecast accuracy (Bofinger and Schmidt; 2003 and 2004). Specifically, we use the Theil's inequality coefficient, the coefficient of determination, correlation coefficient and a special evaluating technique, the direction-of-change forecasts.

### 4.2.1 Theil's inequality coefficient

Theil's inequality coefficient represents a relative assessment of market consensus forecast to a simple model of a driftless random walk by comparing their RMSE:

$$Theil'sU = \frac{\sqrt{\frac{1}{S-1}\sum_{t=1}^{S}(F_{t+1}-A_{t+1})^2}}{\sqrt{\frac{1}{S-1}\sum_{t=1}^{S}(A_{t+1}-A_t)^2}} \qquad (4)$$

where F represents a market consensus forecast, A stands for the actual exchange rate and S signifies the number of forecasted series. The value of the Theil's inequality coefficient indicates whether the market consensus predicts a future FX rate perfectly (Theil's U = 0), if the professional forecasts underperform a random walk benchmark (Theil's U > 1) or are able to beat a naive model of a random walk (Theil's U < 1). Following Table 6 illustrates the overall inability of professionals to beat a random walk benchmark in their FX forecasts with an exception for GBP/USD predictions. As we already mentioned, this superior and unexpected forecasting ability provides evidence for the expertise of financial professionals (although it might be questioned at the same time by underperformance in EUR/USD and USD/JPY forecasts).

**Table 6 Theil's inequality coefficient for major dollar rate FX predictions**

| Theil's U | 1M | 3M | 6M | 1Y |
|---|---|---|---|---|
| **EUR** | 1.0931 | 1.143 | 1.1452 | 1.1283 |
| **GBP** | 0.9755 | 1.0363 | 0.9847 | 0.9517 |
| **JPY** | 1.0148 | 1.1657 | 1.2177 | 1.2775 |

### 4.2.2 Correlation coefficient and coefficient of determination

The correlation coefficient ρ explains the relationship between the real exchange rate (A) and the forecasted FX rate (F):

$$r = \frac{\sum_{t=1}^{S}\left(F_t - \overline{F}\right)\left(A_t - \overline{A}\right)}{\sqrt{\sum_{t=1}^{S}\left(F_t - \overline{F}\right)^2 \sum_{t=1}^{S}\left(A_t - \overline{A}\right)^2}} \tag{5}$$

where $\overline{A}$ and $\overline{F}$ stand for the simple averages of a certain FX rate and S represents a total number of forecasted series. If the actual FX rate is perfectly foreseen by the forecast, then ρ=1, whereas if there is no relationship between a forecast and an actual rate then ρ=0. The coefficient of determination ($R^2$; $|R^2|\leq 1$) represents the ratio of the sum of squares of errors and the sum of squares of deviations from the average of the FX rate.

$$R^2 = 1 - \frac{\sum_{t=1}^{S}\left(F_t - A_t\right)^2}{\sum_{t=1}^{S}\left(A_t - \overline{A}\right)^2} \tag{6}$$

The value of $R^2$ explains how big fraction of the variance of the real FX rate is covered in professional FX forecasts. However, comparing $R^2$ might be misleading, as Armstrong and Collopy (1992) warn that higher values need not necessarily mean a better model. Table 7 illustrates the comparison of correlation coefficients and coefficients of determination (in brackets) between professional FX rate forecasts and a random walk model. As we can see, professional EUR/USD forecasts completely underperform a random walk model, whereas in case of USD/JPY they do also in 3 out of 4 cases. Only professional GBP/USD forecasts are able to keep a balanced position relative to a random walk model. What might be noteworthy is the fact that there are extremely low values of ρ and $R^2$ for one-year USD/JPY FX predictions signaling almost zero correlation between the forecasted and the actual FX rates and no explanatory power of the professional forecast variance.

**Table 7 Correlation coefficients and coefficients of determination (January 1999 – May 2007)**

| FX rate | Professional forecasts | | | | Random Walk | | | |
|---|---|---|---|---|---|---|---|---|
| | **1M** | **3M** | **6M** | **1Y** | **1M** | **3M** | **6M** | **1Y** |
| **EUR** | 0.9801 | 0.923 | 0.851 | 0.6299 | 0.9834 | 0.9413 | 0.8886 | 0.7395 |
| | [0.9607] | [0.8519] | [0.7243] | [0.3968] | [0.9672] | [0.886] | [0.7897] | [0.5469] |
| **GBP** | 0.9789 | 0.9386 | 0.8705 | 0.7245 | 0.9779 | 0.9446 | 0.8726 | 0.7188 |
| | [0.9581] | [0.881] | [0.7578] | [0.5249] | [0.9563] | [0.8922] | [0.7615] | [0.5166] |
| **JPY** | 0.9152 | 0.6948 | 0.4254 | 0.0784 | 0.9142 | 0.736 | 0.4626 | 0.1527 |
| | [0.8376] | [0.4828] | [0.1809] | [0.0061] | [0.8357] | [0.5417] | [0.214] | [0.0233] |

### 4.2.3 Direction-of-change forecasts

Direction-of-change forecasts might be of particular interest of importing and exporting companies whose business is often dependant on the exchange rate movement. In order to evaluate direction-of-change forecasts Diebold and Lopez (1996) suggest comparing to a naive benchmark model of a coin flip that is built on a 2 x 2 contingency table:

**Table 8 2 x 2 contingency table**

| | Real up ($\Delta A_{t+h}>0$) | Real down ($\Delta A_{t+h}<0$) |
|---|---|---|
| Expectation up ($\Delta F_{t+h}>0$) | $O_{11}$ | $O_{12}$ |
| Expectation down ($\Delta F_{t+h}<0$) | $O_{21}$ | $O_{22}$ |

The areas $O_{11}$ and $O_{22}$ represent correct estimates of the exchange rate movement and together divided by the total number of predictions constitute a hit rate ($(O_{11} + O_{22})/O$). The hit rate should be, according to a flip coin theory, close to 50% (our null hypothesis), as it is assumed that the forecast realizations are totally independent and random, and therefore, it can be approximated by a coin toss. Diebold and Lopez (1996) propose the corresponding contingency table statistic that should follow under the null hypothesis a chi-square distribution:

$$C = \sum_{i,j=1}^{2} \frac{\left(O_{ij} - E_{ij}\right)}{E_{ij}} \tag{7}$$

where O denotes the observed and E the expected frequency of two possible outcomes – “ups” and “downs”. Table 9 summarizes the results for hit rates and C-statistics. As we can see, EUR/USD professional forecasts seem to be rather poor predictors of the movement of the exchange rate, while USD/JPY forecasts seem to be more or less balanced in terms of predicting a correct direction. Finally, GBP/USD predicting seems to be generally superior also in forecasting the movement of the exchange rate.

**Table 9 Professional FX rate forecasts as direction-of-change forecasts**

| | EUR | | GBP | | JPY | |
|---|---|---|---|---|---|---|
| | Hit rate | C - Test Stat. | Hit rate | C - Test Stat. | Hit rate | C - Test Stat. |
| **1M** | 0.5824 | [2.4725] | 0.4945 | [0.011] | 0.5109 | [0.0435] |
| **3M** | 0.4875 | [0.05] | 0.5281 | [0.2809] | 0.4598 | [0.5632] |
| **6M** | 0.4578 | [0.5904] | 0.5181 | [0.1084] | 0.5 | [0] |
| **1Y** | 0.4286 | [1.4286] | 0.5949*[15] | [2.8481] | 0.5231 | [0.1385] |

However, C-statistics do not allow us to reject the null hypothesis about the 50% hit rate in almost all cases. The only statistically significant hit rate value is connected with one-year GBP/USD professional FX predictions, which is, next to beating a random walk model in accuracy, another proof of superior forecasting abilities in one-year GBP/USD forecasts.

Comparison of our hit rates results (ranging from 0.43 to 0.59) to the outcomes of Bofinger and Schmidt (2004) that scrutinized EUR/USD professional FX forecasts from 1999 until 2003 (range from 0.37 to 0.47) might imply that the forecasting ability of professionals in terms of predicting the movement of the exchange rate has improved in recent years.

Finally, Diebold and Lopez (1996) caution against relying completely only on direction-of-change forecasts, as they do not necessarily have to bring profitable strategies (after accounting for transaction costs). Hence, they conclude that a valuable forecast brings information not only about the direction of the movement, but also about the magnitude of the exchange rate movement.

[15] The 10% significance level for chi-square distribution with degrees of freedom = 1 is 2.7055

# 5. Rational expectations

Previous studies have decisively rejected the rational expectation hypothesis when applied to the actual professional FX rate forecasts (Bofinger et. all, 2004; Dreger and Stadtmann, 2006). Not only that the rationality assumption has been rejected, but also a biased behavior of professional forecasters has been discovered. Therefore, in this section we analyze professional FX rate forecasts with the aim of finding out whether financial professionals stick to the macroeconomic approach when deciding about their exchange rate forecasts and are able to make unbiased rational forecasts. Following rational expectation hypothesis (Muth, 1961), we expect professional forecasters to form their exchange rate predictions in a rational way. According to the rational expectation hypothesis, forecast errors ($\varepsilon_{t+1}$) are completely and only random and they depend on a certain information set ($\Omega$):

$$e_{t+1} = S_{t+1} - E(S_{t+1}|\Omega_t) \quad \text{where} \quad e_{t+1} \approx (0, s^{2}) \tag{8}$$

The assumption of unbiased forecasts is based on the underlying principle of the rational expectation hypothesis – forecasts errors are believed to be zero, as they should be purely random and we should not detect any significant deviations of the real exchange rate from the expected FX rate. This assumption can be tested by a linear regression of the real change in the exchange rate on the FX rates change expected by the financial professionals. Thus, the rational expectation hypothesis can be expressed as the following equation representing a benchmark model to which we will compare the actual behavior of professional forecasters:

$$s_{t+h} - s_t = a + b(E_t s_{t+h} - s_t) + e_{t+h} \tag{9}$$

where s denotes the natural logarithm of the exchange rate and, so, the equation is expressed in terms of changes rather than in terms of absolute FX rate values what is commonly used in the financial literature (i.e. Stadtmann, 2004; Bofinger et. all, 2004). Should the exchange rate forecasts be unbiased, then all of following three conditions have to be satisfied, as they are inevitable to the unbiasedness: $\alpha$ has to equal 0, $\beta$ must be equal to 1 and $\varepsilon_{t+h}$ has the mean prediction error of 0. Table 9 summarizes our results of the regressions for the professional forecasts of three currency pairs (EUR/USD, GBP/USD and USD/JPY) done for four forecasted periods. We use the method of ordinary least squares (OLS) to regress the change in the actual rates on the expected change and we employ a Wald test to test the null joint hypothesis of α=0 and β=1 representing the rational expectations. The related F-statistics with p-values are also illustrated in Table 10[16].

**Table 10 Rationality of professional forecasts**

| FX forecast | | Alpha | | Beta | | F-statistic | |
|---|---|---|---|---|---|---|---|
| EUR | 1M | 0.0005 | (0.151) | 0.1959 | (0.7132) | 4.2947** | [0.0164] |
| | 3M | 0.0004 | (0.1202) | 0.3436*** | (4.0677) | 30.2576*** | [0] |
| | 6M | 0.0003 | (0.1081) | 0.4848*** | (5.935) | 19.9652*** | [0] |
| | 1Y | 0.0015 | (0.445) | 0.5177*** | (5.1007) | 11.5975*** | [0] |
| GBP | 1M | 0.0004 | (0.1274) | 1.1596*** | (4.4548) | 0.1964 | [0.822] |
| | 3M | 0.0002 | (0.0605) | 0.6439*** | (7.2851) | 8.1206*** | [0.0006] |
| | 6M | 0.0001 | (0.0212) | 0.741*** | (7.187) | 3.158** | [0.0472] |
| | 1Y | 0.0006 | (0.2136) | 0.7997*** | (7.9374) | 2.014 | [0.1397] |
| JPY | 1M | -0.0002 | (-0.06) | 0.9677*** | (3.4233) | 0.0084 | [0.9916] |
| | 3M | 0.0002 | (0.0593) | 0.5699*** | (6.0276) | 10.3467*** | [0.0001] |
| | 6M | 0.0012 | (0.3602) | 0.5532*** | (6.4835) | 13.8167*** | [0] |
| | 1Y | 0.0019 | (0.5367) | 0.585*** | (5.682) | 8.6142*** | [0.0004] |

(t-statistics in parentheses[17]; p-values in brackets[18])

As we can see in the table, none of the results (p values) has rejected α not to be zero. Moreover, all of the alpha (intercept) values are very close to zero. In contrary, 11 out of 12 beta (slope) values are significantly different from zero showing also a substantial deviation from one in most of the cases (9 out of 12). To test our null joint hypothesis about the rational expectations we use the Wald test that represents a combination of linear restrictions on coefficients. The performed Wald test has shown us that in 9 out of 12 cases we can reject the hypothesis about the rational expectations. In particular, we can see that EUR/USD predictions are least associated with the rational expectations, as the Wald test strongly rejects rationality among all EUR/USD predictions. GBP/USD forecasts achieved better results, as only the three-month predictions were strongly rejected. So were the six-month predictions, but at a less significant level. The

[16] ***, ** and * denote significance at the 1%, 5% respectively 10% level;
[17] A critical value for the t-distribution with α=0.01 is 2.63 (after rounding for each of four cases with various degrees of freedom - 96, 95, 92 and 86).
[18] The critical values for the F distribution are as follows:
α=0.01 : 4.833 for df = 2, 96; 4.836 for df = 2, 95; 4.844 for df = 2, 92 and 4.861 for df = 2, 86;
α=0.05 : 3.091 for df = 2, 96; 3.092 for df = 2, 95; 3.095 for df = 2, 92 and 3.103 for df = 2, 86;
α=0.1 : 2.36 for df = 2, 96; 2.36 for df = 2, 95; 2.361 for df = 2, 92 and 2.365 for df = 2, 86.

other two types of FX rate predictions (one-month and one-year) cannot be considered to be irrational, which is already a surprising result. Forecasting the last currency pair USD/JPY is significantly rejected in 3 out of 4 cases, which leaves one-month USD/JPY predictions with the lowest F-statistic at all not to be rejected as rational. Overall, in our dataset we have found 3 types of FX forecasts that cannot be categorized as deviators of the principles of the rational expectation hypothesis.

We investigate these three types of predictions further and relate them to the results from the previous chapter about forecast accuracy. The one-month GBP/USD and USD/JPY forecasts that cannot be perceived as biased and irrational do not significantly differ from the random walk in forecast accuracy, whereas one-year GBP/USD professional forecast dominates a simple forecasting model. It seems to be no coincidence that those EUR/USD and USD/JPY predictions that significantly underperform a random walk model are not able to meet the criteria for the rational expectations. Following this logic we might deduce that biased FX forecasts are not able to beat a random walk model in forecast accuracy. Overall, we have provided evidence on the rejection of the rational expectation hypothesis among the majority of the professional forecasts which supports the results from the previous research. However, we have also found out that there are some professional forecasts that cannot be rejected as irrational, which already changes until now rather one-sided perception of the professional forecasters.

# 6. Biases in professional FX rate forecasts

In Chapter 5 we found evidence for irrationality in professional FX rate forecasts. In order to better understand and explore behavior behind the professional forecasts that are not consistent with the rational expectation hypothesis we run several regressions to check FX predictions for various biases. In particular, we test our dataset if the professional forecasts are too strongly influenced by the past predictions (extrapolative expectations), if they depend on the recent changes in expectations (adaptive expectations) or, finally, if there are some levels that professional forecasters keep in their mind and anchor their FX predictions to them (regressive expectations). Then we scrutinize data for topically oriented trend adjustment that explains the influence of the current exchange rate on the FX rate predictions. Moreover in this chapter, we analyze the professional FX rate forecasts for the overconfidence related measures. First, we investigate FX rate predictions with respect to the accuracy-informativeness tradeoff that compares accuracy of the FX prediction to the width of interval estimation, which helps us address the question if professional forecasters place too narrow interval forecasts. Second, we analyze the forecasting abilities of individual banks and relate our results to the better than average effect.

## *6.1 Extrapolative expectations*

Is it important to look at past data when predicting future FX rates? If we ask chartists (the users of technical analysis) to answer this question, they will strongly agree, as they base their forecasts on evaluating past price (exchange rate) development. As we already mentioned in the literature overview, the most common forecasting models comprise insights from both technical analysis and fundamental analysis, where the usage of technical analysis generally decreases for longer forecasted horizons. In order to find out, whether professional forecasts (represented by a market consensus) tend to consider past predictions as a significant part of their forecasting models, we run the following regression:

$$E_t[s_{t+1}] - s_t = a + b(s_t - s_{t-1}) + e_t \tag{10}$$

If professional forecasters stick to the rational expectation hypothesis, then β should equal zero representing no influence of historical data on future exchange rate forecasts. However, our previous results rather rejected rationality in professional FX predictions, which leads us to the expectation that there might be some extrapolative biases among professional forecasts, especially for short-run predictions. In case that $\beta > 0$, professional forecasters expect current trend to continue and keep the same direction in future. Cavaglia et all. (1993) name succinctly this type of extrapolative expectations as bandwagon effects influencing expectation formation. However, there is also evidence for $\beta < 0$ (i.e. Stadtmann, 2004) that represents a correction of the prevailing trend and returning point. Bofinger et. all (2004) have named this extrapolative bias as stabilizing expectations meaning that forecasters await depreciation after former appreciation and vice versa. Table 11 [19] summarizes our results on the extrapolative expectations in professional FX forecasts.

**Table 11 Extrapolative expectations in professional FX forecasts (January 1999 – May 2007)**

| | **EUR** | | **GBP** | | **JPY** | |
|---|---|---|---|---|---|---|
| | alpha | beta | alpha | beta | alpha | beta |
| **1M** | 0.0001<br>(0.1138) | 0.0071<br>(0.1891) | 0.0001<br>(0.0611) | -0.1261***<br>(-3.6767) | -0.0002<br>(-0.1593) | -0.1171***<br>(-3.6582) |
| **3M** | -0.0005<br>(-0.1491) | -0.6523***<br>(-6.8992) | -0.0001<br>(-0.041) | -0.5656***<br>(-7.4151) | -0.0006<br>(-0.2194) | -0.5298***<br>(-6.9383) |
| **6M** | -0.0009<br>(-0.2627) | -0.5015***<br>(-5.1076) | -0.0002<br>(-0.1082) | -0.4626***<br>(-6.7399) | -0.0013<br>(-0.4081) | -0.524***<br>(-6.0689) |
| **1Y** | -0.0021<br>(-0.6986) | -0.5054***<br>(-5.9126) | -0.0007<br>(-0.3086) | -0.5062***<br>(-7.2934) | -0.0035<br>(-1.1101) | -0.4595***<br>(-5.6084) |

As we can see in Table 11, our results suggest almost pervasive occurrence of extrapolative expectations – 11 out of 12 betas are significantly different from zero. What is interesting, all statistically significant betas are negative which implies occurrence of stabilizing expectations. This is consistent with extensive research of Cavaglia et. all. (1993). It seems that professional FX forecasts (except one-month EUR/USD predictions) tend to return back to some equilibrium level. To document this on an example, let us take one-month GBP/USD prediction – after a 10% increase in exchange rate, there will be an adjustment of only 8.74% made in exchange rate expectations. The intuitive hypothesis about the decreasing extrapolative expectations for longer forecasted horizons cannot be fully satisfied, as the one-month forecasts seem to be least affected by extrapolative expectations. However, the common characteristic for every currency pair is that the three-month forecasts have higher betas than forecasts for longer horizons and, therefore, are mostly influenced by stabilizing expectations.

[19] *** denotes significance at the 1% level (t-statistics in parentheses).

Another interpretation of the extrapolative expectations can be done by adjusting regression equation (10) as suggested by Stadtmann (2004) - by adding $s_t$ to both sides of equation and not including the error term we get:

$$E_t[s_{t+1}] = a + (1+b)s_t + b(s_{t-1}) \tag{11}$$

It follows that the future spot rate forecast is based on the weighted average of the actual exchange rates from both the current and the previous period. In our example of 10% increase in GBP/USD, it would lead the one-month GBP/USD forecast to depend on 8.74% of the current FX rate and 1.26% of the former FX rate.

## *6.2 Adaptive expectations*

The theory of adaptive expectations offers another model to explain forecasting biases. This time, we are interested in the expectation error ($s_t$ - $E_{t-1}(s_t)$) and how it affects the change in forecast expectations ($E_t(s_{t+1})$ - $E_{t-1}(s_t)$) that we test in the following regression:

$$E_t[s_{t+1}] - E_{t-1}[s_t] = a + b(s_t - E_{t-1}[s_t]) + e_t \tag{12}$$

Stadtmann (2004) offers again an adjustment in the equation in order to easily interpret the results. After dropping the error term and deducting $E_{t-1}(s_t)$ from both sides of the equation we get the equation (13), where $E_{t-1}(s_t)$ can be expressed by the lagged $E_{t-2}(s_{t-1})$ what is illustrated in the equation (14). Using this principle of n substitutions representing the lagged expectations, we finally arrive at equation (15).

$$E_t[s_{t+1}] = a + bs_t + (1-b)E_{t-1}[s_t] \tag{13}$$

$$E_t[s_{t+1}] = a + a(1-b) + bs_t + (1-b)bs_{t-1} + (1-b)^2 E_{t-2}[s_{t-1}] \tag{14}$$

$$E_t[s_{t+1}] = \frac{a}{b} + \sum_{0}^{n}(1-b)^n s_{t-n} \tag{15}$$

Equation (15) implies that the exchange rate expectations are affected by the set of past exchange rate movements. Coefficient β, if equal to 1, can, however, completely diminish the influence of historical data and together with α equal to zero would represent a model that has the same characteristics as a naive random walk forecasting model that depends only on the current exchange rate. Therefore, we estimate the equation (12) with OLS regression to find the values for α and β that enable us to discuss the occurrence of adaptive expectations in the professional forecasts. Table 12 summarizes our results that unanimously reject β to be equal to zero showing substantial deviations from one that is in line with our previous results where we significantly differentiated professional forecasts from a random walk model. We support our finding by the Wald's test checking the joint hypothesis about $\alpha=0$ and $\beta=1$ in Appendix 4a. Moreover, $\beta$ values lower than one signify the dependence on past exchange rates which supports our results on extrapolative expectations. The key finding about the adaptive expectations for our data suggest decreasing $\beta$ values in forecasted horizon (with one exception for one-year USD/JPY predictions). The results imply that the short-run forecasts are least affected by the historical rates and depend more on recent data, whereas the long-run predictions show greater regard for past FX rates.

**Table 12 Adaptive expectations in professional FX forecasts (January 1999 – May 2007)**

| | EUR | | GBP | | JPY | |
|---|---|---|---|---|---|---|
| | **alpha** | **beta** | **alpha** | **beta** | **alpha** | **beta** |
| **1M** | -0.0001<br>(-0.0338) | 0.5956***<br>(7.4422) | -0.0001<br>(-0.035) | 0.5079***<br>(6.3981) | 0.0001<br>(0.0203) | 0.4948***<br>(5.8278) |
| **3M** | -0.0001<br>(-0.0228) | 0.3403***<br>(4.1501) | -0.0001<br>(-0.046) | 0.3518***<br>(4.427) | -0.0002<br>(-0.0845) | 0.3432***<br>(4.6423) |
| **6M** | -0.0001<br>(-0.0306) | 0.3104***<br>(3.6114) | 0.0002<br>(0.093) | 0.3268***<br>(5.4363) | -0.0004<br>(-0.1819) | 0.2334***<br>(3.7049) |
| **1Y** | -0.0004<br>(-0.1476) | 0.2973***<br>(4.2317) | 0.0001<br>(0.035) | 0.232***<br>(3.7867) | -0.0014<br>(-0.4412) | 0.3518***<br>(3.9001) |

## *6.3 Regressive expectations*

The theory of regressive expectations directly addresses behavioral heuristic of anchoring. In this part we are interested if there is an anchor that affects professional forecasters in their predictions. In order to find the regressive expectations a certain anchor, a value or an equilibrium level to which forecasters attach their predictions, has to be set. We use the principle proposed by Frankel and Froot (1987) to set the equilibrium level equal to current long-run predictions that should reflect the long-run equilibrium to which exchange rate is believed to converge. We estimate the following regression using one-year FX predictions from May 31$^{st}$, 2007 as the equilibrium levels – anchors (EUR/USD 1.32, GBP/USD 1.86, USD/JPY 104):

$$E_t[s_{t+1}] - s_t = a + b\,(s_t - s_{equi1ib}) + e_t \qquad (16)$$

Stadtmann suggests estimating a regression that comprises extrapolative and regressive expectations to see if they occur simultaneously and which one has a greater impact on the professional FX forecasts. We run an OLS regression for the equation (17) to check the hypothesis whether extrapolative and regressive expectations play some role in the whole expectation process:

$$E_t[s_{t+1}] - s_t = a + b_1(s_t - s_{t-1}) + b_2(s_t - s_{equilib}) + e_t \qquad (17)$$

**Table 13 Regressive and extrapolative expectations (January 1999 – May 2007)**[20]

| | alpha | | beta1 | | beta2 | |
|---|---|---|---|---|---|---|
| **EUR1M** | 0.0004 | (0.1883) | 0.0072 | (0.1906) | 0.0014 | (0.1505) |
| **EUR3M** | -0.0001 | (-0.0099) | -0.6522*** | (-6.8614) | 0.0023 | (0.1008) |
| **EUR6M** | -0.002 | (-0.3521) | -0.5017*** | (-5.0828) | -0.0056 | (-0.2428) |
| **EUR1Y** | 0.0009 | (0.1984) | -0.504*** | (-5.8846) | 0.0162 | (0.8266) |
| **GBP1M** | -0.0003 | (-0.2073) | -0.126*** | (-3.6565) | -0.0035 | (-0.3298) |
| **GBP3M** | -0.0007 | (-0.1868) | -0.5653*** | (-7.3721) | -0.0051 | (-0.2162) |
| **GBP6M** | -0.0002 | (-0.0751) | -0.4626*** | (-6.7015) | 0 | (-0.0017) |
| **GBP1Y** | -0.0013 | (-0.4065) | -0.5059*** | (-7.2486) | -0.0055 | (-0.2683) |
| **JPY1M** | 0.0011 | (0.4858) | -0.1172*** | (-3.6514) | -0.0129 | (-0.687) |
| **JPY3M** | -0.0022 | (-0.4126) | -0.5299*** | (-6.9062) | 0.0157 | (0.3502) |
| **JPY6M** | -0.0012 | (-0.2017) | -0.524*** | (-6.0353) | -0.0016 | (-0.0317) |
| **JPY1Y** | -0.0081 | (-1.3375) | -0.4626*** | (-5.6335) | 0.0449 | (0.887) |

The results[21] from regression (16) collectively do not generate any significant beta, which is also supported by the results from the regression (17) that are illustrated in Table 13. In the table we can see the dominant role of extrapolative expectations and no power of regressive expectations. To check whether the change in the equilibrium level might affect position of regressive expectations, we also run regressions for the anchors that represent the average of the exchange rates for the observed period (counted from monthly rates – EUR/USD 1.1, GBP/USD 1.67 and USD/JPY 115) and, so, we are actually testing for the mean reversion trait of the time series. However, adjusting an equilibrium level do not affect the expectation process in forecasting and, hence, we can claim that we did not find any evidence for the anchoring heuristic in professional forecasts unlike Stadtman 2004 that has found a some explanatory power of regressive expectations. Thus, the most robust finding in the expectation process seems to be extrapolative stabilizing expectations and adaptive expectations reflecting the strongest influence of recent market development on the short-term FX rate predictions and the more prevalent influence of historical data on the long-term forecasts.

## *6.4 Topically oriented trend adjustment*

We have shown that professional forecasts estimate future exchange rates imperfectly and with biases in the expectation process. Influence of the current exchange rate development represents another important factor affecting FX rate forecasting. It is often the case that financial professionals adjust their forecasts too frequently according to

[20] *** denotes significance at the 1% level (t-statistics in parentheses).
[21] See Appendix 4b

present market development and this might finally lead to a complete loss of forecasts' future-oriented character. This finding has been discovered by Andres and Spiwoks (1999) who named it topically oriented trend adjustment (TOTA) and, basically, stands for the relationship between the forecasted FX rate values and the current FX rate values compared to the relation between shifted-to-the-left forecasted FX rate values and the current future FX rates. The presence of TOTA in professional forecasts is already obvious from the first glimpse at graphs in Appendix 5 that illustrate an evident connection between the current rate and shifted predictions. Andres and Spiwoks propose the TOTA coefficient that should be able to explain this relationship in numbers:

$$TOTA\_coeff = \frac{R^2_{forecast,actual}}{R^2_{forecast,actual-h}} = \frac{\dfrac{Cov(x,y)^2}{Var(x)*Var(y)}}{\dfrac{Cov(x,y_{(-h)})^2}{Var(x)*Var(y_{(-h)})}}, \tag{18}$$

where $R^2$ denotes the coefficient of determination and h signifies the forecasted horizon.

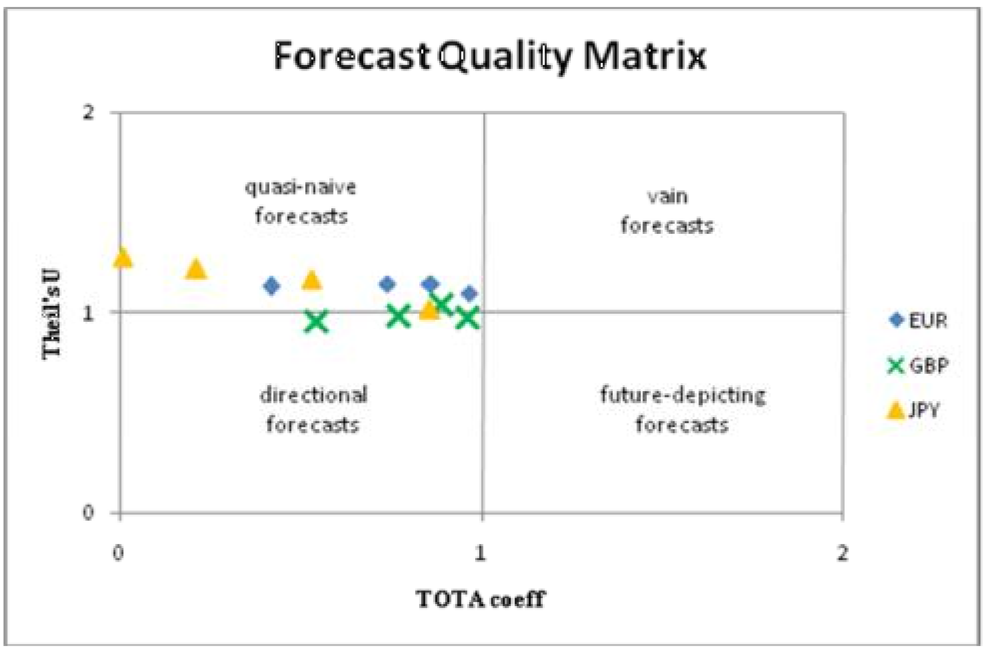
TOTA coefficient lower than one reflects more presence than future or, in other words, there is a higher correlation between the forecasted FX rates and the current exchange rates than between the forecasts and the exchange rates for which these forecasts were made. Table 14 offers an overview about the TOTA coefficients for all currencies and time horizons. As we can see, all TOTA coefficients of professional forecasts are lower than one which represents a strong signal for pervasive occurrence of topically oriented trend adjustment.

**Table 14 Topically oriented trend adjustment (January 1999 – May 2007)**

| TOTA coeff | 1M | 3M | 6M | 1Y |
|---|---|---|---|---|
| **EUR** | 0.9654 | 0.8599 | 0.7397 | 0.4177 |
| **GBP** | 0.964 | 0.8886 | 0.769 | 0.5437 |
| **JPY** | 0.8583 | 0.5298 | 0.2121 | 0.0073 |

TOTA coefficient represents another important parameter when judging professional forecast accuracy and together with Theil's U inequality coefficient (Chapter 4) forms a basis for the forecast quality matrix (Andres and Spiwoks, 1999). When we use forecast quality matrix our interests are usually twofold. First, we are interested if forecast models are able to beat a naive model of random walk (Theil's U). Second, we search for existence of the topically oriented trend adjustment (TOTA coefficient). The outcomes of the matrix can be of four different types. First, the quasi-naive forecasts (Theil's U > 1, TOTA < 1) are underperforming a random walk model and reflect too strongly presence in forecasting. Such forecasts are not suitable for financial decision making. Second, the directional forecasts (Theil's U < 1, TOTA < 1) show the signs of TOTA, but still are able to beat a naive model of random walk in predicting future FX rates. Therefore, these, although not perfect, predictions meet criteria to be relevant for financial decisions. Third, the vain forecasts (Theil's U > 1, TOTA > 1) are unable to outperform random walk even though they are clear of TOTA. Overall, their weak accuracy forecasting makes them useless in financial decision making. Forth, the future-depicting forecasts (Theil's U < 1, TOTA > 1) are undoubtedly the best predictors, as they beat a simple random walk model and do not show signs of TOTA. Such forecasts are future-oriented, as they do not let present market actions affect the forecasting process. Figure 5 summarizes our results in the forecast quality matrix.

**Figure 5 Forecast quality matrix (1M, 3M, 6M and 1Y forecasts; January 1999 – May 2007)**




As we can see, most of the professional forecasts can be categorized as quasi-naive with no ability to outperform a naive random walk model. The GBP/USD exchange rate is the only exception, as 3 FX rate forecasts belong to the category of directional forecasts. Overall the results suggest rather inferior role of professional forecasts, as the topically oriented trend adjustment seems to be always present in the forecasting process of financial professionals. The results also suggest that TOTA is apparently stronger for USD/JPY predictions which enables us to conclude that the current market actions are likely to affect professional forecasters especially in USD/JPY FX rate forecasts.

### *6.5 Miscalibration as an accuracy-informativeness tradeoff*

As we already mentioned in the literature overview, informativeness of the FX rate predictions might be equally important as forecast accuracy. In this subsection we focus on evaluating forecast accuracy with respect to the width of the interval forecasts. To examine the interval forecasts we follow the procedure of Hilton (2003) who suggested a merger of point forecasts of individual banks into a single interval forecast where the minimum and maximum point forecasts represent the low and the high of an interval. Generally, it has been proven that people tend to set too narrow subjective confidence intervals which often leads to poor forecasting results, as they frequently exclude the correct answers from their interval predictions (Yaniv and Foster, 1997). We base our analysis of professional FX forecasts on the normalized error, a measure proposed by Yaniv and Foster (1997) that is explained by the following equation:

$$E_{norm} = \frac{|A - F|}{w_{\text{int}}}, \tag{19}$$

where A represents an actual value of FX rate, F denotes the forecasted value and $w_{\text{int}}$ stands for the interval width. Now, the forecast error depends not only on accuracy of the prediction, but also on the precision of the FX rate forecasts (width of interval forecasts). As we can see from the definition of the normalized error, the width of interval forecast has the ability to neutralize the forecast error. Therefore, our naive assumption is that professional forecasters when facing more uncertain tasks (= predicting longer horizons) should incorporate their uncertainty into wider interval forecasts. Then, we should not be able to observe any patterns of the normalized errors among different forecasted horizon predictions. Our results in Table 15, however, suggest that there is the same pattern as with Absolute percentage error (APE) – increasing error in time (with only one exception of one-year USD/ JPY predictions).

**Table 15 Normalized errors vs. Absolute percentage errors (FX forecasts Jan 1999 – May 2007)**

| | **EUR** | | **GBP** | | **JPY** | |
|---|---|---|---|---|---|---|
| | **normERROR** | **APE** | **normERROR** | **APE** | **normERROR** | **APE** |
| **1M** | 0.2932 | *0.0231* | 0.2759 | *0.0172* | 0.2708 | *0.0217* |
| **3M** | 0.3491 | *0.0477* | 0.2868 | *0.0295* | 0.3103 | *0.0434* |
| **6M** | 0.3565 | *0.0691* | 0.2987 | *0.0445* | 0.3272 | *0.0665* |
| **1Y** | 0.3994 | *0.1083* | 0.3445 | *0.0681* | 0.3191 | *0.0951* |

Hence, we can conclude that professional forecasters are inconsistent in their forecasts and do not sufficiently adjust their FX predictions. In other words, the interval predictions for longer horizons are too narrow, which might suggest that professional forecasts discount and neglect uncertainty. Although this might point out the incapability of professionals to predict future FX rates accurately, we should bear in mind that flawed accuracy might be partially counterbalanced by informativeness that (also faulty) predictions offer. When it comes to the comparison of the normalized errors across currencies, EUR/USD predictions, every time with the highest error values, seem to be clearly underperforming predictions of two other currency pairs.

## 6.6 Better than average effect

In the last subsection we investigate individual professional forecasts in order to find out if there are certain individual professionals that are able to predict future FX rates more accurately compared to the market consensus. We relate our results to the well-known better than average effect and prove that, actually, the opposite is true – most of the banks underperform the market consensus in FX predictions. We construct a variable $E_{i,t}$ in order to decide whether an FX rate prediction of an individual bank dominates the market consensus or not:

$$E_{i,t} = \frac{\left| consensus_t - actual_t \right|}{\left| forecast_{i,t} - actual_t \right|} \tag{20}$$

Should there be a bank with extraordinary forecasting skills that would really make the bank above the average, then we would observe a high frequency of $E_{i,t} > 1$ for this bank. Appendix 6 summarizes the observed FX rate predictions of individual banks in 2006 which already on first sight supports the hypothesis about rather inferior forecasting abilities of individual banks compared to the market consensus. The number of contributors is limited first to 36, as only 36 banks provided all forecasts during the year 2006 and second to 22, as there are only 22 contributors that have available further data, i.e. on the market capitalization or number of employees that we use as the explanatory variables for estimating following equations with OLS regression where we try to find out what might determine the better than average forecasting ability:

$$BTA_{2006,i} = a + b_1 BTA_{2005,i} + b_2 MCAP_i + b_3 INST_i + b_4 MF_i + b_5 LON + e_i \,, \tag{21}$$

where BTA denotes the percentage ratio of better than the market consensus forecasts for a particular year, MCAP stands for the natural logarithm of the market capitalization in billions USD, INST and MF represent the institutional and the mutual fund ownership of the bank in percents, and finally a dummy variable LON checks if a bank is based in London. In the regression we test if the forecasting ability of an individual bank can be explained by the success from the previous year, market capitalization or the ownership structure. Moreover, we are interested if the city of London has a significant effect on the forecasting ability of a bank. Table 16 summarizes our results overall, whereas Appendix 7 takes a closer look at summary statistics of independent variables and results of regressions for different currencies and time horizons.

**Table 16 Regression on better than average (BTA) effect of individual banks**[22]

| Coefficients | | Std. Error | t-statistic |
|---|---|---|---|
| α (Constant) | 0.1314 | (0.1871) | [0.7024] |
| β1 ($BTA_{ALL2005}$) | 0.3555 | (0.307) | [1.1577] |
| β2 (MCAP) | 0.0079 | (0.029) | [0.2718] |
| β3 (INST) | 0.0581 | (0.1528) | [0.3803] |
| β4 (MF) | 0.1913 | (0.2668) | [0.717] |
| β5 (LON) | 0.0092 | (0.0614) | [0.15] |

The results in Table 16 suggest that the independent variables have a poor explanatory power when examining overall BTA in the year 2006. When we analyze the regression results for particular forecasted time horizons and currency pairs[23], we find the same poor explanatory power of independent variables. In fact, no variable is statistically significant which might imply that there are other variables that could better explain the better than average effect. We document no importance of past performance in FX rate predictions by not significant $BTA_{ALL2005}$. Positive and significant $BTA_{ALL2005}$ would represent evidence for superior (inferior) forecasting abilities where successful (underperforming) forecasters are able to maintain their position from the previous year. Negative and significant coefficient would imply that past success (undeperformance) leads to underperformance (success) in the current year which is a typical finding in finance literature. The other scrutinized variables describing the market capitalization or the ownership structure as well as the basement in London seem to also have no significant effect on the better than average effect at all. However, it should be taken into account that BTA analysis was based only on one year data.

[22] Each of 22 contributors made 126 FX rate predictions in the year 2006; twelve one-month, three-month and six-month forecasts plus six one-year forecasts for each of the three currency pairs – EUR/USD, GBP/USD and USD/JPY

[23] See Appendix 7b

# 7. Conclusion

This study has again demonstrated rather poor forecasting ability of professional forecasters as it was documented by former research. We have shown on the example of forecasting future FX rates that although financial professionals are supposed to be the best forecasters possessing expert forecasting abilities, they do not comply with the rational expectation hypothesis. Our results suggest that the Statman's theory of behavioral people also applies to the field of financial professionals.

Our first and very basic finding when scrutinizing Reuters FX poll data is that the forecast error increases in the forecasted period. This finding is robust, because it is true for each of observed currency pairs and all predictions varying in forecasted horizon. The explanation why forecast accuracy declines in time is quite intuitive, as the longer the predicted horizon is, the higher uncertainty occurs and thus more unpredictable events are.

Next we compare the professional forecast to a benchmark model of a random walk and to a forward as an estimate of future spot rate. Our results support the overall inability of professionals to beat a random walk model, as 8 out of 12 kinds of predictions underperform it. The rather weak forecasting abilities of professionals become even more prominent when we check for differences among currencies. The EUR/USD exchange rate predictions are the obvious weakest link among professional forecasts. Not only that professional forecasters significantly underperform random walk model in all time horizon forecasts, but they also get outperformed by the forward estimates that are far from ideal FX rate predictors. It is followed by the USD/JPY predictions that are also, in line with previous literature, underperforming naive benchmark models most of the time (Bofinger and Schmidt, 2004; Stadtmann, 2004). When it comes to GBP/USD forecasts some of our results surprisingly show signs of beating simple forecasting models. This could shed a new light on forecasting in currency markets that needs not to be necessarily rejected as rational after all. In comparison to two other currency pairs, GBP/USD predictions are significantly more accurate across all time horizons. This might lead us to the conclusion that financial professionals have a superior forecasting ability for predicting GBP/USD exchange rate. Examining of reasons why this could be true is beyond the scope of this study, but undoubtedly might represent a challenging issue for further research. When we evaluate professional FX rate forecasts as predictors of direction of an exchange rate movement, we cannot reject any professional forecast as a significant underperformer of 50% probability of guessing the right direction of an exchange rate movement. In contrary, one-year GBP/USD predictions confirm the dominance of predicting the British pound against the American dollar, as we find a significant 59.5% probability of guessing the correct direction. This might lead us to another interesting conclusion suggesting that the professional forecasts are better and more accurate predictions when they reflect only direction of the movement and do not comprise the magnitude. Although this approach could improve the forecasts in terms of accuracy, it might be not sufficient in real life where the clients of financial institutions often require very specific forecasts and are not satisfied with only directional predictions.

The pillar finding of our study rejects professional FX forecasts to be complying with the rational expectation hypothesis in most of the cases (9 out of 12 types of predictions). Our finding is in line with former research that investigates rational expectations in financial markets (Frankel and Froot, 1987; Frankel and Rose, 1995). What is interesting, only the EUR/USD currency pair shows significant rejection of rational expectation hypothesis for all time horizon predictions which again documents the poorest forecasting ability of professionals to predict the most important currency pair in the world. However, our findings also point out that some of professional forecasts of GBP/USD exchange rates might be an exception – especially, the one-year GBP/USD exchange rate forecasts cannot be rejected as irrational. Additionally, if we take the forecast error results, we can mark the one-year GBP/USD predictions to be the closest forecasts to the rational expectations.

After concluding that professional FX rate forecasts are not rational, we investigate them for the biases. When checking for the extrapolative biases we find a strong evidence for stabilizing expectations suggesting that the professional forecasters expect usually a correction of the prevailing trend. Furthermore, when examining for adaptive expectations we find out that the short-term predictions are most affected by the recent exchange rate development, whereas the long-term predictions are more affected by the historical development of the exchange rate. These findings are further supported by the TOTA results that imply that the current exchange rate importantly affects FX rate predictions, which is of special significance for USD/JPY exchange rate. Testing for regressive expectations does not provide any significant results, which implies that we do not find clear evidence for the anchoring heuristics in professional FX rate forecasts.

Finally, we investigate our data on the overconfidence related measures as miscalibration and better than average effect. First, we have found out that professional forecasters tend to underestimate uncertainty when predicting longer horizons and, therefore, place too narrow interval forecasts. However, as we pointed out, it is not only forecast accuracy that counts but also informativeness of FX forecasts that can be also achieved by flawed but timely FX rate predictions. Second, when analyzing FX rate forecasts of individual professional banks, we find out that most of the banks are unable to outperform the market consensus, hence, they cannot claim that they are better than average. We analyze the better than average effect (BTA) in more details, but we do not find any significant determinants of it. It might be the case that there are other important variables than those on which the BTA has been regressed that could explain BTA with greater power. Moreover, our results on the BTA effect should be taken cautiously, as they are based only on FX forecasts within one year. To complete the enumeration of possible pitfalls of our analysis, we have to mention that we have merged point forecasts into a single but artificial interval forecast when we examine data for miscalibration. Therefore, it should be also taken into account when interpreting our results on miscalibration as an accuracy-informativeness tradeoff.

All in all, we do believe that despite strong evidence for not rational and biased FX rate predictions, they are still needed and of particular importance, especially because of their informative capabilities. We are also convinced that further research on other currency pairs or dealing with longer observed period could shed more light on professional forecasting FX rates and expectation process in currency markets.

# Appendix

## Appendix 1 - Reuters FX 2006 and 2007 Accuracy League

| No. | CITY | BANK **(YEAR 2006)** | SCORE | No. | CITY | BANK **( APRIL '07)** | SCORE |
|---|---|---|---|---|---|---|---|
| 1 | ATH | ALPHA CREDIT | 448 | 1 | ATH | ALPHA CREDIT | 111 |
| 2 | LON | BARCLAYS | 399 | 1 | LON | BNP PARIBAS | 111 |
| 3 | LON | CITIBANK | 363 | 1 | BER | LANDESBANK | 111 |
| 3 | LON | CALYON | 363 | 4 | LON | 4CAST | 109 |
| 5 | COP | DANSKE BANK | 359 | 5 | CLT | WACHOVIA NC | 108 |
| 6 | CLT | WACHOVIA NC | 350 | 6 | NY | BANK OF AMERICA | 106 |
| 7 | FFT | COMMERZBANK | 344 | 7 | LIS | BANCO BPI | 102 |
| 8 | BOS | INVESTORS BK | 332 | 8 | LON | CALYON | 101 |
| 9 | LIS | BCOSANTANDER | 327 | 9 | LON | THOMSON IFR | 100 |
| 10 | LON | INFORMA MKTS | 324 | 10 | LON | BARCLAYS | 97 |
| 11 | LON | 4CAST | 321 | 11 | LON | MIZUHO CB | 95 |
| 12 | ATH | EFG EUROBANK | 318 | 12 | MUN | BAYERN LB | 90 |
| 13 | LON | BNP PARIBAS | 316 | 13 | FFT | DZ BANK | 86 |
| 13 | BER | LANDESBANK | 316 | 13 | VIE | RZB | 86 |
| 15 | LON | GLOBAL INST | 314 | 15 | FFT | COMMERZBANK | 85 |
| 16 | LON | RBC | 305 | 16 | LON | DEUTSCHE BANK | 83 |
| 17 | DUS | WEST LB | 293 | 17 | MEL | ANZ | 81 |
| 18 | LON | CBA | 292 | 18 | LIS | BCOSANTANDER | 79 |
| 18 | LON | LLOYDS | 292 | 18 | PAR | NATIXIS | 79 |
| 20 | LIS | BANCO BPI | 285 | 18 | ZUR | ZKB | 79 |

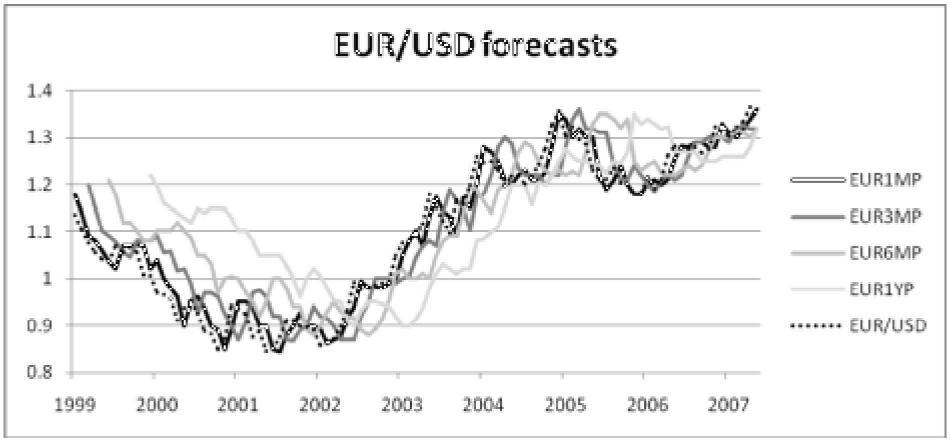
The top 50 most accurate contributors each month are awarded points, with the bank whose forecasts diverged the least from the actual close getting 50 points. The bank which gave the second most accurate set of forecasts gets 49 points and so on. Points from the January to December polls were added up to give a running total.

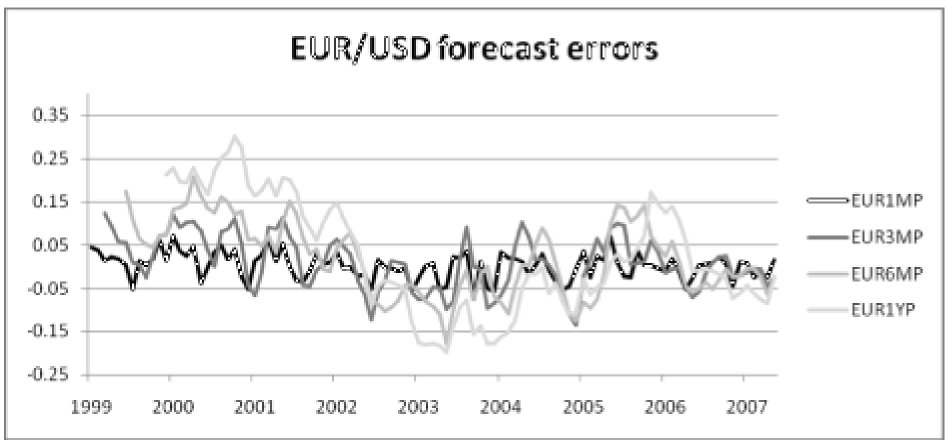
**Source: Reuters**

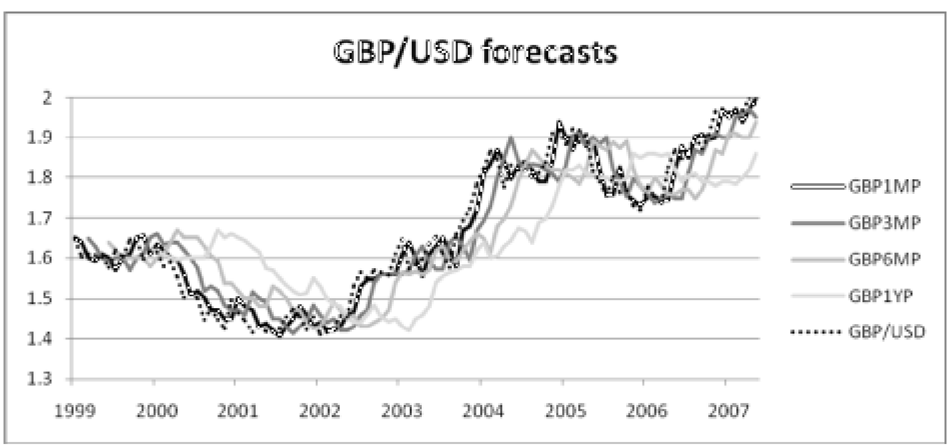
## Appendix 2 - Barclays Capital individual FX predictions (January 1st, 2006)

| Instrument code | Predicted Date | Prediction | Instrument code | Predicted Date | Prediction |
|---|---|---|---|---|---|
| EUR1MP=BARL | 1/31/2006 | 1.21 | GBP6MP=BARL | 6/31/2006 | 1.77 |
| EUR3MP=BARL | 3/31/2006 | 1.23 | GBP1YP=BARL | 12/31/2006 | 1.77 |
| EUR6MP=BARL | 6/31/2006 | 1.24 | JPY1MP=BARL | 1/31/2006 | 118 |
| EUR1YP=BARL | 12/31/2006 | 1.26 | JPY3MP=BARL | 3/31/2006 | 121 |
| GBP1MP=BARL | 1/31/2006 | 1.76 | JPY6MP=BARL | 6/31/2006 | 122 |
| GBP3MP=BARL | 3/31/2006 | 1.78 | JPY1YP=BARL | 12/31/2006 | 120 |

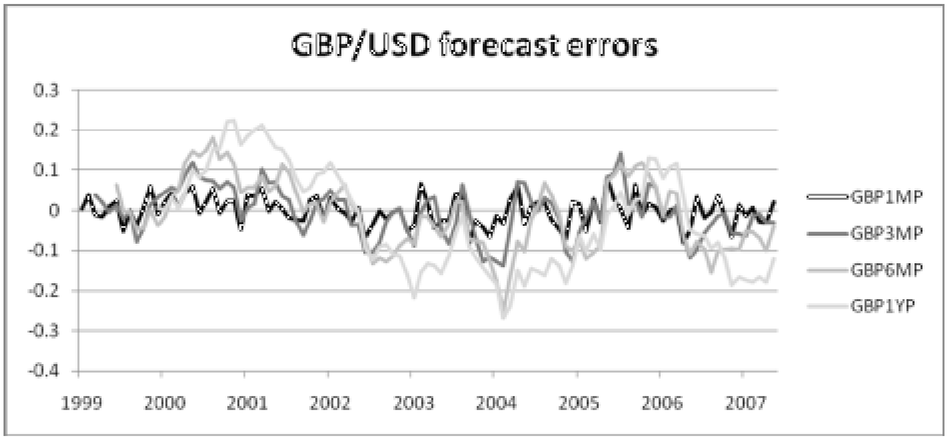
**Appendix 3 – Actual exchange rates vs. forecasts and forecast errors (1999-2007)**

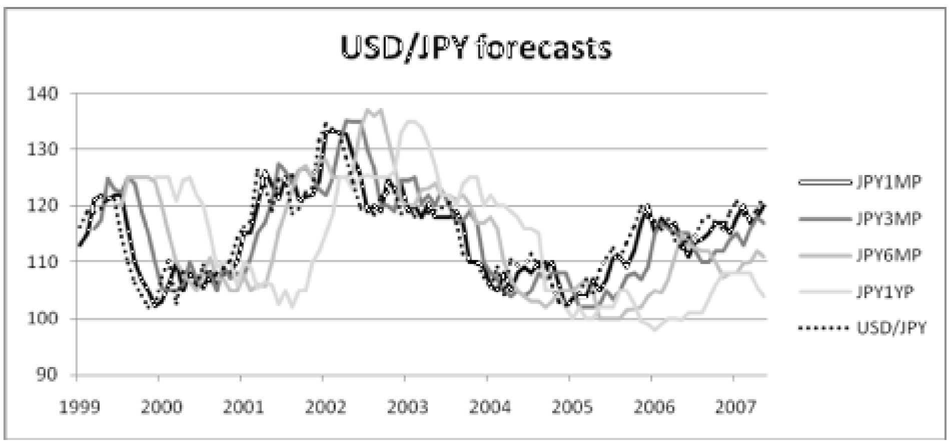


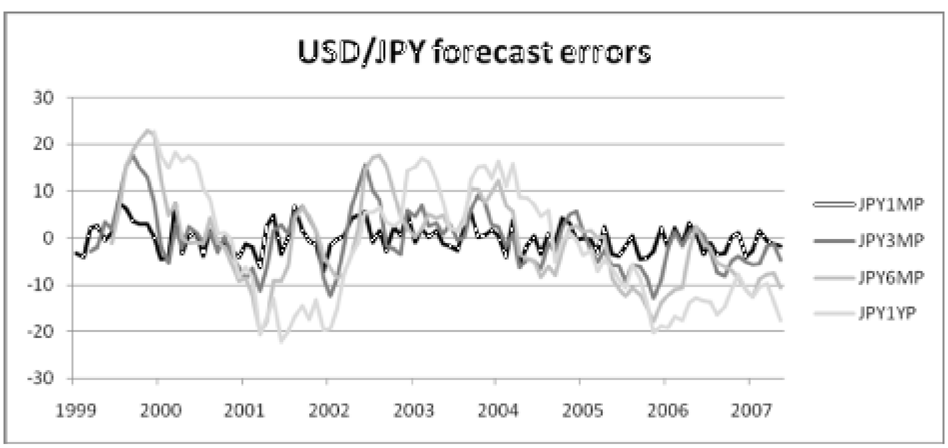



**Appendix 3 – Actual exchange rates vs. forecasts and forecast errors (1999-2007) (continued)**



**Appendix 4a – Adaptive expectations – Wald's test for testing the joint hypothesis $\alpha = 0$ and $\beta = 1$**

| **FX rate prediction** | **F - Value** | **df** | **Probability** |
|---|---|---|---|
| EUR1MP | 12.77518*** | (2, 96) | 0 |
| EUR3MP | 32.41144*** | (2, 95) | 0 |
| EUR6MP | 32.29065*** | (2, 92) | 0 |
| EUR1YP | 50.54605*** | (2, 86) | 0 |
| GBP1MP | 19.2204*** | (2, 96) | 0 |
| GBP3MP | 33.26292*** | (2, 95) | 0 |
| GBP6MP | 62.73588*** | (2, 92) | 0 |
| GBP1YP | 78.67649*** | (2, 86) | 0 |
| JPY1MP | 17.70817*** | (2, 96) | 0 |
| JPY3MP | 39.47738*** | (2, 95) | 0 |
| JPY6MP | 74.26986*** | (2, 92) | 0 |
| JPY1YP | 26.48456*** | (2, 86) | 0 |

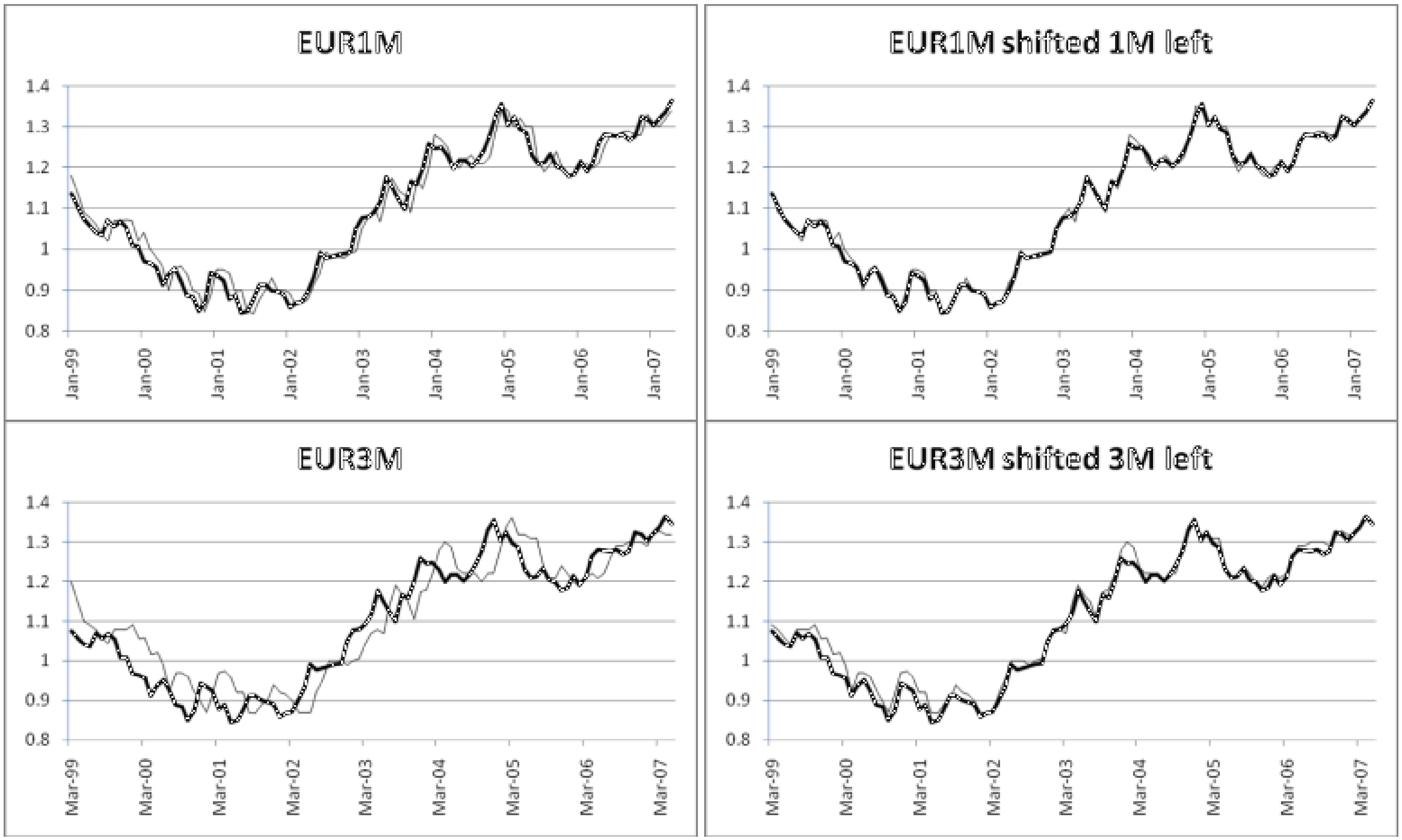
(*** denotes significance at the 1% level)

**Appendix 4b – Regressive expectations (the results of the estimation of equation (16) with an OLS regression)**

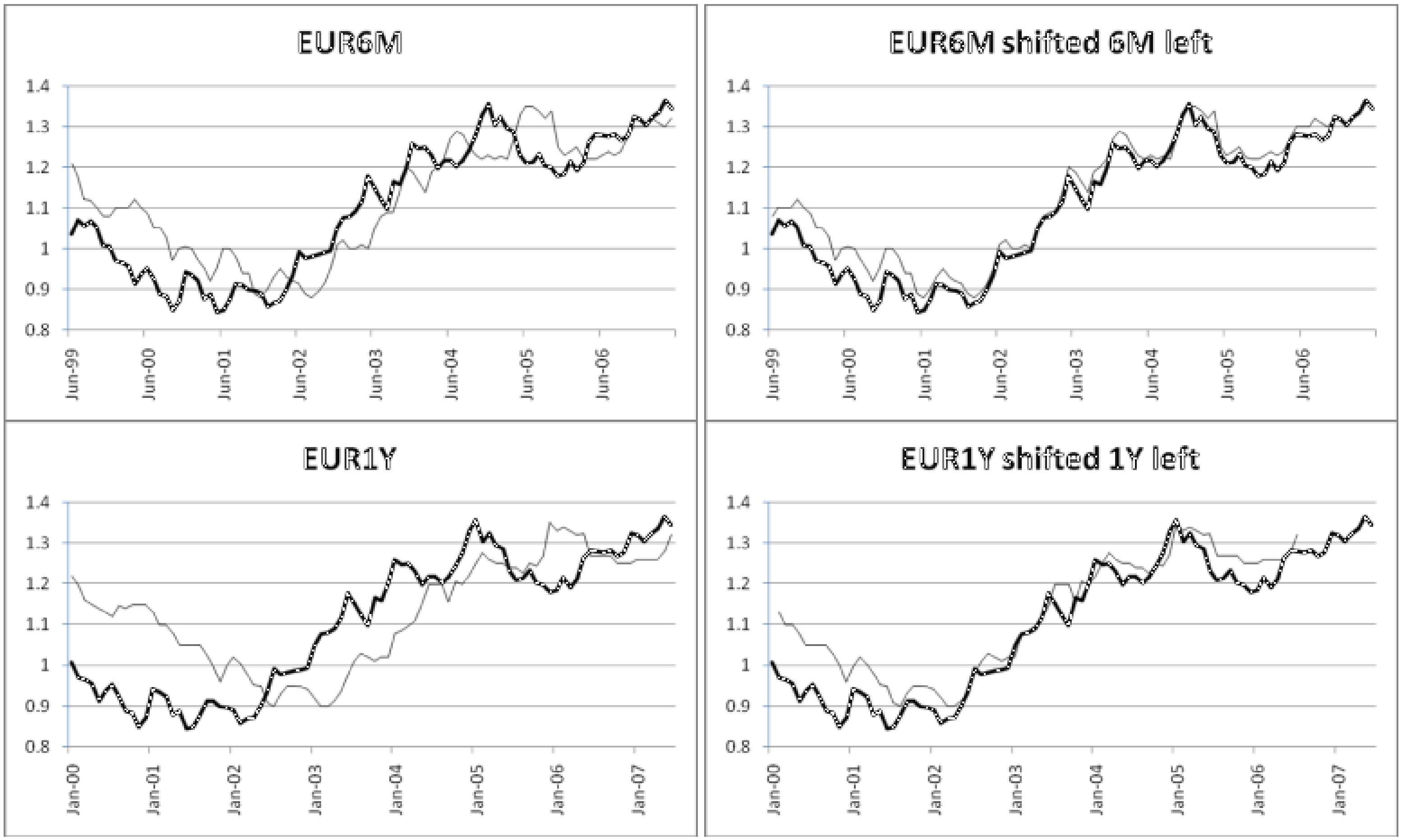
| | **alpha** | | **beta** | |
|---|---|---|---|---|
| **EUR1M** | 0.0004 | (0.0148) | 0.0072 | (0.1354) |
| **EUR3M** | -0.0001 | (-0.2425) | -0.6522 | (0.1526) |
| **EUR6M** | -0.002 | (-0.448) | -0.5017 | (-0.1507) |
| **EUR1Y** | 0.0009 | (0.1825) | -0.504 | (0.7735) |
| **GBP1M** | -0.0003 | (0.0104) | -0.126 | (-0.3456) |
| **GBP3M** | -0.0007 | (-0.1412) | -0.5653 | (-0.2659) |
| **GBP6M** | -0.0002 | (-0.2267) | -0.4626 | (-0.0739) |
| **GBP1Y** | -0.0013 | (-0.2997) | -0.5059 | (-0.297) |
| **JPY1M** | 0.0011 | (0.0747) | -0.1172 | (-0.4925) |
| **JPY3M** | -0.0022 | (-0.0096) | -0.5299 | (0.382) |
| **JPY6M** | -0.0012 | (-0.1739) | -0.524 | (-0.0401) |
| **JPY1Y** | -0.0081 | (-1.0461) | -0.4626 | (0.7071) |

(t-statistics in parentheses)

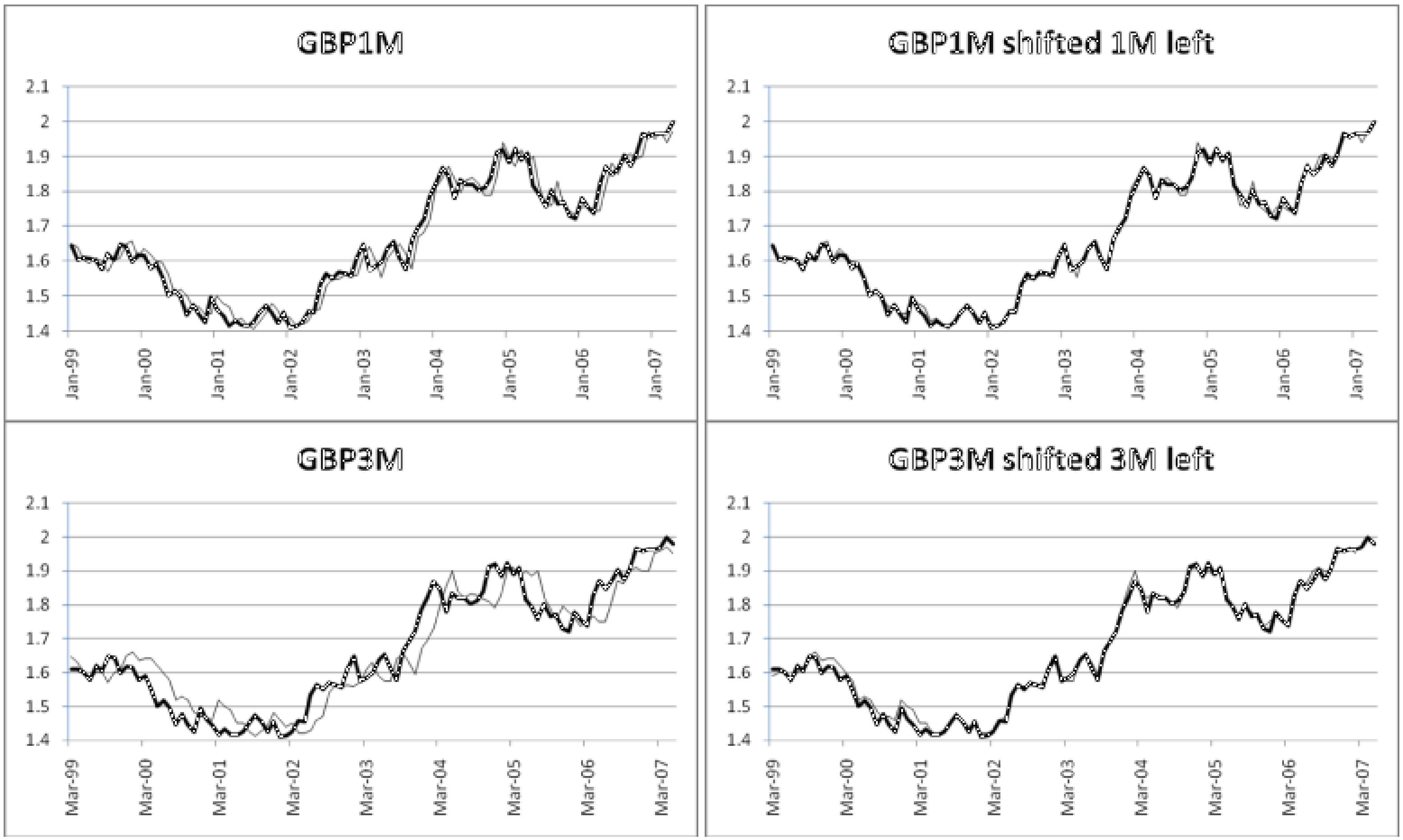
**Appendix 5 Topically oriented trend adjustment** (bold line – actual rate; thin line – FX forecast)



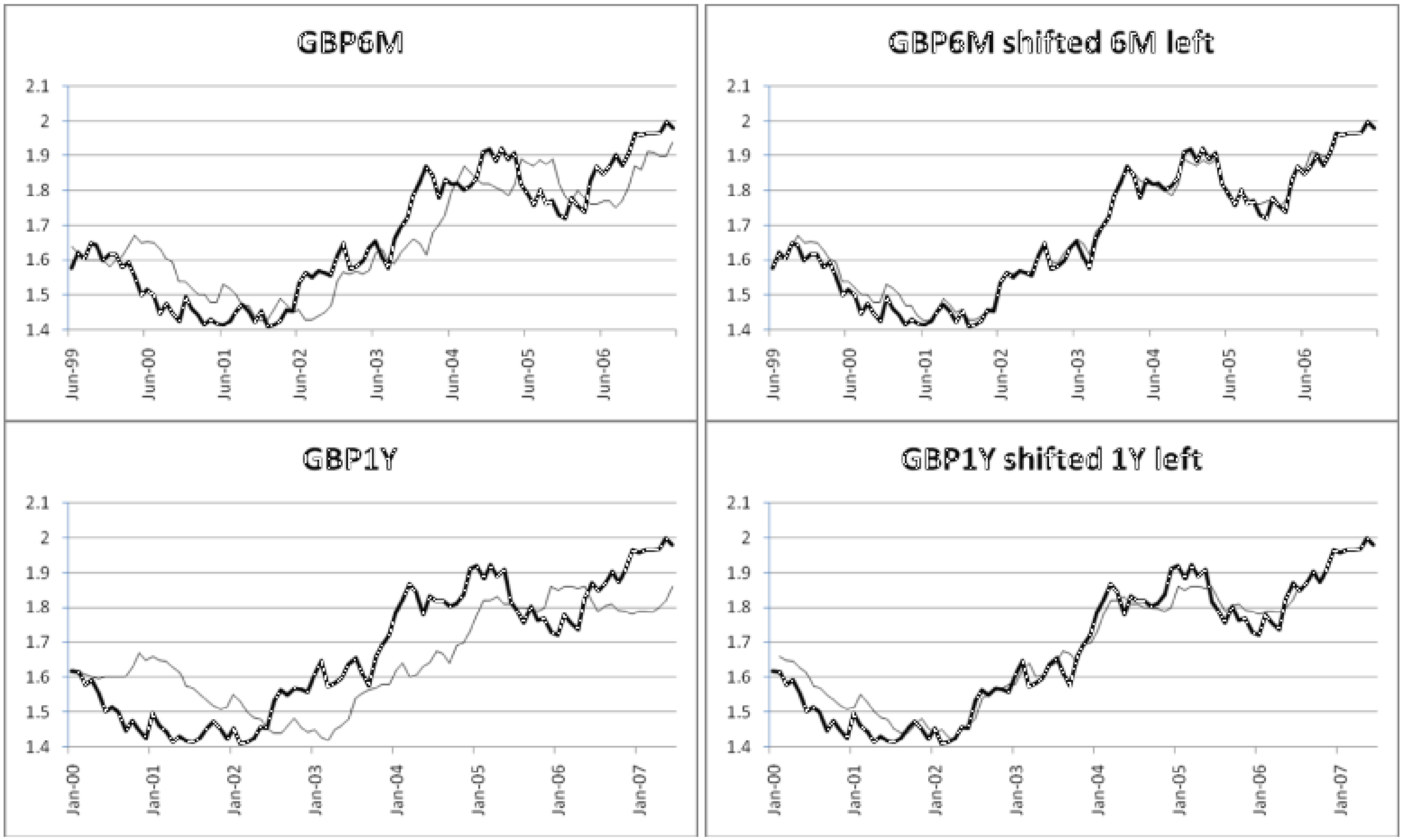
**Appendix 5 Topically oriented trend adjustment (continued)** (bold line – actual rate; thin line – FX forecast)



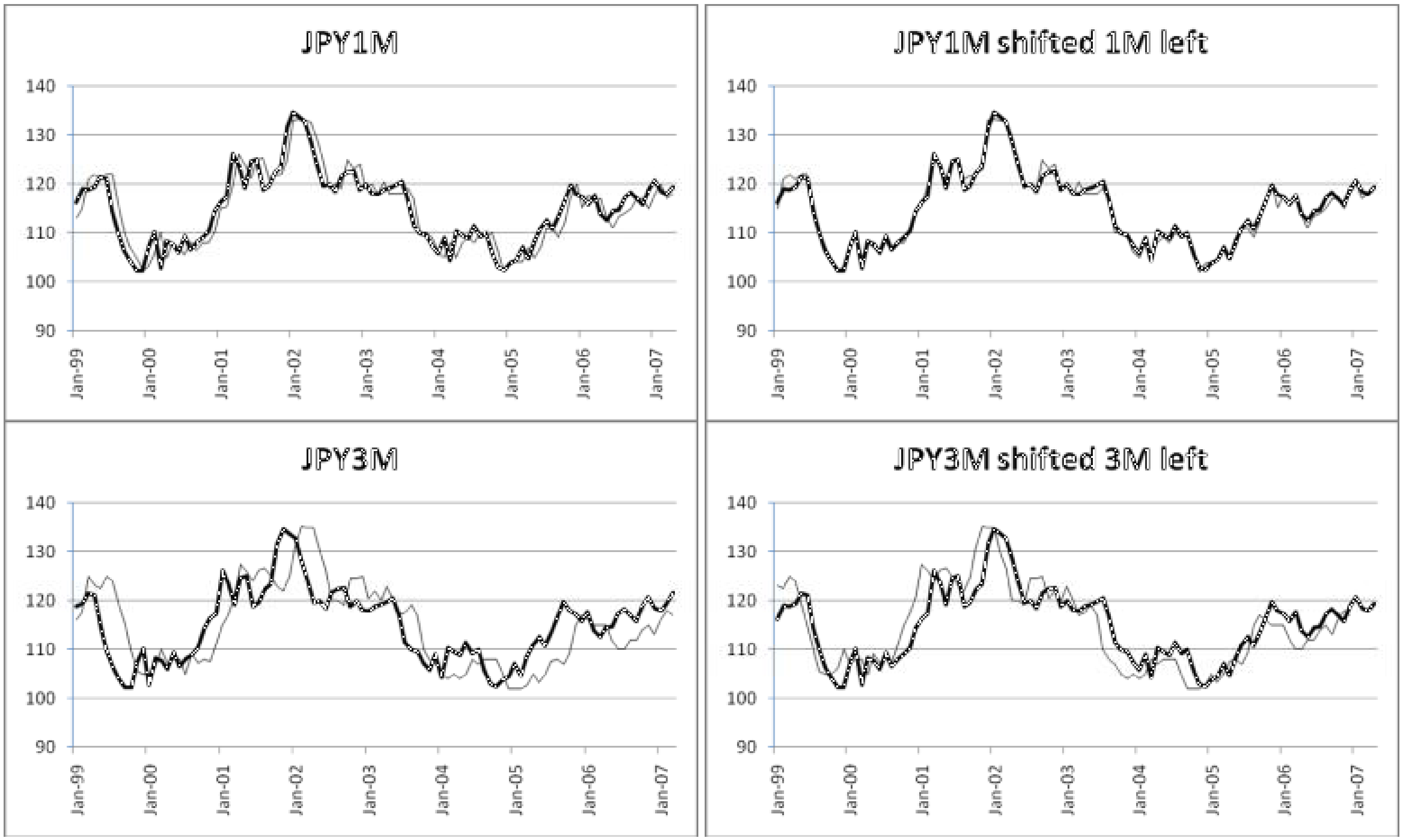
**Appendix 5 Topically oriented trend adjustment (continued)** (bold line – actual rate; thin line – FX forecast)



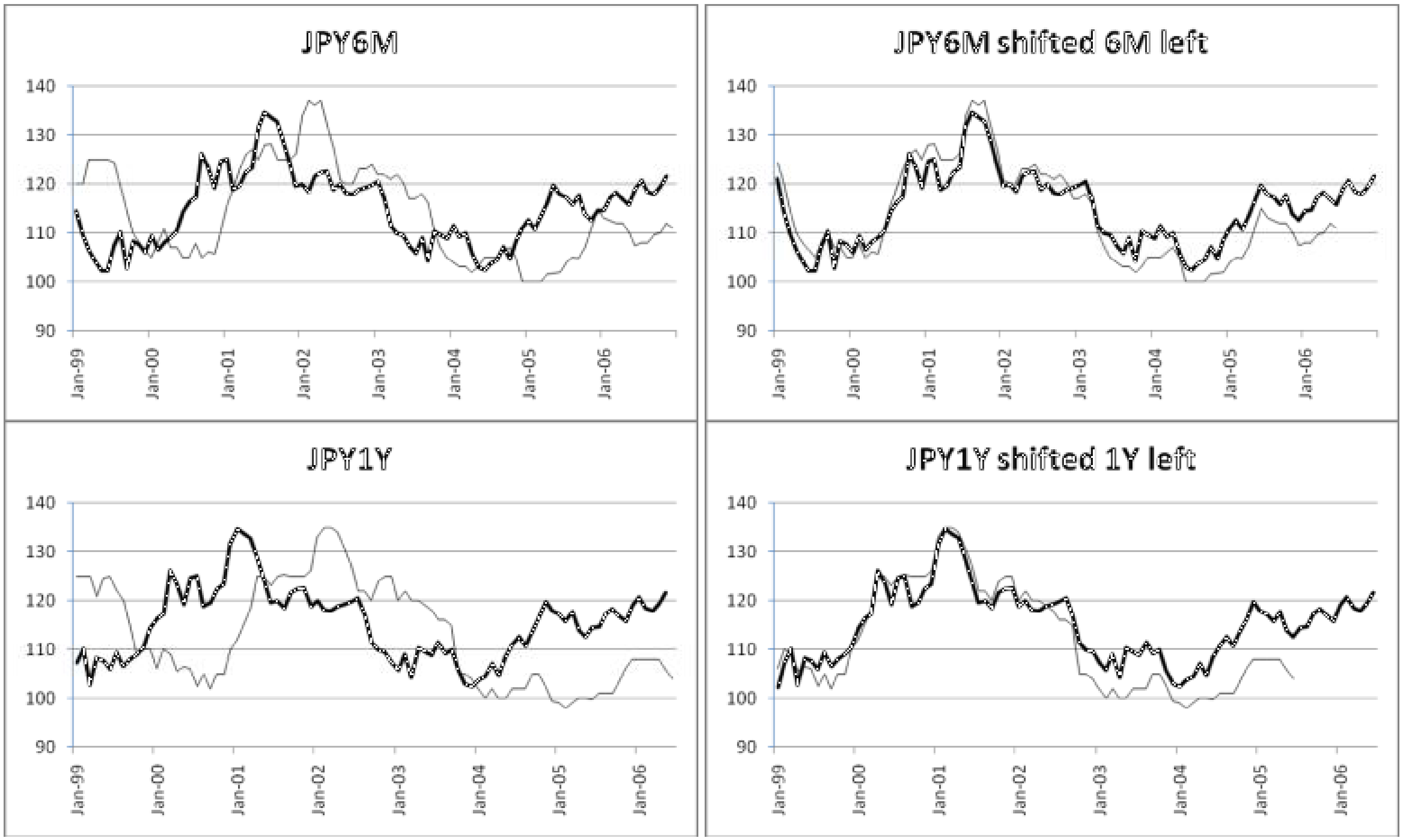
**Appendix 5 Topically oriented trend adjustment (continued)** (bold line – actual rate; thin line – FX forecast)



**Appendix 5 Topically oriented trend adjustment (continued)** (bold line – actual rate; thin line – FX forecast)



**Appendix 5 Topically oriented trend adjustment (continued)** (bold line – actual rate; thin line – FX forecast)



**Appendix 6 Better than average effect – comparing FX rate forecasts of the individual banks to the market consensus**

Numbers in the table represent how many times a particular bank was able to predict FX rate more accurately than the market consensus. Each bank made for each of three different currency pairs (EUR/USD, GBP/USD and USD/JPY) twelve one-month, three-month and six-month predictions and six one-year predictions which totally accounts for 126 different FX rate predictions in the year 2006.

| Year 2006 | EUR1M | GBP1M | JPY1M | EUR3M | GBP3M | JPY3M | EUR6M | GBP6M | JPY6M | EUR1Y | GBP1Y | JPY1Y | sum | BTA |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ALPHA CREDIT | 4 | 7 | 6 | 4 | 8 | 3 | 6 | 10 | 8 | 2 | 2 | 4 | 64 | 0.51 |
| ANZ | 2 | 5 | 4 | 1 | 3 | 2 | 1 | 1 | 7 | 1 | 0 | 1 | 28 | 0.22 |
| BCOSANTANDER | 5 | 4 | 4 | 6 | 3 | 4 | 1 | 5 | 7 | 0 | 4 | 4 | 47 | 0.37 |
| BANKAMERICA | 3 | 3 | 3 | 5 | 4 | 7 | 7 | 9 | 4 | 5 | 5 | 0 | 55 | 0.44 |
| BARCLAYS | 6 | 4 | 6 | 5 | 7 | 6 | 7 | 5 | 8 | 3 | 3 | 5 | 65 | 0.52 |
| BNP | 3 | 6 | 4 | 6 | 6 | 2 | 5 | 9 | 3 | 5 | 2 | 1 | 52 | 0.41 |
| BANCO BPI | 4 | 2 | 3 | 3 | 7 | 4 | 6 | 6 | 4 | 0 | 0 | 3 | 42 | 0.33 |
| CBA | 5 | 6 | 4 | 4 | 5 | 6 | 0 | 4 | 6 | 0 | 3 | 2 | 45 | 0.36 |
| CS | 5 | 4 | 5 | 4 | 1 | 4 | 1 | 1 | 8 | 0 | 0 | 6 | 39 | 0.31 |
| DANSKE BANK | 3 | 4 | 7 | 2 | 6 | 5 | 1 | 4 | 7 | 2 | 2 | 5 | 48 | 0.38 |
| HSBC | 3 | 1 | 4 | 4 | 0 | 5 | 5 | 0 | 3 | 3 | 0 | 3 | 31 | 0.25 |
| ING FIN MKTS | 3 | 1 | 6 | 5 | 6 | 2 | 5 | 10 | 2 | 4 | 6 | 1 | 51 | 0.40 |
| LEHMAN | 2 | 3 | 4 | 2 | 1 | 0 | 4 | 1 | 2 | 0 | 0 | 0 | 19 | 0.15 |
| LLOYDS | 6 | 5 | 4 | 3 | 5 | 4 | 6 | 8 | 4 | 5 | 4 | 1 | 55 | 0.44 |
| MERRILL LYN | 5 | 5 | 1 | 5 | 5 | 0 | 5 | 5 | 0 | 2 | 0 | 1 | 34 | 0.27 |
| NAB | 4 | 5 | 1 | 3 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 17 | 0.13 |
| NATIXIS | 1 | 4 | 5 | 0 | 2 | 6 | 0 | 0 | 7 | 0 | 0 | 6 | 31 | 0.25 |
| OKO BANK | 1 | 4 | 4 | 3 | 4 | 4 | 2 | 3 | 4 | 0 | 6 | 1 | 36 | 0.29 |
| RBS | 5 | 2 | 5 | 2 | 0 | 6 | 0 | 0 | 7 | 3 | 1 | 0 | 31 | 0.25 |
| SOCGEN | 3 | 1 | 4 | 3 | 0 | 1 | 4 | 5 | 2 | 6 | 4 | 4 | 37 | 0.29 |
| THOMSON IFR | 3 | 3 | 3 | 6 | 5 | 3 | 4 | 9 | 8 | 3 | 4 | 4 | 55 | 0.44 |
| WACHOVIA NC | 4 | 5 | 7 | 6 | 8 | 2 | 8 | 11 | 0 | 6 | 6 | 0 | 63 | 0.50 |

**Appendix 7a Descriptive statistics on independent variables in BTA regressions**

| | $BTA_{ALL2005}$ | MCAP | MFSH | INSTSH | LON |
|---|---|---|---|---|---|
| Mean | 0.3525 | 3.9851 | 0.1352 | 0.4091 | 0.399 |
| Median | 0.3784 | 4.2267 | 0.0932 | 0 | 0.3355 |
| Maximum | 0.5397 | 5.385 | 0.3909 | 1 | 0.7619 |
| Minimum | 0.127 | 1.1337 | 0.0006 | 0 | 0.0494 |
| Std. Dev. | 0.107 | 1.045 | 0.126 | 0.5032 | 0.2286 |
| Skewness | -0.2521 | -1.1658 | 0.7647 | 0.3698 | 0.1669 |
| Kurtosis | 2.5576 | 4.0511 | 2.3509 | 1.1368 | 1.6775 |
| Observations | 22 | 22 | 22 | 22 | 22 |
| Jarque-Bera | 0.4124 | 5.9963 | 2.5305 | 3.6838 | 1.7053 |
| Probability | 0.8137 | 0.0499 | 0.2822 | 0.1585 | 0.4263 |

**Appendix 7b Regression results on better than average effect**

FX rate forecasts are divided into various groups based on time horizons and currencies. ** and * signify the significance at 5% and 10% level. T-statistics are shown in parentheses. $BTA_{i2005}$ stands for the better than average effect in the year 2005 where i=1m, 3m, 6m, 1y, eur, gbp and jpy.

| **Year 2006** | **α (constant)** | **$\beta_1$ ($BTA_{i2005}$)** | **$\beta_2$ (MCAP)** | **$\beta_3$ (INST)** | **$\beta_4$ (MF)** | **$\beta_5$ (LON)** |
|---|---|---|---|---|---|---|
| $BTA_{1M}$ | 0.1796<br>(1.6383) | 0.3476<br>(1.4891) | 0.009<br>(0.4463) | 0.0867<br>(0.7479) | -0.0893<br>(-0.5081) | -0.0149<br>(-0.3404) |
| $BTA_{3M}$ | 0.2696*<br>(1.8468) | 0.135<br>(0.5419) | -0.0013<br>(-0.0416) | 0.0566<br>(0.3427) | -0.0971<br>(-0.3356) | -0.0205<br>(-0.3039) |
| $BTA_{6M}$ | 0.1759<br>(0.7503) | 0.2914<br>(1.0666) | -0.0058<br>(-0.1351) | 0.0111<br>(0.0511) | 0.4338<br>(1.1561) | 0.0556<br>(0.6216) |
| $BTA_{1Y}$ | 0.0624<br>(0.23) | 0.1791<br>(0.79) | 0.0412<br>(0.7382) | 0.0452<br>(0.1585) | 0.4373<br>(0.8633) | 0.03<br>(0.2549) |
| $BTA_{eur}$ | 0.0289<br>(0.191) | 0.1007<br>(0.4422) | 0.0278<br>(0.903) | 0.2521<br>(1.4795) | 0.218<br>(0.7945) | 0.0276<br>(0.4164) |
| $BTA_{gbp}$ | 0.4766**<br>(2.2132) | -0.2224<br>(-0.5061) | -0.0209<br>(-0.4091) | 0.0828<br>(0.3131) | 0.2415<br>(0.5627) | -0.0385<br>(-0.3594) |
| $BTA_{jpy}$ | 0.1818<br>(0.6702) | 0.3167<br>(1.1024) | 0.0303<br>(0.6754) | -0.18<br>(-0.8989) | -0.0375<br>(-0.1015) | 0.0358<br>(0.4356) |

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