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BIASES OF PROFESSIONAL EXCHANGE RATE FORECASTS: PSYCHOLOGICAL EXPLANATIONS AND AN EXPERIMENTALLY-BASED COMPARISON TO NOVICES

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ABSTRACT

Biases of Professional Exchange Rate Forecasts: Psychological Explanations and an Experimentally-Based Comparison to Novices

The empirical performance of macroeconomic exchange rate models is more than disappointing. This dismal result is also reflected in the forecasting capabilities of professional analysts: all in all, analysts are not in a position to beat naïve random walk forecasts. The root for this deficient outcome stems from the fact that professional forecasts are to a large extend influenced by actual changes in exchange rates. A reasonable explanation for this behaviour can be taken from the behavioural finance literature. To test whether this characteristic tends to be general human behaviour in an uncertain environment, we analyse the forecasting behaviour of students experimentally, using a simulated currency series. Our results indicate that topically-oriented trend adjustment behaviour (TOTA) is a general characteristic of human forecasting behaviour. Additionally, we apply a simple model to explain professional and student forecasts.

JEL Classification: C53, C92, D70, D81, E27, F31, F47 and G12
Keywords: Foreign exchange market, forecasting, behavioural finance, anchoring heuristics, judgement and expertise

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1 Introduction

A common empirical fact in economics is that standard macroeconomic exchange rate models fail to explain or even predict actual exchange rate movements accurately. This dismal result is also reflected in the poor forecasting performance of professional analysts (see for a detailed analysis of professional forecasts Bofinger and Schmidt, [2003a], Bofinger and Schmidt, [2003b]). Thus, analysing the forecasting performance of professional analysts appears to be tediously at first glance. However, analysing subjective forecasts of individuals may reveal interesting characteristics of human decision making in uncertain environments. As, until now no empirically persuasive exchange rate model exist, exchange rate forecasters are confronted with an extremely high degree of uncertainty. Preceding studies have demonstrated that the forecast errors of professional forecasters all follow a similar pattern (see Bofinger and Schmidt, [2003a], Bofinger and Schmidt, [2003b] and Spiwoks, [2003]). Instead of predicting future exchange rate movements, professional forecasts predominantly reflect the current trend. Such behaviour can be classified as a topically oriented trend adjustment behaviour (TOTA) of professional forecasters (see Andres and Spiwoks, [1999]). A reasonable explanation for this behaviour can be found in the literature of behavioural finance. A central element of behavioural finance is the relevance of simple heuristics or rule of thumbs, which allow quick and often efficient decisions, but sometimes lead to serve biases. According to Bofinger and Schmidt, [2003a], Bofinger and Schmidt, [2003b] the poor forecasting performance of professional forecasters stems from psychological factors which likely affect human decision making in general (see for e.g. Plous, [1993] and Strack and Deutsch, [2002]), so we are concerned whether similar results can be reproduced in an experimental environment.

The experimentally based analysis of expectation formation has a long tradition in economic research. When experts lack time, sufficient data or useful models, they predict future values of a time series judgementally. Several empirical studies prove that the practice of forecasting is dominated by judgmental approaches. Although statistical methods are widely used, forecasts are not solely based on the output of forecast models, but are adjusted by their users (see e.g. Dalrymple, [1975], Dalrymple, [1987], Sanders and Manrodt, [1994], Klassen and Flores, [2001]). Due to the practical importance of subjective forecasting, human behaviour has been analysed in numerous experimental studies. The main characteristic of these experiments is the experimental procedure: Subjects have to forecast a time series judgementally; in most studies only the past values of the time series are the only available information. A few experimental designs include additional sources of information, e.g. the output of time series analysis models, in order to observe behaviour in settings closer to reality. For a detailed discussion we refer to Webby and O'Connor, [1996], who reviewed the literature about judgmental and statistical time series forecasting intensively.

Despite the increasing interest in exploring forecasting behaviour experimentally, there are comparatively few approaches of modelling human expectation formation. We apply a very simple model to the experimentally generated forecasts of students and the empirically observed forecasts of experts in the sense of the Reuters 1 month forecasts. The model – the so-called bounds & likelihood heuristics (b&l heuristics) by Becker and Leopold-Wildburger [1996] – has been developed to explain collective one-period point forecasts. This heuristics has been tested successfully on a large scale and we want to explore, whether the good results hold for forecasting situations that are closer to reality.

The remainder of the study is as follows. In the next section we briefly expose the empirical failure of economic exchange rate models. Afterwards the empirical characteristics of Reuters one-month ahead forecasts are evaluated. Chapter 4 gives a psychological

explanation for the poor forecasting performance. Finally, we analyse the forecasting performance of novices in an experimental setting and test the b&l heuristics.

2 Exchange rate economics: Where do we stand?

The economic approach to exchange rate determination is characterised by the idea that macroeconomic factors such as the money supply or real income drive exchange rates. This view has been manifested through various exchange rate models (see for a comprehensive illustration of these models Hallwood and MacDonald, [2000]). However, the explanatory power of economic exchange rate models appears to be low. After more than two decades of intensive empirical testing, the empirical results are summarised by the following two main conclusions:

- In the short-run (1-2 years) macroeconomic exchange rate models perform less accurately than forecasts that do not rely at all on macroeconomic fundamentals. Even assuming that market participants can perfectly anticipate the future path of macroeconomic fundamentals, their forecasts are worse than naïve random walk forecasts. This result was originally put forth by Meese and Rogoff, [1983a], Meese and Rogoff, [1983b] who found that a random walk forecast typically outperforms a forecast based on a macroeconomic exchange rate model although their forecasts were based on actual realised values of future explanatory variables. Until today, this unfruitful awareness is still valid (see e.g. Chinn and Meese, [1995], Rogoff, [1999], Flood and Rose, [1999] and most recently Cheung et al., [2003]). Rogoff, [2001] summarises the present academic consensus precisely:

  "To make a long story short not only have a subsequent twenty years of data and research failed to overturn the Meese-Rogoff result, they have cemented it…" (Rogoff, [2001])

- In the long-run (3-5 years), however, the recent empirical literature on the validity of macroeconomic exchange rate models suggests that fundamentally based models have some explanatory power. Mark, [1995] shows in his seminal paper that for long horizons there exist economically significant predictable components in the long-horizon changes of the log exchange rate. These systematic exchange rate movements are determined by economic fundamentals. Furthermore, the study of Mark, [1995] reveals that the explanatory power of fundamental based forecasts measured by the coefficient of determination (R^2) increases with the forecast horizon and the out-of-sample point predictions generally outperform the driftless random walk at longer horizons. Likewise Chinn and Meese, [1995] and, more recently, Mark and Sul, [2001] confirm the findings of Mark, [1995]. Chinn and Meese, [1995] examine the predictive power of structural exchange rate models using parametric and non-parametric techniques and found that, for longer horizons, error correction terms can explain exchange rate movements significantly better than a naïve random walk forecast. Mark and Sul, [2001] study the long-run relationship between nominal exchange rates and monetary fundamentals for a panel of 19 countries and find that exchange rates are cointegrated with long-run determinants predicted by economic theory and that panel based forecasts have a significant forecasting power. However, others remain still sceptical and begin to criticise Mark, [1995] methodology and the resultant conclusions (see Kilian, [1999], Berkowitz and Giorgianni, [2001], Faust et al., [2003] and Neely and Sarno, [2002]).

To summarise the preceding evidence for fundamental based exchange rate models, we refer to Kilian and Taylor, [2003] who conclude:

"After nearly two decades of research since Meese and Rogoff's pioneering work on exchange rate predictability (…), the goal of exploiting economic models of exchange rate determination to beat naïve random walk forecasts remains as elusive as ever" (Kilian and Taylor, [2003], pp. 85)

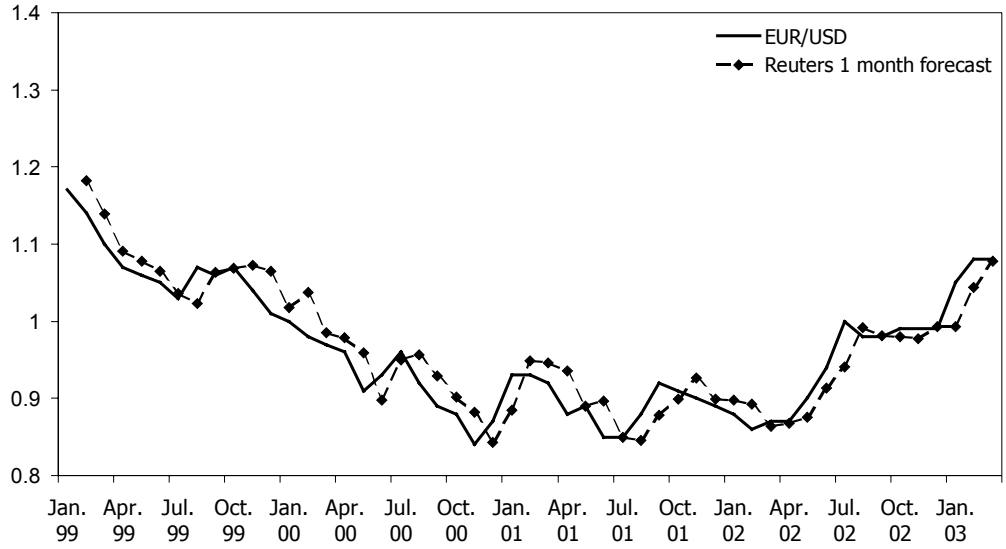
3 Evaluation of professional exchange rate forecasts

One way to manifest the dismal empirical evidence of economic exchange rate models is to evaluate the forecasting performance of financial analysts, who are mostly employed by banks or other financial institutions and should produce best possible forecasts because of their comparative advantage in the field of exchange rate economics. As no persuasive exchange rate model exist, analysts must make their forecasts in situations of high uncertainty and should therefore perform worse than naïve random walk forecasts. This study investigates the characteristics of professional exchange rate forecasts to evaluate their performance and to explain their failure.

3.1 Description of the available data

Our analysis of professional forecasts is based on survey data provided by Reuters. Reuters asks about 50 financial analysts every month for their assessment of the future exchange rate development. The period under consideration starts in January of 1999 and ends in March of 2003. The length of the analysed forecasting horizon corresponds to one month. Figure 1 illustrates the professional forecasts and the corresponding US-$/€ spot exchange rates. The spot €/US-$ exchange rate is taken from the IFS CD-ROM of the International Monetary Fund (IMF). Here we use the end-of-month values of the preceding month since the market forecasts are made at the end or the beginning of a month: for instance, the December one-month forecast for January is typically made at the end of November/beginning of December. Thus, we compare this value with the actual end of December spot rate.

Figure 1: Market forecasts and €/US-$



3.2 Empirical results

3.2.1 Rationality of professional exchange rate forecasts

Following the macroeconomic approach to exchange rate determination, professional forecasters should form their expectations concerning future exchange rates in a rational manner. This suggestion is made clear within the rational expectation hypothesis (Muth, [1961]). According to the rational expectations hypothesis (REH), expectations errors (ξ_{t+1}) conditioned on the available information set (Ω_t) are purely random,

$$\xi_{t+1} = S_{t+1} - E\left(S_{t+1} \middle| \Omega_t\right), \qquad \text{with } \xi_{t+1} \sim \left(0, \sigma^2\right) \tag{1}$$

where S denotes the nominal spot exchange rate and E is the rational expectations operator. This unbiasedness hypothesis implies that under REH forecasts errors are expected to be zero, i.e. they fluctuate randomly so that ex post no systematic deviations of the actual spot rate from the expected rate should be observed.
The unbiasedness hypothesis can be tested by regressing the actual change in the spot exchange rate on the expected change according to the professional forecasts. Thus, the null hypothesis of unbiasedness implies that it is possible to decompose s_{t+h}-s_t as

$$s_{t+h} - s_t = \alpha + \beta\left(E_t s_{t+h} - s_t\right) + \varepsilon_{t+h} \tag{2}$$

where s denotes the logarithm of the nominal spot exchange rate, $\alpha = 0$, $\beta = 1$ and ε_{t+h} has mean zero and is uncorrelated with $E_t s_{t+h}$-s_t (see Cavaglia et al., [1994], p. 327). Table 1 summarises the results of estimating equation (2) via ordinary least square (OLS). For an evaluation of the joint null hypothesis of $\alpha = 0$ and $\beta = 1$, we perform a Wald-Test. The corresponding F-statistics are also reported in Table 1. As the results reveal, the α coefficients may be close to zero, but the β coefficients departs significantly from one. The Wald-Test suggests that joint hypothesis of $\alpha = 0$ and $\beta = 1$ cannot be maintained for the one month Reuters forecasts. Thus, the characteristics of professional exchange rate forecasts are inconsistent with the concept of rational expectations.

Table 1: Rationality of professional forecasts

	α	β	**F-statistic**
Reuters 1 month forecasts	-0.0011 (0.0045)	-0.1094 (0.3905)	5.0224 [0.0105]

Standard errors in parentheses; p-values in brackets.

3.2.2 Accuracy of professional exchange rate forecasts

For an evaluation of the forecasting accuracy of professional analysts we refer to the relative mean error (ME), the relative mean squared error (MSE) and the relative mean absolute error (MAE).[1] In addition we use the Theil's inequality coefficient to directly compare the forecasting performance of professional forecasts with naïve random walk forecasts. Finally,

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[1] The mean error is defined as $ME = \frac{1}{T}\sum_{t=1}^{T}\left(\hat{x}_t - x_t\right)$, the mean squared error as $MSE = \frac{1}{T}\sum_{t=1}^{T}\left(\hat{x}_t - x_t\right)^2$ and the mean absolute error as $MAE = \frac{1}{T}\sum_{t=1}^{T}\left|\hat{x}_t - x_t\right|$, whereby $\hat{x}_t = \frac{\hat{S}_t - S_{t-1}}{S_{t-1}}$ and $x_t = \frac{S_t - S_{t-1}}{S_{t-1}}$.

we also investigate the appropriateness of professional forecasts as direction of change forecasts (see Moosa, [2000]).

Table 2: Accuracy of professional forecasts

	ME	MSE	MAE	Theil's U	Hit rate
Reuters 1 month forecasts	0.0056 (0.0012)	0.0010 (0.0009)	0.0265 (0.0233)	1.0952	44 % [0.54255]

Comparative values of random walk forecasts in parenthesis;
Test statistic of the χ^2 – Test in brackets

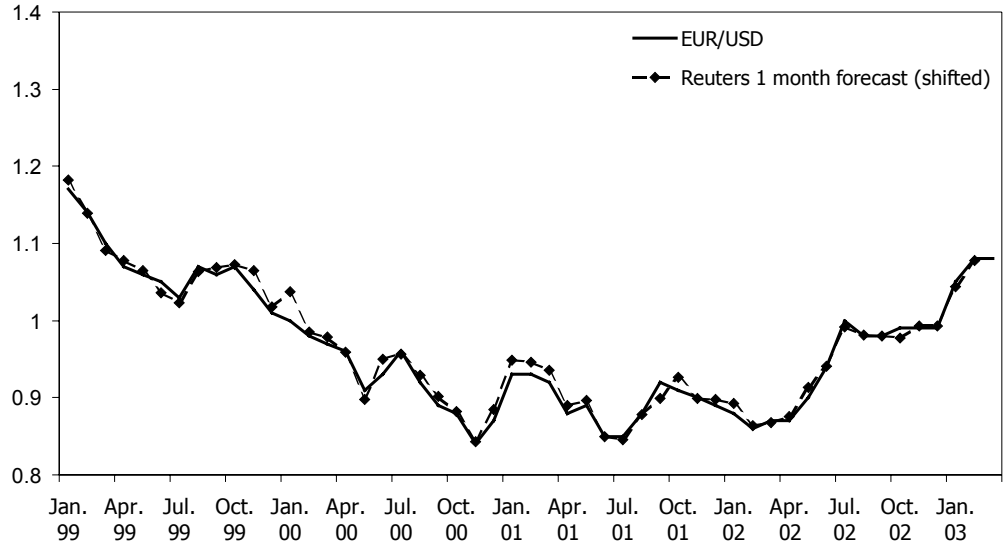
The positive value of the mean error indicates that professional forecasters tend to overestimate the future development of the Euro against the US-dollar. In addition, a comparison of the accuracy of professional forecasts with a naïve random walk forecasts reveals that for all measures the random walk beats professional forecasts. This result is also highlighted by the Theils's inequality coefficient, which is above one. To evaluate the accuracy of professional forecasts as direction of change forecasts we perform a simple χ^2-test of independence (see Diebold and Lopez, [1996]). However, the professional forecasts fail to anticipate the future direction of change; the corresponding hit rate is well below 50 per cent and the test statistic is insignificant.
Altogether, the results show that the professional forecasts perform worse than a naïve random walk forecast. Thus, the results correspond with the results of the forecasting performance of macroeconomic exchange rate models (see Meese and Rogoff, [1983a], Meese and Rogoff, [1983b]).

4 A behavioural explanation for the poor forecasting performance of US-$/€ market forecasts

4.1 Topically oriented trend adjustment behaviour of professional forecasts

The previous results have shown that professional forecasts are flawed predictors of future exchange rates. An important cause for this dismal performance of market forecasts is a very strong impact of current exchange rate developments on professional exchange rate forecasts. Figure 2 illustrates this finding and shows that professional forecasts move very much in line with the development of the actual spot exchange rate.

Figure 2: TOTA behaviour of market forecasts



Thus, if the current €/US-$ exchange rate depreciates, analysts tend to reduce their forecasts by about the current depreciation rate. Andres and Spiwoks, [1999] denote this regularity as a topically orientated trend adjustment behaviour (TOTA), which has the effect that forecasts can lose at worst their future-oriented characteristic. For an evaluation of the TOTA behaviour of professional forecasts Andres and Spiwoks, [1999] recommend the following coefficient:

$$TOTA\text{-}coefficient = \frac{R^2_{forecast,\ actual}}{R^2_{forecast,\ actual\text{-}h}} \tag{3}$$

where $R^2_{forecast;\ actual}$ is the coefficient of determination for the actual exchange rate and the corresponding market forecasts and $R^2_{forecast;\ actual-h}$ is the coefficient of determination for the forecast and the actual exchange rate at the time of the forecast formation. Values of the TOTA-coefficient smaller than one indicate that forecasts exhibit a higher correlation with the actual exchange rate at the time of producing the forecast than with the exchange rate for which the forecast was made. For the one-month Reuters professional forecasts the corresponding TOTA-coefficient is 0.8781. Thus, – on average – professional forecasts have a stronger relationship with past €/US-$ exchange rates than with the future €/US-$ exchange rates. This finding is in line with results of other studies evaluating capital market forecasts. Bofinger and Schmidt [2003a], [2003b] and Spiwoks [2003] report that market forecasts for exchange rates, stock indices and government bonds all reveal TOTA-coefficients less than one.

4.2 Psychological explanations for the topically oriented trend adjustment behaviour of market forecasts

An important explanation for the topically oriented trend adjustment behaviour of professional forecasters can be derived from the behavioural finance literature. Within behavioural finance, limitations in the acquisition and the processing of information play a decisive role. Especially in very difficult decision problems, economic agents try to reduce the complexity of the world by using simple rules of thumb or "heuristics" which allow quick and efficient decisions even under high uncertainty (see Fiedler and Bless, [2001], p. 135). As Gigerenzer and Todd, [1999] have shown there are many heuristics, which provide a good

compromise between economic rationality and an efficient use of scarce human cognitive resources. Of course, there are also circumstances where the usage of simple heuristics leads to systematically biased judgements (see e.g. Kahneman et al., [1999]).
Forecasting exchange rates is a very complex and difficult task. On the one hand, no reliable macroeconomic models are available to determine relevant fundamental variables and explain their concrete impact on future exchange rates. On the other hand, the speculative nature of the foreign exchange market requires for an individual forecaster to take into account the forecasts of other market participants confronted with the same problem. This problem has already been addressed by Keynes, [1936]. Therefore, it is not astonishing that forecasters tend to rely on simple heuristics.
A very simple rule of thumb that is important in our context, is the anchoring heuristics. It implies that quantitative judgements are often biased towards an initial anchor, which has come to the mind of the decision maker implicitly or explicitly but is often completely irrelevant for the decision problem. An illustrative example for the anchoring effect is provided by Tversky and Kahneman, [1974]. They asked test persons whether the percentage of African nations in the United Nations (UN) is higher or lower than an arbitrary number, which serves as an anchor. The test persons were divided into two groups; one group was given a value of 65 % and the other a value of 10 %. The results showed that the mean estimates were biased towards the specific anchor. For the "high-anchor group" (65 %) the mean estimate was 45 %, for the "low-anchor group" (10 %) the mean estimate was 25 %.
The effects of the anchoring heuristics can also be identified in financial decisions (see Wärneryd, [2001], pp. 130). In this context, it is interesting that Jacowitz and Kahneman, [1995] find that the degree of anchoring effects depend on the degree of uncertainty about the decision process. For example, they demonstrate that the more judges were uncertain about their judgements, the more the numeric estimates were assimilated to the provided anchor (see Jacowitz and Kahneman, [1995] and Mussweiler and Strack, [2000]). Already Keynes, [1936] illustrates a mechanism of human expectations formation in a financial context that is very similar to the above-mentioned 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 practise 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." (Keynes, [1936], p. 148).

5 Experimental Evidence

The dismal performance of professional forecasts can be attributed to common human decision behaviour under uncertainty; namely the anchoring heuristics. Thus, we now analyse the forecasting behaviour of decision makers in an experimental setting to evaluate whether TOTA is a common phenomenon of forecasting. The advantage of using experiments is to establish a comparable decision situation for the participants of the experiment.

5.1 Experimental economics and expectation formation

The experimental analysis of the formation of expectations goes back to the early 1960's. The first experiments by economists were independently conducted by Fisher, [1962] and Becker, [1967]. Later studies by Schmalensee, [1976], Garner, [1982], Bolle, [1988], Hey, [1994] and Becker and Leopold-Wildburger, [1996] focused on developing and testing

expectation models. Generally, the results indicate a poor ability of economic models to explain the subjects' behaviour and inconsistencies with rational expectations in the sense of Muth [1961].
However, Becker and Leopold-Wildburger, [1996] developed a very simple model for explaining *collective* forecasting behaviour, called the bounds & likelihood heuristics. In the past years experiments in different settings with more than 550 subjects were conducted. The results prove that the model performs well and a simulation study verifies that the findings are not limited to the applied time series.
Nevertheless, the general applicability of this heuristics is limited to few experimental settings, because time series of similar characteristics were used. Therefore our interest is to apply an exchange rate time series to an experiment with subjects. We are concerned with the following two questions:

- Are there any similarities between the empirically observed forecasting behaviour of experts and the forecasts of students in a laboratory environment?
- Can the bounds & likelihood heuristics model the average opinion of subjects in this new experimental setting?

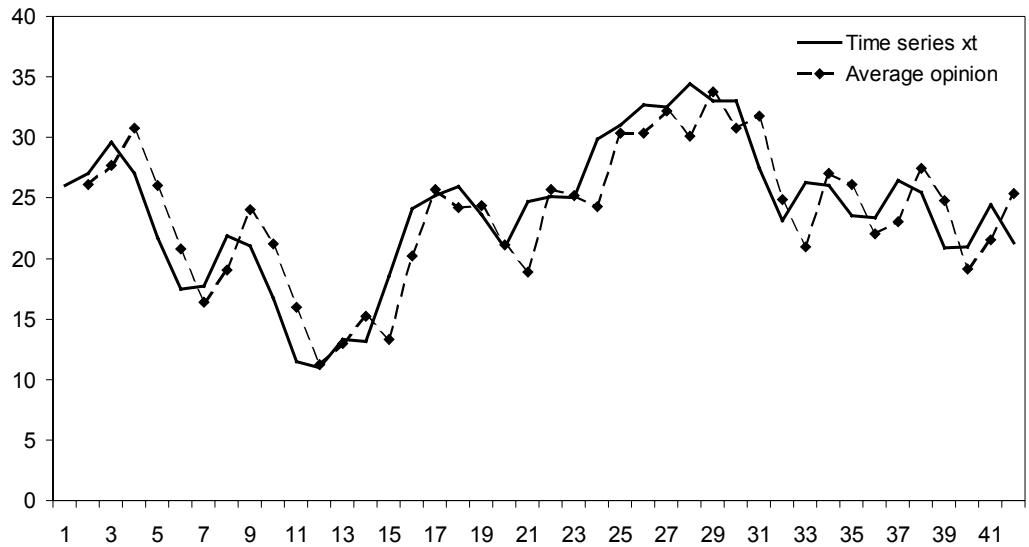
5.2 The experiment

Within the experiment, subjects were confronted with forecasting a time series (x_t) judgementally, i.e. predicting the value of the next period by eyeballing the past observations without any help of statistical or econometrical models. The forecasting horizon included 42 periods. The initial value was given to the subjects at the time of their first prediction, thus each subject made 41 forecasts. The time series x_t is a realisation of an autoregressive process of second order,

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \varepsilon_t ,$$

with the coefficients $\alpha_0 = 0.09$, $\alpha_1 = 1.19$, $\alpha_2 = -0.28$ and the error term ε_t being uniformly distributed in the interval [-5;5]. The coefficients were estimated from the US-$/€ exchange rate. All values have two decimal places. The subjects were given no contextual information about the time series background. Figure 3 shows the time series x_t.

Figure 3: Average opinion



The experiment was conducted in the summer semester 2003 at the Department of Economics, University of Wuerzburg. Altogether 46 undergraduate students participated voluntarily. They were recruited from a lecture in economics. Overall, the number of students is comparable to the sample size of the Reuters survey.
To ensure a high level of motivation, subjects were paid according to their forecasting performance. Thereby the payments $p_t = 3 - \left| x_t - \hat{S}_t \right|$ correspond to a linear function of the prediction errors based on absolute deviations that are cut off to zero at a value of 3. The experiment was conducted with a computer. The subjects were asked four sample questions to ensure they had completely understood the payment scheme. The subjects set their pace individually according to personal preferences. The average payment was 3,3 € for an average duration of about 20 minutes.

5.3 Experimental results

5.3.1 Rationality of judgmental forecasts

We test the unbiasedness hypothesis of the group opinion, defined as the simple average of *n* individual forecasts,

$$\overline{S}_t = \frac{1}{n}\sum_{i=1}^{n} \hat{S}_t^i, \quad \text{for } t = 2,3,...,42\,, \tag{4}$$

by estimating equation (2). The results of the regression and the Wald-Test are presented in Table 3. The α coefficient is close to zero, but the β coefficient departs significantly from one. However, the Wald-Test suggests that the joint null hypothesis of α = 0 and β = 1 can not be rejected. Thus, subjects' average forecasts are consistent with the concept of rational expectations in the sense of Muth [1961], which is in line with results of other studies (see e.g. Becker and Leopold [2000], Leitner [2003]).

Table 3: Rationality of judgmental forecasts

	α	β	F-statistic
Average opinion of students	-0.0004 (0.0224)	0.6535 (0.3516)	0.4895 [0.6167]

Standard errors in parentheses; p-values in brackets.

5.3.2 Accuracy of judgmental forecasts

In order to evaluate the accuracy of average judgmental forecasts, we apply the measurement categories used above. The results – summarised in Table 4 – show that professional and judgmental forecasts perform somewhat differently. In contrast to the forecast errors of professional analysts, the negative mean error implies that the judgmental forecasts underestimate the time series systematically. A comparison of the forecasting performance of judgmental forecasts and naïve forecasts suggests that the subjects in the experiment may slightly beat the random walk forecasts as the corresponding value of Theil's U is somewhat below one. However, a comparison of average judgmental forecasts with naïve forecasts by the means of ME and MAE indicates that random walk forecasts are superior. The hit rate of subjects' average opinion exceeds 50% and is thus larger than the professionals' hit rate. However, this result is not statistically significant. Overall, subjects' forecasting performance seems to be comparable to that of a naïve random walk, but subjects show a better forecasting performance than professional analysts.

Table 4: Accuracy of judgmental forecasts

	ME	MSE	MAE	Theil's U	Hit rate
Average opinion	-0.0104 (-0.0056)	0.0201 (0.0213)	0.1118 (0.1094)	0.9697	56.1% [0.563]

Comparative values of random walk forecasts in parenthesis;
Test statistic of the χ^2 – Test in brackets

Despite the distinctive forecasting performance of judgmental and professional forecasts, both forecasts reveal a common characteristic. The TOTA-coefficient for subjects' forecasts indicates a stronger relationship of forecasts with past observations than with future values of the time series; the corresponding value for the average opinion of the subjects equals 0.7754. Due to these surprising findings we analyse the experimental sample of Becker and Leopold-Wildburger [1996] and Leitner [2003] of 267 and 32 subjects respectively. In these experiments the students had to forecast a univariate time series judgementally without any additional information, which makes their experimental setting comparable to ours. The analysis supports our results: the Theils' U of the average opinions are 0.7592 and 0.9842 respectively, the TOTA-coefficients are far below 1 at 0.7229 and 0.4587. Thus, the experimental results prove that the topically oriented trend adjustment behaviour is a general characteristic of human forecasting behaviour in situations under uncertainty (see Figure 4). Furthermore, it indicates that subjects may on average outperform the random walk forecasts. These findings directly raise a question on the forecasting performance of professional analysts.
Why do professionals especially trained in economic exchange rate analysing perform worse than completely ignorant subjects?

Thomson et al. [2003] report similar findings in their recent experimental study on comparing probability forecasts of experts and students for simulated exchange rates. The students achieved higher scores of accuracy than the experts. The authors explain the results by the expert's believe in a fundamental value of the exchange rate, that causes an unwillingness to accept strong trends (see also Van Hoek [1992]). Therefore, our suggestion is that professional analysts are misguided by the idea of an allegedly fundamental justified value of the US-$/€ exchange rate which was generally expected to be around 1.15 (see Table 5). However, the speculative environment in foreign exchange markets seems to cause that fundamental considerations are more or less unimportant – at least in the short and medium-run. Market participants also share this view. Cheung and Wong [2000] and Cheung and Chinn [2001] report that dealers believe that the poor performance of fundamental exchange rate models is due to excessive speculation.

Figure 4: TOTA behaviour of average opinion

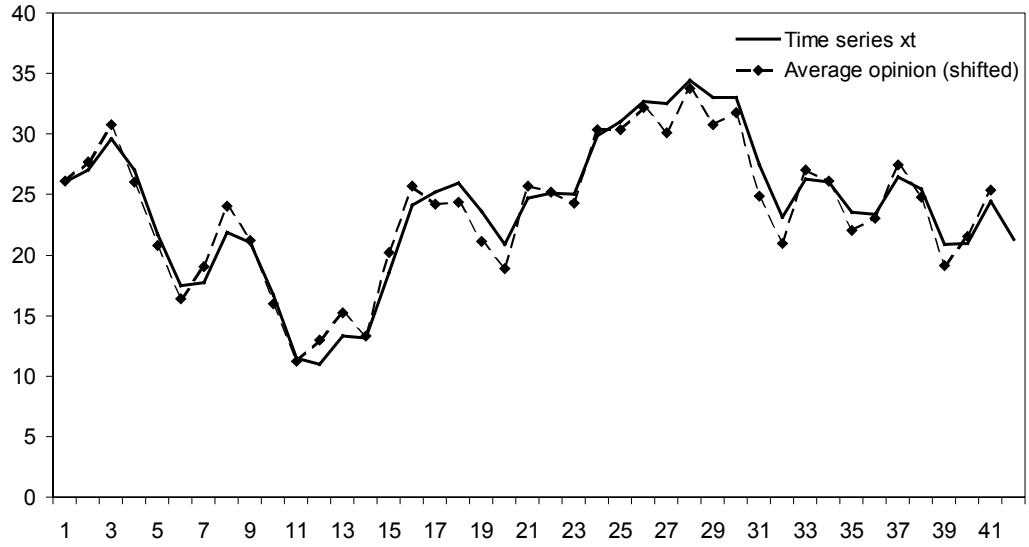


Table 5: Selected estimates of the US-$/€ equilibrium exchange rate

	Reference period	Equilibrium exchange rate(US-$/€)
Wren-Lewis and Driver (1998)	2000	1.19 – 1.45
Borowski and Couharde (2000)	1999 (first half)	1.23 – 1.31
Clostermann and Schnatz (2000)	Winter 1999/2000	Short-run: 1.20 Medium-run: 1.13
Chinn and Alquist (2001)	June 2000	Medium-run: 1.17 – 1.24
Lorenzen and Thygesen (2000)	1999	Long-run: 1.28
Goldman Sachs (2000)	May 2000	1.21

Source: Schneider [2003], European Central Bank [2002]

5.4 Modelling forecasting behaviour

5.4.1 The bounds & likelihood heuristics

In a last step, we now investigate whether the bounds & likelihood heuristics of Becker and Leopold-Wildburger [1996] can serve as a reasonable model for explaining the behaviour of both professional analysts and subjects. The b&l heuristics is a procedure that models the group opinion of subjects. The model assumes that two characteristics of a time series are essential for the forecasts: the average variation and the turning points. The average absolute variation of the time series b_t is calculated as follows:

$$b_t = \frac{1}{t-1}\sum_{j=2}^{t}\left|x_j - x_{j-1}\right| \tag{5}$$

These average variations are the bounds for the predicted change based on the actual time series value x_t. The maximum predicted change varies between the interval $[-b_t, b_t]$. The predicted change depends on the likelihood that x_t is a turning point. In an upswing case ($x_t > x_{t-1}$) $l_{t(peak)}$ is the probability, that x_t is a local maximum. If in period t all local maxima are above x_t, the probability that x_t is turning point is low. If all local maxima are below x_t, i.e. x_t is the highest time series value, it is very likely to be a turning point. For a downswing case ($x_t < x_{t-1}$) the local minima are considered and $l_{t(trough)}$ is calculated. In case of no change ($x_t = x_{t-1}$) it is assumed, that the upswing and downswing have the same probability. So the linear combination of both cases is calculated. At a high level of the time series, subjects will forecast a downswing, for a low level an upswing.

$$\begin{aligned} l_{t(peak)} &= \frac{1 + \text{number of local maxima } \leq x_t}{2 + \text{ number of local maxima}} \qquad \text{for } x_t > x_{t-1} \\ l_{t(trough)} &= \frac{1 + \text{number of local minima } \geq x_t}{2 + \text{ number of local minima}} \qquad \text{for } x_t < x_{t-1} \end{aligned} \tag{6}$$

Based on these assumptions the bounds & likelihood heuristics is calculated as follows:

$$f_{t+1}^{x} = \begin{cases} x_t + b_t\left(1 - 2l_{t(peak)}\right) & \text{for } x_t > x_{t-1} \\ x_t + b_t\left(l_{t(trough)} - l_{t(peak)}\right) & \text{for } x_t = x_{t-1} \\ x_t - b_t\left(1 - 2l_{t(trough)}\right) & \text{for } x_t < x_{t-1} \end{cases} \tag{7}$$

In the first periods, before local extrema arise, the heuristics predicts a naïve forecast. Therefore periods 1 to 8 are excluded from the analysis of the professional forecasts and periods 1 to 6 for the analysis of the judgmental forecasts.

5.4.2 The performance of the bounds & likelihood heuristics

The bounds & likelihood heuristics describes the average forecasts of subjects very well. As presented in Table 6, the performance of the heuristics is superior to the random walk. The Theil's inequality coefficient equals 0.7975 and is far below the critical value of one. The forecasted direction is modelled correct in 72.2% of all cases, which is significant according to the χ^2-test. However, these good results do not hold for the Reuters 1 month forecast. The heuristics performs slightly worse than the random walk. It also fails to forecast the turning points.

These results are very interesting, because they represent the first application of an (artificial) exchange rate time series to the bounds & likelihood heuristics. The heuristics can model collective forecasts very well even for more complex time series than those used by Becker and Leopold-Wildburger [1996]. However, the application to empirically observed professional forecasts failed. The heuristics cannot explain the behaviour of the experts. An important reason for this result may be found in the various sources of information that experts use when making their prediction. The subjects are only given the past values of one single time series and this information is considered by the b&l heuristics very well. The forecasts of experts are based on several sources of quantitative and qualitative information. The believe in a fundamental value can be regarded as such an information, which does not affect the subjects in our experimental setting. Figure 5 and Figure 6 show the relationship between the b&l heuristics and the average opinion of the subjects and the Reuters one month forecasts.

The analysis reveals another interesting fact: the b&l heuristics models the average opinion of forecasters, but it also predicts the €/US-$ exchange rate somewhat better than the experts.

The Theil's inequality coefficient equals 1.05 which means that the heuristics forecasts the exchange rate worse then the random walk, but still better than professionals, who achieved a corresponding value of 1.0952. The hit rate at 47.62% is not significant, but slightly higher than the hit rate of professional forecasts. These results underline the poor forecasting performance of professional forecasts. Even the b&l heuristics, a simple rule of thumb, outperforms the experts.

Table 6: The performance of the bounds & likelihood heuristics

	ME	MSE	MAE	Theil's U	Hit rate
b&l heuristics forecasting average opinion of students	-0.0056 (0.0053)	0.0029 (0.0046)	0.0456 (0.0542)	0.7975	72.2% [6.756]
b&l heuristics forecasting Reuters 1 month	0.0009 (-0.0055)	0.0002 (0.0002)	0.0098 (0.0094)	1.0208	66.67 % [0.875]
b&l heuristics forecasting €/US-$ exchange rate	0.0055 (-0.0009)	0.001 (0.0009)	0.0263 (0.0233)	1.05	47.62% [0.573]

Comparative values of random walk forecasts in parenthesis;
Test statistic of the χ^2 – Test in brackets

Figure 5: Average opinion and b&l heuristics

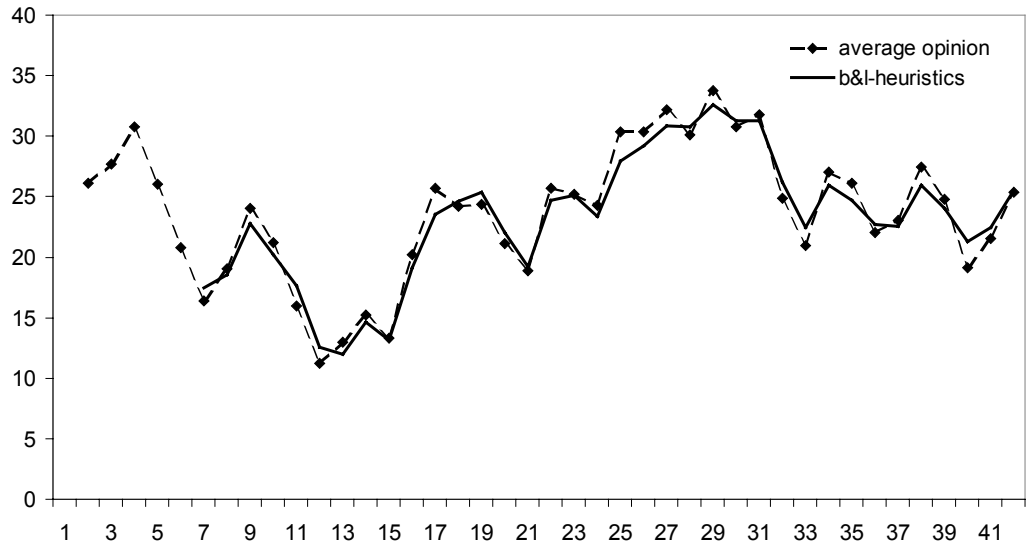
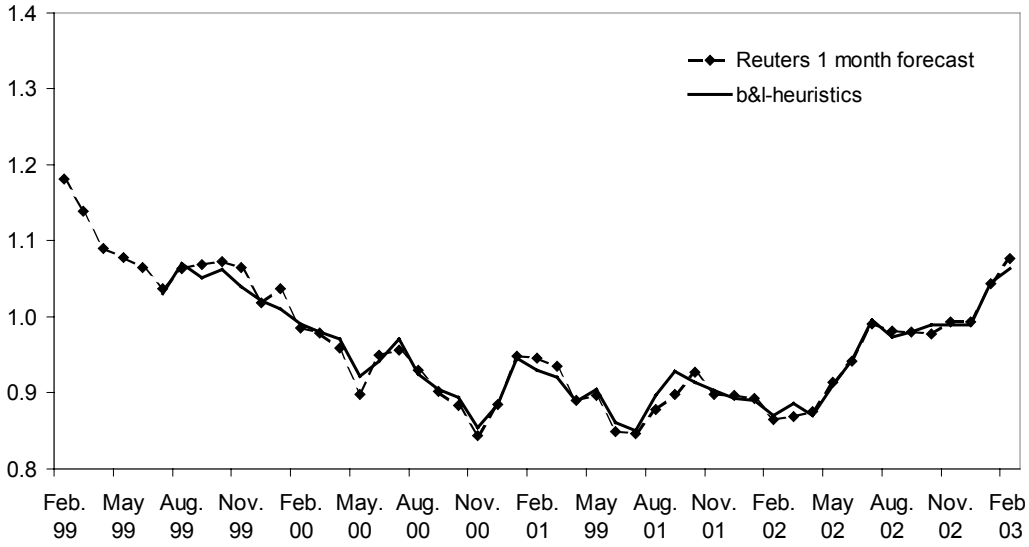


Figure 6: Market forecasts and b&l heuristics



6 Conclusion

This study has again demonstrated economists' poor forecasting capability concerning exchange rates. Furthermore, a typical characteristic of capital market forecasts has been revealed by the TOTA coefficient. In our experimental analysis, we prove that topically oriented trend adjustment behaviour is a general characteristic of human forecasting behaviour in situations under uncertainty. However, although experimental forecasts were also affected by subjects' TOTA behaviour, they match – on average – with the economic concept of rational expectations. Moreover, subjects give better forecasts than experts. These unexpected results may be explained by an unreasonable strong orientation of professional analysts on an allegedly fundamental justified value which was supposed to be around 1.15 €/US-$.

Applying the b&l-heuristics to our experimental results, reveals that this simple rule of thumb explains the average forecasts of subjects very well, but not the Reuters one month forecasts. However, the b&l heuristics results in slightly better forecasts than professional analysts.

The experimentally based comparison of professional and judgmental forecasting behaviour is an interesting domain of future research. Two approaches are considered: the first approach concentrates on further analysis of empirically observed data. In our study, only one month Reuters forecasts were explored, but there are also professional forecasts for horizons of three, six and twelve months. Therefore, it is an obvious consequence to widen the forecasting horizon of the experiment, in order to observe whether our findings hold true in such situations. The second approach is focused on the advantage of research in a laboratory environment. In an experiment all available information can be varied systematically. The analysis of professional forecasting behaviour in experimental environment could give valuable insights into the reasons for their inferior performance. Even though there already exists some relevant literature and basic explanations have been derived from several studies, these reasons remain unclear to us. Due to the relevance of professional forecasts and their performance the analysis on a larger scale is necessary. Experiments with differently trended, labelled and generated times series may help to answer those questions. We also think that the application of additional quantitative and qualitative information is an interesting aspect, that has not yet been considered in experimental studies.

Reference List

Andres, Peter and Markus Spiwoks (1999), Prognosequalitätsmatrix, Ein methodologischer Beitrag zur Beurteilung der Güte von Kapitalmarktprognosen, in: Jahrbücher für Nationalökonomie und Statistik, Vol. 219, 513-542.

Becker, Otwin (1967), Experimentelle Untersuchung der Erwartungsbildung für eine Zeitreihe, in: Heinz Sauermann (ed.), Beiträge zur experimentellen Wirtschaftsforschung, Tübingen, 226-254.

Becker, Otwin and Ulrike Leopold-Wildburger (1996), The Bounds and Likelihood-Procedure - A Simulation Study Concerning the Efficiency of Visual Forecasting Techniques, in: Central European Journal of Operations Research and Economics, Vol. 4, 223-229.

Berkowitz, Jeremy and Lorenzo Giorgianni (2001), Long-Horizon Exchange Rate Predictability?, in: Review of Economics and Statistics, Vol. 83, 81-91.

Bofinger, Peter and Robert Schmidt (2003a), Should One Rely on Professional Exchange Rate Forecasts? An Empirical Analysis of Professional Forecasts for the €/US-$ Rate, Würzburg Economic Papers No. 38, University of Wuerzburg.

Bofinger, Peter and Robert Schmidt (2003b), Wie gut sind professionelle Wechselkursprognosen?, in: ifo-Schnelldienst, Vol. 56, 7-14.

Bolle, Friedel (1988), Learning to Make Good Predictions in Time Series, in: Reinhard Tietz (ed.), Bounded Rational Behavior in Experimental Games and Markets, Berlin, 37-50.

Cavaglia, Stefano M. F. G., Willem F. C. Verschoor, and Christian C. P. Wolff (1994), On the Biasedness of Forward Foreign Exchange Rates: Irrationality or Risk Premia?, in: Journal of Business, Vol. 67, 321-343.

Cheung, Y. and M. Chinn (2001), Currency Traders and Exchange Rate Dynamics: A Survey of the US Market, in: Journal of International Money and Finance, Vol. 20, 439-471.

Cheung, Yin-Wong, Menzie D. Chinn, and Antonio G. Pascual (2003), What Do We Know About Recent Exchange Rate Models? In-Sample Fit and Out-of-Sample Performance Evaluated, CESifo Working Paper No. 902.

Cheung, Yin-Wong and Clement Yuk-Pang Wong (2000), A Survey of Market Practitioners' Views on Exchange Rate Dynamics, in: Journal of International Economics, Vol. 51, 401-419.

Chinn, Menzie D. and Richard A. Meese (1995), Banking on Currency Forecasts: How Predictable is Change in Money?, in: Journal of International Economics, Vol. 38, 161-178.

Dalrymple, Douglas J. (1975), Sales Forecasting Methods and Accuracy, in: Business Horizons, Vol. 18, 69-73.

Dalrymple, Douglas J. (1987), Sales Forecasting Practices: Results from a United States Survey, in: International Journal of Forecasting, Vol. 3, 379-391.

Diebold, Francis X. and Jose A. Lopez (1996), Forecast Evaluation and Combination, in: G. S. Maddala and C. R. Rao (eds.), Handbook of Statistics, Vol. 14, Amsterdam, 241-268.

European Central Bank (2002), ECB Monthly Bulletin January 2002, Frankfurt a.M.

Faust, Jon, John H. Rogers, and Jonathan H. Wright (2003), Exchange Rate Forecasting: The Errors We've Really Made, in: Journal of International Economics, Vol. 60, 35-59.

Fiedler, Klaus and Herbert Bless (2001), Social Cognition, in: Miles Hewstone and Wolfgang Stroebe (eds.), Introduction to Social Psychology, Oxford, 115-149.

Fisher, Franklin M. (1962), A priori Information and Time Series Analysis, Amsterdam.

Flood, Robert P. and Andrew K. Rose (1999), Understanding Exchange Rate Volatility Without the Contrivance of Macroeconomics, in: Economic Journal, Vol. 109, F660-F672.
Garner, A. (1982), Experimental Evidence on the Rationality of Intuitive Forecasters, in: Vernon L. Smith (ed.), Research in Experimental Economics, Greenwich, 113-128.
Gigerenzer, Gerd and Peter M. Todd (1999), Simple Heuristics That Make Us Smart, Oxford.
Hallwood, C. and R. MacDonald (2000), International Money and Finance, Oxford.
Hey, John D. (1994), Expectations Formation: Rational or Adaptive or ...?, in: Journal of Economic Behavior & Organization, Vol. 25, 329-349.
Jacowitz, Karen E. and Daniel Kahneman (1995), Measures of Anchoring in Estimation Tasks, in: Personality and Social Psychology Bulletin, Vol. 21, 1161-1166.
Kahneman, Daniel, Paul Slovic, and Amos Tversky (1999), Judgment Under Uncertainty: Heuristics and Biases, Cambridge.
Keynes, John M. (1936), The Genral Theory of Employment, Interest, and Money, London.
Kilian, Lutz (1999), Exchange Rates and Monetary Fundamentals: What Do We Learn from Long-Horizon Regressions?, in: Journal of Applied Econometrics, Vol. 14, 491-510.
Kilian, Lutz and Mark P. Taylor (2003), Why is it so Difficult to Beat the Random Walk Forecast of Exchange Rates?, in: Journal of International Economics, Vol. 60, 85-107.
Klassen, Robert D. and Benito E. Flores (2001), Forecasting Practices of Canadian Firms: Survey Results and Comparisons, in: International Journal of Production Economics, Vol. 70, 163-174.
Leitner, Johannes (2003), Die experimentell gestüzte Modellierung kollektiver Prognosen, unpublished doctoral thesis, Karl Franzens University Graz.
Mark, Nelson C. (1995), Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictabillity, in: American Economic Review, Vol. 85, 201-218.
Mark, Nelson C. and Donggyu Sul (2001), Nominal Exchange Rates and Monetary Fundamentals: Evidence from a Small Post-Bretton Woods Panel, in: Journal of International Economics, Vol. 53, 29-52.
Meese, Richard A. and Kenneth Rogoff (1983a), Empirical Exchange Rate Models of the 1970s: Do They Fit Out of Sample?, in: Journal of International Economics, 14, 3-24.
Meese, Richard A. and Kenneth Rogoff (1983b), The Out-of-Sample Failure of Empirical Exchange Rate Models: Sampling Error or Misspecification?, in: Jacob A. Frenkel (ed.), Exchange Rates and International Macroeconomics, Chicago, 67-105.
Moosa, Imad A. (2000), Exchange Rate Forecasting: Techniques and Applications, Basingstoke.
Mussweiler, Thomas and Fritz Strack (2000), Numeric Judgmnets under Uncertainty: The Role of Knowledge in Anchoring, in: Journal of Experimental Social Psychology, Vol. 36, 495-518.
Muth, John F. (1961), Rational Expectations and the Theory of Price Movements, in: Econometrica, Vol. 29, 315-335.
Neely, Christopher J. and Lucio Sarno (2002), How well Do Monetary Fundamentals Forecast Exchange Rates?, in: Federal Reserve Bank of St.Louis Review, Vol. 84, 51-74.
Plous, S. (1993), The Psychology of Judgement and Decision Making, New York.
Rogoff, Kenneth (1999), Monetary Models of Dollar/Yen/Euro Nominal Exchange Rates: Dead or Undead?, in: Economic Journal, Vol. 109, F655-F659.
Rogoff, Kenneth (2001), The Failure of Empirical Exchange Rate Models: No Longer New but Still True, Economic Policy Web Essay, October 2001, Issue 1, volume 1.
Sanders, N. and K. Manrodt (1994), Forecastin Practices in US Corporations - Survey Results, in: Interfaces, Vol. 24, 92-100.
Schmalensee, Richard (1976), An Experimental Study of Expectation Formation, in: Econometrica, Vol. 44, 17-41.

Schneider, Stefan (2003), The Euro - What Went Down Must Go Up?, Deutsche Bank Research, Frankfurt Voice, March 5, 2003.

Spiwoks, Markus (2003), Die Währungs-, Anleihen- und Aktienmarktprognosen des Zentrums für Europäische Wirtschaftsforschung, forthcoming in Zeitschrift für betriebswirtschaftliche Forschung.

Strack, Fritz and Roland Deutsch (2002), Urteilsheuristiken, in: Dieter Frey and Martin Irle (eds.), Theorien der Sozialpsychologie. Band III: Motivations- und Informationsverarbeitungstheorien, Bern, 352-384.

Thomson, Mary E., Dilek Önkal-Atay, Andrew C. Pollock, and Alex Macaulay (2003), The Influence of Trend Strength on Directional Probabilistic Currency Predictions, in: International Journal of Forecasting, Vol. 19, 241-256.

Tversky, Amos and Daniel Kahneman (1974), Judgment under Uncertainty: Heuristics and Biases, in: Science, Vol. 185, 1124-1131.

Van Hoek, T. H. (1992), Explaining Mark/Dollar and Yen/Dollar Exchange Rates in the 1980s, in: Economic Letters, Vol. 38, 467-472.

Wärneryd, K. (2001), Stock-Market Psychology: How People Value and Trade Stocks, Cheltenham.

Webby, Richard and Marcus O'Connor (1996), Judgemental and Statistical Time Series Forecasting: A Review of the Literature, in: International Journal of Forecasting, Vol. 12, 91-118.