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Inefficiency in Survey Exchange Rates Forecasts

Francesca Pancotto, Filippo Maria Pericoli and Marco Pistagnesi*

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Abstract

We use a novel database of a panel of quarterly survey of exchange rates forecasts available on the Bloomberg platform, for the following five bilateral exchange rates: EUR/GBP, EUR/JPY, EUR/USD, GBP/USD and USD/JPY, for the timespan ranging from the third quarter 2006 up to the fourth quarter of 2011. We find that forecasters are on average irrational, failing to identify the true data generating process of bilateral exchange rates and generally *overreacting* to past observed information. Moreover, exploring individual performance, we can state that financial analysts irrationally do not look at their past forecast errors to improve the quality of their later forecasts.

1 Introduction

Forecast inefficiency can be defined as the failure by professional financial analysts to incorporate all the available information in a timely and unbiased fashion into their predictions. Such behavior generates irrational forecasts, an empirical puzzle that received considerable attention in the recent financial literature. Our aim lies in explaining along the lines of behavioural finance what, according to the standard neoclassical approach, would be considered simply as an irrational behavior. In particular, we are interested in considering which behavioural elements may cause professional forecasters to depart from statistically optimal predictions, i.e. projections responding to the dictates of rationality.

The concept of rationality in decision making, first introduced by Muth (1961), states that subjective expectations of economic agents should be the same as the conditional mathematical expectations based on the 'true' probabilities that govern the behavior of the phenomena being forecast. In other words, to be rational, forecasts should be based on the full information set available at any time, which

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constitute the sigma algebra on which the true probabilities of the exchange rates realized values are conditioned.

From Pesaran (1987), we learn that the following four conditions need to be met in for predictions to be rational: forecasts must be unbiased; survey-based forecast errors must be orthogonal to variables in the information set of agents; forecast errors must follow a moving average process of order k-1, due to the presence of overlapping predictions, where k is the number of periods ahead the prediction is made [1]; forecast errors must be efficient, i.e. orthogonal to past values of variables conditioning the forecast. We test these hypotheses and extend the interpretation of these results using a similar framework to the one of Easterwood and Nutt (1999), i.e. exploring whether error orthogonality exists and if this is not the case, whether the resulting bias can be systematically identified as heading in a particular direction.

Considerable empirical evidence has been produced showing that decision making in forecasting departs from rationality. Previous studies found that the inefficiency may result in a disproportioned reaction to new information that becomes available to the market. For example, analysts may *overreact* to stock price changes if, following the change, they forecast a price increase that is higher than the price change that would be justified on the basis of the historical autocorrelation pattern. On the other hand, analysts *underreact*, following a price change, they forecast a price increase that is lower of that implied by the past autocorrelation pattern.

While a large part of the literature has focused on stock market analysts' forecasts, there is no reason to believe that such non-rational biases should not be observed in other financial markets as well. For example, on foreign exchange markets one may potentially observe biased predictions, that is forecasts that are systematically lower (higher) than the subsequent realisations. Similarly, forecasts may be characterised by over (under) reaction. This happens if, following an increase (decrease) in the exchange rate, the successive forecast error is systematically negative (positive); that is, following an appreciation (depreciation) [2], it is predicted an exchange rate that is systematically more appreciated (more depreciated) than the observed one.

The aim of this paper is to provide empirical evidence of the fact that professional forecasters of foreign exchange rates respond inaccurately to available information in the market, by systematically under or over predicting the underlying exchange rate and/or under or overreacting to it. We also take

[1] As we are dealing with one step ahead forecasts, k is one in our case, thus making this condition equivalent to saying that forecast errors should be serially uncorrelated. This is exactly what we do in the following, where we test for serial correlation of forecast errors.

[2] This definition holds true if the exchange rate of is defined in such a way that an increase corresponds to an appreciation, as it is in the case of the EUR/USD exchange rate where an increase corresponds to an appreciation of the Euro versus the US dollar.

the argument a step further and ask ourselves whether the biased reaction to the available information may be related to the past performance of the analysts.

Thus, the core of the paper consists in performing simple regression-based rationality tests along several dimensions, following the methodological contribution by Mankiw et al. (1984) as adapted by Easterwood and Nutt (1999) in order to cope with behavioral analysis of the departure from rationality. In particular following the latter, we evaluate the role of the individual performance of the predictors dividing our sample of individuals into high, medium and low performing forecasters and evaluate whether there is a differential effect of these performances on the prediction of the rate.

Our results confirm are in line with the wide existing empirical literature in the field Macdonald and Marsh (1996); Frankel and Froot (1987); Dokko and Edelstein (1989); Keane and Runkle (1990); Ito (1990); Chionis and MacDonald (1997); Jongen et al. (2008) and it also confirms what observed by Easterwood and Nutt (1999), despite the fact that their framework is related to earnings with a very different structure of the data. In our context, where we cannot distinguish among positive versus negative information, we find that on average forecasters tend to *overreact* to past information contained in the exchange rate itself. Moreover, we find a significant autocorrelation pattern in forecast errors, a fact that is also not consistent with the hypothesis of rationality.

Our results provide extensive evidence of irrationality and overreaction across markets, currencies, and professional categories that we are not aware to exist to such great extent form previous studies, thanks to our novel and large dataset: this is an innovation in two dimensions. First, the forecasts provided by the subjects composing the panel of predictors per each currency are available directly on the Bloomberg platform and is updated with a frequency ranging from the single week to the quarter. This allows subjects to revise continously their predictions and compare their decisions of forecasts with the others composing the panel of predictors for the same currency. This fact could suggest that the efficiency of information diffusion should be larger with a continous distribution of information as this is rather than the one based on a regular monthly publication: this elements should increase the ability of predictors to include information present in the market and consequently reduce irrationality. This is not what we observe: the presence of a systematic bias in all currencies considered (and in different bilateral rates) suggests the presence of a bias in the direction of overreaction. All in all we suspect an effect of beauty contest bias in the survey predictions that is rather enhanced than reduced by the presence of a regular and ready available update of predictions from other components of the panel of predictors, along the lines of Morris and Shin (2002), Bacchetta and Wincoop (2006), Bacchetta and Wincoop (2008).

The paper is organized as follows: in Section 2 we present a review of the relevant literature related to irrationality and overreaction in survey predictions and survey data on exchange rates. In Section 3, we provide a detailed description of our database; in Sections 4 and 5 we describe the empirical methodology and report main results. Section 6 reports conclusions.

2 Literature Review

A considerable amount of research tackled the presence of inefficiencies due to behavioral biases in professional analysts' predictions of financial variables, with most studies concentrating on stock return predictions. An early important contribution in this respect is provided by Bondt and Thaler (1985, 1987); De Bondt and Thaler (1990). Based on the well established finding in experimental psychology that individuals tend to overreact to unexpected and dramatic news, they find empirical evidence that such behavior holds for professional analysts forecasting stock prices. Specifically, they find evidence of excessive price rebounds in stock returns following strong bad past performance. They attribute this to positive overreaction to bad news (bad performance) that causes excessive pessimism on bad performing companies. Subsequently, they extend the analysis to test a more general overreaction hypothesis: is forecast error in earnings systematically linked to forecasted earnings? If this is the case and thus a bias exists, does such bias get stronger with increasing uncertainty (meaning with increasing forecast horizon)? They use a simple regression model of half-yearly earning forecasts for a large number of companies and find substantial support to both these claims. Still looking at stock prices, Brown and Harlow (1988) find empirical evidence (mainly in the short term) for three different types of overreaction in price movements: the directional effect (extreme movements in equity prices are followed by movements in opposite direction), the magnitude effect (the reaction follows the magnitude of the initial price change), and the intensity effect (the magnitude of the reaction is inversely proportional to the duration of the initial movement). Ikenberry and Ramnath (2002) find evidence on market undereaction to the information contained in corporate news event (such as the announcement of a stock split made by a company). Another important stream of research has taken the view that market over or underreaction might be caused by analysts not producing statistically optimal forecasts, but rather acting under different incentives. For example, professional forecasters may be motivated to follow the market consensus (so showing a beauty contest type of behavior), or to take a benevolent view toward a particular company not to disappoint that company management with whom the analyst may be linked professionally. For example, by producing an optimistically biased earning forecast for a company, the analyst may increase his chances to gain better access to the management of that company, thus improving his company knowledge and/or the market it belongs to. Lim (2001) interestingly points out that such behavior is not necessarily irrational; in other words, the under or overreaction resulting in these cases may be compatible with optimal and rational earnings forecasts, under the assumption of a nonstandard definition of the loss function of the professional forecasting activity. The predictability of expectational error has an important role also in potentially shedding lights into the excess return predictability puzzle. Bacchetta and Wincoop (2008) find empirical evidence that whenever some variables are able to predict the expectational error, they also play a role in predicting the excess returns. These findings are consistent across prices for variety of asset classes, including exchange rates; however, for the latter, the evidence of predictability of both excess return and expectational error is mixed and less robust. Still within the behavioral research stream, a recent contribution from Fujiwara et al. (2012) also stress how professional stock and bond forecasts are significantly influenced by their own past forecast, thus showing a behavioral bias. This is because a forecast error arising from rational expectations cannot be temporally correlated. If it was, then analysts would fail to incorporate past forecast error information in future predictions, thus making the current forecast not rational. The authors show that while forecasts in the stock market tends to be pooled by past forecasts, thus showing a herding behavior, forecasts in the bond market seem to be bold: their current value tend to be negatively related to past forecasts.

Some contributions aim at assessing whether the forecast biases described above may be found in markets other than corporate securities, such as foreign exchange markets. Several studies highlight how the issue of rationality of the professional expectation formation processes is closely linked to the performance of the predictions formed as well as to the heterogeneity of forecasting performances across time and across forecasters. If the forecasting performance is related to differential beliefs about the future path of exchange rates, the heterogeneity of forecasting performances may be considered as a consequence of differential model assumptions (chartists versus fundamentalists, (Frankel and Froot (1987)), differential information sets (informed versus uninformed, Evans and Lyons (2002)) or differential capabilities (sophisticated versus naive agents; young versus old agents; experienced or unexperienced institutional setting, Long et al. (1990)); Cho and Hersch (1998); Beine et al. (2007).

Some other literature contributions try to extrapolate possible forecasts biases through the observation of spot rate dynamics. For example, Manzan and Westerhoff (2005) start form the psychologists' findings about heuristics of representativeness. This theory predicts that *probability assessment are made by individual in a heuristic and unsophisticated way, rather than by means of proper probability theory.* The theory is applied to the exchange rate markets through the hypothesis that agents underreact to news in calm periods (low volatility), and overreact after a distinct series of exchange rate changes (turbulent periods). This is because the event 'many changes' (i.e. high volatility) is seen as representative of a situation of turbulence, where news coming to the market are seen as very important. Hence they study a 2-states model with speculators only, where they under or overreact to news depending on historical volatility and they find that their simulation replicate the observed exchange rate dynamics relatively well.

Similarly to us, a number of other contributions in the literature concentrate on evidence from survey data concerning exchange rates forecast biases. Frankel and Froot (1987) and Cavaglia et al. (1994) use survey data on foreign exchange markets to examine whether the failure of the forward premium puzzle is attributed to irrational behavior on behalf of market participants or due to the existence of time-varying risk premium; Marsh and Power (1996) and Elliott and Ito (1999) examine the forecast performance of survey based exchange rate forecasts. Cheung and Chinn (2001), in a survey on exchange rate dynamics, discover strong presence of technical trading strategies and report the belief among practitioners that large players dominate in selected currency markets. Finally, Jongen et al. (2012) describe predictors' behavior heterogeneity and identify the presence of chartist and fundamentalists strategies in foreign exchange rate forecasts.

In an important contribution, Ito (1990) use survey-based data collected by the Japan Center for International Finance (JCIF) in Tokio consisting of individual responses by several foreign exchange rate experts of various nature on the yen/dollar exchange rate forecast for a variety of horizons. The author finds that contributors are heterogeneous in their expectation formation and that expectations are irrational. Significantly, amongst the contributors surveyed, they find that exporters are characterized by 'wishful expectations', e.g. their expectations are biased towards yen appreciation. In another seminar contribution, Chinn and Frankel (1994) also use survey data, collected through Currency Forecasters' Digest, covering forecasts for about twenty-five exchange rates provided by 45 contributors, including multinational firms, forecasting firms and banks' economists teams. They find that biased non-rational forecasts exist, and that major currencies appear to exhibit a greater bias than the minor currencies. Also, forecasts for small countries appear to contain more relevant information than forecasts formulated for big countries. For major currencies especially, investors would do better by forecasting the exchange rate as a random walk and ignoring other current information. The authors observe that perhaps forecasters are reluctant to issue predictions of future rates that are the same as today's rate, and this reluctance is more justified when it comes to smaller, less stable, currencies.

Jongen et al. (2012) also stress the importance to depart from the Muth standard rationality assumption in order to understand more clearly the expectation formation process of economic agents. They use individual monthly data for forecasts of three currencies. Abandoning the agent homogeneity and the rationality assumptions, they find evidence of heterogeneity in the data, and then they construct an heterogeneous agent model to assess that agents use three forecast techniques (fundamentalist, chartist, and carry trade rules) and also switch between them according to how a certain technique has proven successful in the past.

3 Data Description

We use a novel dataset drawn from publicly available foreign exchange rate forecasts provided by the data collection platform Bloomberg. Up to our knowledge, there are no contributions so far using this database to evaluate exchange rate forecasts efficiency. The use of survey data undoubtedly represents an advantage with respect to frameworks where beliefs are modeled as latent unobserved factors. Indeed, in the former context the researcher disposes of an explicit measurement of beliefs and it is not required to specify a data generating process linking expectations to observed variables.

Although the issue of efficiency in forecasting exchange rates has been analysed by many contributions before, data used are typically extracted from periodic publications issued by market research institutions, generally available to a restricted target of professionals. On the other hand, our data are available on the Bloomberg platform and thus potentially to every professional operator on financial markets worldwide. This is relevant when measuring efficiency in predictions, as we may reasonably assume that these forecasts can be included in the information set available to professional forecasters. Moreover, we believe that this feature of the data increases the impact of behavioral elements of analysts' predictions, with respect to database used so far.

Our dataset analyses quarterly forecasts of the following five bilateral exchange rates, related to four currencies: EUR/GBP, EUR/JPY, EUR/USD, GBP/USD and USD/JPY. We have considered the set of forecasts relative to the end-of-quarter exchange rate over the period July 2006 to December 2011, for a total of 22 quarters.

A relevant aspect of our dataset consists in the fact that forecasts are not formulated simultaneously, meaning that one professional forecaster may formulate its forecast at the beginning of the quarter, while another one may formulate its own forecast, relatively to the same period, up to three months later, that is at the end of the quarter. In order to guarantee an acceptable degree of homogeneity in the information set on which the forecasts are based, we have chosen to restrict the analysis to the first forecast issued by each forecaster during each quarter. In the resulting dataset the overwhelming majority of forecasts are issued within the end of the first month of each quarter.

Given that not all forecasters issue forecasts at monthly frequency, the resulting dataset is disseminated of a relatively high number of missing values, a problem that is amplified by the need to include lagged values of individual forecasts in the econometric analysis. Therefore, in order to increase the degree of freedom associated with our estimates, we have chosen to exclude from our dataset those professional forecasters with a number of missing values greater than 7, which represents about the 30% of the temporal dimension of our dataset. This choice has been dictated by the willingness of minimizing the impact of missing values imputation on our econometric results.

After these selections, we end up with five unbalanced panel datasets of end-of-quarter forecasts on EUR/GBP, EUR/JPY, EUR/USD, GBP/USD and USD/JPY exchange rates, formulated respectively by 14, 13, 18, 14 and 15 forecasters over a total of 22 quarters, from the third quarter of 2006 to the fourth quarter of 2011.

As a last step of the database construction, we have filled in the remaining missing values by means of the Kalman smoother (Kalman (1960), Harvey (1990)), after having estimated univariate linear Gauss state space models for every professional forecaster and for each of the five considered currencies. We denote by $f_{i,t+1|t}$ the one step-ahead forecast of the spot exchange rate made by the i-th professional forecaster at date t and by s_t the spot exchange rate at date t. Thus, for each professional forecaster and for each currency, we have estimated by maximum-likelihood the following state-space model of the local-level type, where the two equations represent respectively the measurement and the state equation:

$$f_{i,t+1|t} = \mu_t + s_t \tag{1}$$

$$\mu_{t+1} = \mu_t + \xi_t, \qquad \xi_t \sim N(0, \sigma_\xi^2) \tag{2}$$

Therefore we have employed the bilateral Kalman smoother to interpolate the missing values on the observable variables of the system, that is the sequence of one step-ahead forecasts.

Taking into account the 5 currencies together, we have 33 contributors to our survey based forecasts dataset. Tables 1 and 2 summarize some of their features. In fact, in Table 2 predictors are classified by the location of their legal incorporation. For example, if bank A has its headquarters in England, it will be listed under the first column (EU). In Table 2 predictors are classified by the extension of their operations irrespectively of their formal headquarters location. For example, if predictor A is a typical multifunction global bank head-quartered in England, but with global operations, it will be listed under the fourth column (Global). According to these classifications, our sample is characterized as follows: 21 are large multifunctional financial institutions, 5 are non-banking operators such as asset managers or financial advisors, 5 others are retail or private banks, and the last 2 are purely investment banks. The majority of these institutions (20) are based in Europe and (to a lesser extent) in North America (8), although many of them operate at the global level irrespectively of their headquarters location (19 out of 33)

Not surprisingly, large multifunction financial operators and pure investment banks are those whose operations have a more distinct global reach, while the more specialized asset managers, advisers and smaller retail banks do not typically extend their business beyond their base area.

In order to compare the forecasting performance across currencies, we have standardized the forecast error to the value of the spot exchange rate in the previous period. Thus, if we denote by s_t a generic bilateral spot exchange rate and by $f_{i,t|t-1}$ the one-step-ahead forecast made by the i-th forecaster at date t-1 ($i = 1, 2, ..., N,\ t = 1, 2, ..., T$), where N is the number of forecasters and T is the number of periods, we can define the percentage forecast error ($FE_{i,t|t-1}$) as follows:

$$FE_{i,t|t-1} = \frac{s_t - f_{i,t|t-1}}{s_{t-1}}. \tag{3}$$

The main desciptive statistics on this variable are reported in tables from 3 to 7. We observe that the average forecast error is generally quite heterogeneous among currencies and among predictors. While for the EUR/JPY bilateral rate the forecast error is mostly negative except that for 3 predictors, the EUR/GBP error is systematically positive: EUR/USD and GBP/USD rate has mixed (among predicting institutions) positive and negative forecast error, while for USD/JPY the error is always negative with the only exception of one predictor. From the t-test on the difference of the average forecast error from zero, it follows that in the case of the EUR/JPY exchange rate, 5 out of 14 average individual forecast errors are significantly different from zero; in the case of the EUR/GBP exchange rate, only 1 of 13 errors is different from zero; in the case of the EUR/USD exchange rate, no forecaster is affected by a systematic bias; in the case of the GBP/USD exchange rate, 1 out of 14 forecast errors is significantly different from zero; for the USD/JPY exchange rate, 3 out of 15 forecasts are systematically biased.

From a summary inspection of data, it results that the average percentage forecast error, for a given currency, tends to be equally signed. This fact may be explained by the existence of unpredictable events which have induced the forecasters to incur in an error of the same sign. Another possible explanation might be the existence of bounded-rationality forecasting behaviors. In this second case, the high degree of concordance among the signs of forecast errors can be taken as an evidence of some imitative behavior among forecasters which generates a cross-sectional dependence among individual forecast errors.

Moreover, we have also considered the average percentage forecast error made on a given currency at a given date, by the set of professional forecasters included in the sample (see table 8). The main results is that the fact of averaging individual forecast does not remove the existence of errors significantly different from zero, a fact wich point toward the existence of some form of aggregate irrationality.

4 Predictors use of previous periods spot information

In this section we are interested in testing the hypothesis of rationality of professional forecasters and exploring the characteristics of this irrationality that we were hinted at in the previous section. The methodology that we implement follows Easterwood and Nutt (1999) but has been modified in order to take into account the different nature of the forecasts that we use with respect to their contribute.

Forecast rationality implies that conditional on all available information and provided that this information is used efficiently, forecast error should be unpredictable. Following Mankiw (1984), we use the following equation to test the hypothesis:

$$FE_{i,t|t-1} \; = \; \alpha_{0,i} + \sum_{i=1}^{4} \alpha_i \, RSC_{t-i} + \epsilon_{i,t} \tag{4}$$

where $RSC_t = (s_t - s_{t-1})/s_{t-1}$ is the percentage change of the realized spot exchange at time t. If the rationality hypothesis holds true, all the coefficient of the previous equation 4 should be equal to zero: forecasters are using efficiently all available information and are able to predict correctly, on average, the evolution of the exchange rate. Possible errors in prediction would be wiped out by the presence of market operators that on average would compensate each other errors.

The estimate of eq. (4) provides us also with a second source of information. It is also possible to interpret the sign of the coefficients that should result significantly different from zero, in order to discriminate between different irrational behaviours of the forecasters. If one of the autoregressive parameters of Eq. (4) is positive (negative), this means that exchange rate changes are followed, on average, by systematic positive (negative) forecast errors. A regularly positive forecast error in this context qualifies the behaviour of predictors as underreaction to a change in the exchange rate while a systematic negative forecast error defines overreaction.

To explain why this is true, imagine that the the exchange rate change in a given period increased.

A positive estimated coefficient would imply that the forecast error has a positive sign in the next period. Since the forecast error is defined as the spot exchange rate minus the prediction of the spot(as a percentage of the spot itslef), a positive sign indicates that the prediction has been lower than the realized exchange rate, thus that the forecaster has underestimated the change in the spot rate. In other words, he *underreacted*. To the contrary, a negative estimated coefficient signals that as a reaction to a positive change in the rate, the analyst has expressed (in a systematic way) a prediction higher than the spot that then was realized, meaning that the forecaster has *overreacted*. The same holds true for a negative change in the rate: a positive estimated coefficient corresponds to underreaction and a negative coefficient to overreaction.

In general, overreaction (underreaction) means that forecasters on average revise too much (too little) their projections responding to the current movements of the exchange rate more (less) than it would be rational to do: whether a change is observed, analysts overreact if they predict that the change in the exchange rate will persist in the future more than would be on the basis of the autocorrelation pattern.

Whether this irrationality existed in our database, we could shed further light on the nature of this irrationality, implementing a decomposition of the forecast error first introduced by Easterwood and Nutt (1999):

$$FE_{i,t|t-1} = RSC_t - PSC_{i,t|t-1}. \tag{5}$$

where RSC is the (percentage) realized spot change (RSC) and

$$PSC_{i,t|t-1} \ = \frac{f_{i,t|t-1} - s_{t-1}}{s_{t-1}} \tag{6}$$

is the (percentage) predicted spot change between date $t-1$ and date t. Then, we test the significance of the two components of the decomposition proposed in equation (5) by estimating the following models:

$$PSC_{it|t-1} = \beta_{0,i} + \sum_{i=1}^{4} \beta_i \, RSC_{t-i} + \zeta_{i,t} \tag{7}$$

$$RSC_{it} = \gamma_{0,i} + \sum_{i=1}^{4} \gamma_i \, RSC_{t-i} + \eta_{i,t} \tag{8}$$

where the maximum lag of the four models has been chosen on empirical grounds [3].

It is in fact true that, as recognized by Easterwood and Nutt (1999), testing that the parameters

[3]Indeed, our preliminary empirical analysis has found that the right hand side variables are, for some currency, significant up to the lag of order four, which corresponds to quarter on quarter exchange rate growth one year before the reference period.

of equation (4) are not significantly different from zero is equivalent to testing that the parameters of equation (7) are not significantly different from parameters of equation 8. In fact, if we subtract equation 7 from equation 8, we get

$$
\begin{aligned}
RSC_{i,t} - PSC_{i,t|t-1} = \quad & (\gamma_{0,i} - \beta_{0,i}) + (\gamma_1 - \beta_1)\, RSC_{t-1} + (\gamma_2 - \beta_2)\, RSC_{t-2} + \\
& (\gamma_3 - \beta_3)\, RSC_{t-3} + (\gamma_4 - \beta_4)\, RSC_{t-4} + (\eta_{i,t} - \zeta_{i,t}),
\end{aligned}
\tag{9}
$$

comparing equation 9 to equations 5 and 4 we obtain the following identities:

$$
\begin{cases}
\alpha_{0i} = \gamma_{0,i} - \beta_{0,i} \\
\alpha_1 = \gamma_1 - \beta_1 \\
\alpha_2 = \gamma_2 - \beta_2 \\
\alpha_3 = \gamma_3 - \beta_3 \\
\alpha_4 = \gamma_4 - \beta_4
\end{cases}
\tag{10}
$$

meaning that if forecasts were rational (all the α parameters equal to zero), the parameters of the model driving the projected changes (the β parameters) should be equal to the parameters of the true data generating process of the spot exchange rate (the γ parameters). To further exploit the richness of our database we investigate whether the supposed irrationality is homogeneous or heterogeneous across predictors by implementing a modified version of the Easterwood and Nutt (1999) methodology: we evaluate the performance of each single forecaster of our panel by calculating their absolute percentage forecast error in each period, and for each period we define as high performance predictors (HIGHPERF) those predictors possessing an absolute forecast error which is in the lowest 20th percentile (for that year) of the distribution and as low performance predictors (LOWPERF) as those belonging to the highest 20th percentile of the distribution for the same year. We build dummy variables that correspond to these definitions and include them in the regressions as follows:

$$
FE_{i,t|t-1} \; = \; \alpha_{0,i} + \sum_{i=1}^{4} \alpha_i\, RSC_{t-i} + HIGHPERF + LOWPERF + \epsilon_{i,t} \tag{11}
$$

If the dummies in equation 11 are significantly different from zero, we conclude that there are different degrees of irrationality characterizing the different subgroups of predictors in the sample, captured by the different intercepts identified for the high performing, low performing or average performing group. This is a test of heterogeneity in group behavior that discriminate between the low and high performance predictors. Should this heterogeneity results form the estimates, we would then like to investigate whether the type of irrationality tested in equation 4 (under or overreaction) in the identified subgroups runs in the same direction as that observed in the group as a whole.

To do so, in the following equation we explore the interaction between each autoregressive component in 4 and the dummies HIGH and LOW performance, as follows

$$\begin{aligned} FE_{i,t|t-1} &= \alpha_{0,i} + \sum_{i=1}^{4} \alpha_i \, RSC_{t-i} + \sum_{i=1}^{4} \theta_i \, RSC_{t-i} * HIGHPERF + \\ & \sum_{i=1}^{4} \lambda_i \, RSC_{t-i} * LOWPERF + HIGHPERF + LOWPERF + \epsilon_{i,t}, \end{aligned} \tag{12}$$

where the coefficients θ_i identify the sign of potential irrational behavior of the group of the high performing predictors, while the λ_i identifies the dimension and direction of the irrational behavior of the low performing group.

4.1 Results

We have estimated five set of fixed effects panel models, one for each of the five currencies. The choice of a panel model has been dictated by the relatively temporal extension of our dataset a fact that makes necessary to exploit jointly the temporal and the cross-sectional dimension of our dataset.[4] for each of the five bilateral spot exchange rates.

Observing the results of the estimate of the equation for the forecast error (see equation (4)) reported in the first column of Table 9 we can state that:

Proposition 1 *Exchange rate forecasts are irrational.*

For the five exchange rates considered the hypothesis of rationality is always strongly rejected at least at 5% significance level. The bilateral exchange rates for which the significance is stronger are EUR/USD, EUR/JPY and USD/JPY, while the bilateral rates involving the GBP (EUR/GBP and GBP/USD) show larger efficiency as highlighted by the lower significance of the coefficients of the estimates of Eq. 4 . As a second results we can also state that:

Proposition 2 *Exchange rate forecasters overreact to information contained in the exchange rate itself.*

[4]We also estimated individual time series model for each single predictor separately. These preliminary estimates are not reported here but are available on request and show that no significant and reliable results emerge. The choice of the fixed-effects estimator has been dictated by its consistency given that the Hausman test did not provide any strong and uniform evidence in favour of a model with random effects. Moreover, we have verified that the magnitude and the precision of our estimates are not significantly affected by the choice of a particular estimation technique.

This proposition comes from the negative sign of the estimated coefficients in column (1) of table 9: forecasters make a prediction for the future which is on average higher than the ex-post realized change. They predict a larger (or smaller) value of the rate than the one observed ex-post. This holds for almost all bilateral rates in our sample, with the exception again of the EUR/GBP and GBP/USD rates. For the first, a positive significant coefficient shows that with some lag (3 to 4 quarters) predictors of this rate tend to compensate overreaction observed for short lag, with underreaction (and ultimately the predictions for this horizons are almost efficient.) For the GBP-USD rate, at lag one we conclude that forecasters behavior is characterized by underreaction as they expect a lower than realized variation in the spot rate, on average. We know that if the predictions were efficient the coefficients in columns (2) and (3) of Table 9 should be exactly equal, as identified in Eq. 9: this is almost never the case in our evidence. For those lags and rates for which the coefficients in column (2) are not significant, we can conclude that forecasters fail to include in their predictions the autoregressive component of the rate. When instead the coefficients of the equation for the Predicted change (Column 2) are significant, this suggests that predictors are incorporating in their forecasts a significant autoregressive element but in the opposite direction of the realized spot.

Proposition 3 *Forecasters are heterogeneous in their irrationality.*

In the last model we account for the separate effect of high and low performance forecasters: In table 10, we notice that high performance forecasters do not show significant departure from the average in terms of the quality of their prediction, as the variable HIGHPERF is not significant for any exchange rate. To the contrary, low performers show a more pronounced irrationality: the coefficient of LOWPERF is small and negative, meaning that the overreaction effect (or the mitigation of the underreaction, for those exchange rates that showed overreaction), is larger for this subgroup of our sample. This can be explained in an intuitive but interesting way: past low performers continue to perform worse than the average, because of a lack of ability to learn form their own past errors.

The estimates of Table 11 confirm that 'low' performers are characterized by a systematic forecast error captured by a specific intercept. Moreover, for the we EUR/JPY and USD/JPY bilateral rate, we find that 'high' performers are characterized by a first-order autoregressive parameter that is significantly different from that estimated for the rest of the sample. In other words, 'high' performers compensate the general overreaction of the rest of the sample with a response of the opposite sign, over a three-months forecast horizon. Ultimately, they exploit in a better way the historical autocorrelation at lag one present in the time series. For lag greater than one we do not detect any specific autocorrelation pattern of 'low' or 'high' performing professional forecasters, except that for the USD/JPY bilateral rate for which we observe that the general sample tend to overreact to past realization of the spot rate, while both the high performers and the low performers instead underreact. Ultimately, we can conclude that there is a high degree of heterogeneity in predictions for this currency.

5 Predictors' Response to previous periods Forecast Error

From the previous results we discovered that predictors fail to correctly predict the autoregressive process of bilateral exchange rates and prove to be irrational in the sense of Mankiw et al. (1984) and we also find that forecasters tend to overreact to past observed information. Moreover, this irrationality is not homogeneous among predictors, even in the same panel of forecasters: it is possible to identify subgroups of forecasters characterized by different forecasting performance which substantially reflect the heterogeneous degree of ability in identifying the empirical autocorrelation pattern of exchange rate dynamics. These results are nonetheless limited to information available to market operators through revealed price (the spot), without taking into account other types of information that may influence the market for expectations and the decision process that each forecaster faces. Therefore in this section wwe shift the focus from previous-period (percentage) spot change to previous-period (percentage) forecast error. This shift allows the consideration of a richer set of information including the macroeconomic factors such as changes in the structure of the economy to which the bilateral rate refers, or any other event that might affect also other analysts' forecasts whose prediction is observed by the market operators and taken into account when forming his own prediction, in a beauty contest fashion (Morris and Shin, 2002).

Analyzing a broader definition of information allows us to address the question of whether analysts only misinterpret the information contained in past dynamics in an optimal manner or whether analysts generally misinterpret relevant information. To focus on this larger question, we shift our focus from the incorporation of information in forecasts to the process by which analysts revise their forecasts of earnings at some future date. This is accomplished by examining the change in forecast of year t earnings as the forecast horizon narrows from two years ahead to one year ahead in response to the revelation of the year t-1 forecast error. With these modifications, we re-examine the issue of forecast rationality, trying also to interpret the results obtained in terms of forecasting behavior.

With a parallel to the previous model, we test forecast rationality in the following equation:

$$FE_{it|t-1} = \alpha_{0i} + \alpha_1 \, FE_{it-1|t-2} + \alpha_2 \, FE_{it-2|t-3} + \alpha_3 \, FE_{it-3|t-4} + \alpha_4 \, FE_{it-4|t-5} + \epsilon_{i,t}. \tag{13}$$

A predictor is rational when he does not commit systematic errors given all information available in the market. A condition for rationality would allow forecast errors to be serially correlated only up to a moving average process of order k -1, where k is the number of steps ahead the prediction is made (Pesaran (1987)). As we are dealing with one step ahead forecasts, k is one in our case, thus making this condition equivalent to saying that forecast errors should be serially uncorrelated. Thus we test forecast rationality by looking at the statistical significance of the autoregressive coefficient of equation 13.

Moreover, if the i-th intercept of equation 13 is positive (negative), then the i-th forecast is affected by a systematic positive (negative) bias. Moreover, if some autoregressive parameter of equation 13 are greater than zero, positive (negative) forecast errors are systematically followed by positive (negative) forecast errors, meaning that forecasters do not revise adequately their forecast in light of the updated statistical evidence, meaning that they are *underreacting* to the observed quality of their projections. We could also say that predictors overestimate the quality of their private information and consequently show to be over-confident in their predictions, by responding in less than proportional way to observed past performance.

On the opposite, if some of the parameters are lower than zero, this implies that positive (negative) forecast errors are systematically followed by negative (positive) forecast error: the forecasters revise too much their projections (in the opposite direction) in light of own observed performance, thus making them *overreacting* to the quality of their projections. Also in this case, we could define this as an under-confident behavior that shows in an excessive reaction of predictors to past observed own performance.

In the following we explore instead what is the reaction of the predictors to their own observed performance in the prediction market. It is itself a second type of rationality test that relates more to the perception that predictors have with respect to how they performed in the past, which may also take into account the dimension of error realized by their peers. This is a test of rationality in the sense that they irrationally exclude past forecast errors from the informative set which should instead condition their projections.

$$FE_{i,t|t-1} \; = \; \alpha_{0,i} + \sum_{i=1}^{4} \alpha_i \, FE_{t-i|t-i-1} + HIGHPERF + LOWPERF + \epsilon_{i,t} \qquad (14)$$

$$FE_{i,t|t-1} = \alpha_{0,i} + \sum_{i=1}^{4} \alpha_i \, FE_{t-i|t-i-1} + \sum_{i=1}^{4} \theta_i \, FE_{t-i|t-i-1} * HIGHPERF + \sum_{i=1}^{4} \lambda_i \, FE_{t-i|t-i-1} * LOWPERF + HIGHPERF + LOWPERF + \epsilon_{i,t} \quad (15)$$

5.1 Results

In Tables 12 we report estimates from Eq. 13 and find confirmation of strong autocorrelated forecast errors for EUR/USD USD/JPY rates. For the former, we can identify a correction pattern for the forecasters that react negatively to past committed errors. For USD/JPY instead, there is a compensation among the coefficients at different lags. This seems to design an adjustment pattern that adjusts the myopic short-run behavior. The same happens for the EUR/GBP rate for which the irrationality detected by a significant negative coefficient at lag of order one is compensated in the long run by positive coefficients of higher order.

For the GBP/USD exchange rate, the compensation pattern runs the opposite way: in the very short run for which the autocorrelation pattern is significant, predictors follow the trend which is reversed already when taking into account lag of order two. Our results are in line with those by Abarbanell and Bernard (1992) which find autocorrelation in quarterly earnings forecast error over the first three lags as an evidence of forecast irrationality.

The introduction of the dummies for high and low performance in the regression following Eq. 13 discovers that there is heterogeneity also in this case, as low performing subjects have a significant different intercept from the rest of the predictors, without changing the pattern observed in the regression without dummies.

In table 14 we report the estimates of a more general model, where we have introduced as regressors both dummy for 'high' and 'low' performing forecasters as well as the same dummies interacted with lagged forecast errorr. This equation has been estimated in order to assess if 'high' and 'low' performing forecasters are characterized by heterogeneity in the response to their observed past performance. We observe that 'low' performing forecasters are characterized by different systematic errors captured by group-specific intercepts, a fact which differentiates the quality of the projections made by the two groups, the low performers and the rest (including the average performers and the high performers). Moreover, the inclusion of the dummies for low performance forecasters reduces the significance of the other autoregressive parameters: this evidence would suggest that the irrationality of the forecasts observed in the general regression of Eq. 13 is mainly originated by the subgroup of predictors that is less capable of realizing own mistakes and correct them for the future.

Low-performing forecasters are those whose forecast is further away from the realized rate in absolute terms: we observe that corresponding to this higher distance there is a systematic error in the prediction that is negative. High absolute forecast error corresponds to a forecast error in the next period negative: the forecast is systematically higher than the ex-post realized spot. On average, the low performing forecasters have predicted a depreciation that has not come true in the realized spot, for the bilateral rates considered in our sample[5]. They show a bias that is not common to the general sample of the predictors. Given this evidence, we conclude the following:

Proposition 4 *Forecasters do not efficiently exploit the information contained in past forecast errors: they have a biased reaction to the observation of their own performance.*

6 Conclusion

We test for rationality in exchange rates forecasts, in accordance with the findings of the current debate in behavioural finance, whereby forecasts are often affected by a number of biases. We construct a novel dataset based on historical data available on the Bloomberg platform concerning predictions on 5 bilateral exchange rates based on four currencies issued by a number of different professional forecasters, for each of which we have an explicit indication of an individual –potentially heterogeneous – prediction. We find consistent and articulated evidence of the presence of behavioral biases, which introduce an element of irrationality in the analysts behavour. In particular, exchange rate forecasters overreact to observed information, in the sense that they revise too much their prediction following a change in the exchange rate.

Moreover, forecasters are heterogeneous in their irrationality, in that forecasters who perform worse historically tend to be more irrational, since their overreaction to past information is more pronounced. As an additional perspective on these findings of irrationality, we extend our analysis by looking at how forecasters exploit the information contained in past forecast error, as opposed to only the past dynamic of the spot rate. Again, we find evidence that analysts do not efficiently exploit this information, and react irrationally to the observation to their own past performance.

[5] We are aware that a depreciation of a bilateral rate in volume quotation system corresponds to the appreciation of the corresponding currency in price quotation system. Consequently this statement does not have validity for bilateral rates in general but is a recurring feature of the currencies considered in our sample and for the period considered in our analysis.

7 Tables

Table 1: Predictors distribution by location and type of institution.

Type of institution	EU	North America	Asia	Africa	Total
Large Bank	12	4	4	1	21
Asset mgmt/financial adv	4	1	0	0	5
Retail/private banking	4	1	0	0	5
Investment Bank	0	2	0	0	2
Total	20	8	4	1	33

Table 2: Predictors distribution by location and international extension

Type of institution	EU	North America	Asia	Global	Total
Large bank	3	2	2	14	21
Asset mgmt/financial adv	2	0	1	2	5
Retail/private banking	4	0	0	1	5
Investment bank	0	0	0	2	2
Total	9	2	3	19	33

Table 3: Sample statistics by predictor for the forecast error of EUR-JPY bilateral exchange rate.

	Forecast Error by predictor			
Predictor ID	Mean	Median	St-dev	t-Statistic on Mean
ID 1	-0.04	-0.05	0.09	-1.81
ID 2	0.01	0.01	0.09	0.51
ID 3	0.01	0.02	0.08	0.31
ID 4	-0.04	-0.05	0.07	-2.78
ID 5	-0.01	-0.00	0.07	-0.81
ID 6	-0.01	-0.01	0.09	-0.58
ID 7	-0.01	-0.02	0.09	-0.68
ID 8	-0.03	-0.02	0.07	-1.65
ID 9	-0.04	-0.04	0.09	-2.18
ID 10	0.00	0.02	0.08	0.15
ID 11	-0.01	0.00	0.07	-0.59
ID 12	-0.00	-0.01	0.08	-0.24
ID 13	-0.02	-0.01	0.08	-0.82
ID 14	-0.03	-0.03	0.06	-1.80

Note: t-Statistic on the difference from zero of the mean forecast error.

Table 4: Sample statistics by predictor for the forecast error of EUR-GBP bilateral exchange rate.

	Forecast Error by predictor			
Predictor ID	Mean	Median	St-dev	t-Statistic on Mean
ID 1	0.00	0.01	0.07	0.18
ID 2	0.02	0.00	0.07	1.27
ID 3	0.03	0.02	0.07	2.19
ID 4	0.01	0.00	0.07	0.91
ID 5	0.01	0.01	0.07	0.89
ID 6	0.01	-0.00	0.07	0.39
ID 7	0.01	-0.00	0.07	0.82
ID 8	0.01	0.00	0.07	0.63
ID 9	0.01	0.01	0.06	0.58
ID 10	0.01	0.01	0.07	0.80
ID 11	0.00	0.01	0.07	0.28
ID 12	0.01	0.00	0.08	0.85
ID 13	0.01	0.00	0.07	0.94

Note: t-Statistic on the difference from zero of the mean forecast error.

Table 5: Sample statistics by predictor for the forecast error of EUR-USD bilateral exchange rate.

	Forecast Error by predictor			
Predictor ID	Mean	Median	St-dev	t-Statistic on Mean
ID 1	-0.02	-0.02	0.07	-1.26
ID 2	-0.00	0.00	0.07	-0.27
ID 3	0.02	0.02	0.07	1.39
ID 4	-0.00	0.01	0.07	-0.12
ID 5	0.02	-0.00	0.06	1.15
ID 6	0.01	0.02	0.07	0.54
ID 7	0.00	0.00	0.07	0.01
ID 8	-0.01	-0.01	0.06	-0.71
ID 9	-0.01	0.00	0.07	-0.64
ID 10	-0.00	0.01	0.07	-0.06
ID 11	-0.00	0.01	0.07	-0.21
ID 12	0.02	0.01	0.07	1.36
ID 13	0.01	0.01	0.06	0.93
ID 14	-0.00	0.01	0.07	-0.13
ID 15	-0.00	0.00	0.07	-0.07
ID 16	0.01	0.01	0.08	0.45
ID 17	0.00	0.00	0.06	0.06
ID 18	0.00	0.01	0.06	0.18

Note: t-Statistic on the difference from zero of the mean forecast error.

Table 6: Sample statistics by predictor for the forecast error of GBP-USD bilateral exchange rate.

	Forecast Error by predictor			
Predictor ID	Mean	Median	St-dev	t-Statistic on Mean
ID 1	-0.00	0.00	0.05	-0.34
ID 2	0.00	0.01	0.08	0.20
ID 3	-0.03	-0.03	0.06	-2.52
ID 4	0.00	0.00	0.06	0.00
ID 5	-0.00	0.01	0.06	-0.22
ID 6	-0.02	-0.02	0.06	-1.54
ID 7	-0.01	0.00	0.06	-0.58
ID 8	-0.02	-0.01	0.08	-1.42
ID 9	0.01	0.00	0.06	0.38
ID 10	-0.01	-0.01	0.06	-0.79
ID 11	-0.00	0.00	0.07	-0.06
ID 12	-0.00	-0.01	0.08	-0.11
ID 13	-0.01	0.00	0.06	-0.53
ID 14	-0.01	-0.00	0.05	-1.33

Note: t-Statistic on the difference from zero of the mean forecast error.

Table 7: Sample statistics by predictor for the forecast error of USD-JPY bilateral exchange rate.

	Forecast Error by predictor			
Predictor ID	Mean	Median	St-dev	t-Statistic on Mean
ID 1	-0.02	-0.04	0.07	-1.24
ID 2	0.01	0.00	0.07	0.99
ID 3	-0.01	-0.02	0.07	-0.84
ID 4	-0.02	-0.02	0.07	-1.09
ID 5	-0.01	-0.02	0.07	-0.64
ID 6	-0.02	-0.02	0.05	-1.39
ID 7	-0.04	-0.05	0.06	-2.99
ID 8	-0.02	-0.02	0.06	-1.16
ID 9	-0.01	-0.02	0.06	-0.76
ID 10	-0.01	-0.00	0.05	-0.60
ID 11	-0.01	-0.02	0.06	-0.76
ID 12	-0.02	-0.04	0.06	-1.64
ID 13	-0.03	-0.03	0.05	-2.13
ID 14	-0.01	-0.01	0.06	-0.47

Note: t-Statistic on the difference from zero of the mean forecast error.

Table 8: Mean forecast error and standard deviation of percentage forecast error per quarter

	EUR-USD		EUR-JPY		EUR-GBP		GBP-USD		USD-JPY	
	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev	Mean	St.dev
2006-4	0.02	0.01	0.06	0.02	-0.01	0.01	0.04	0.02	0.04	0.03
2007-1	0.00	0.02	0.02	0.03	0.01	0.02	0.00	0.02	0.02	0.03
2007-2	0.00	0.01	0.06	0.04	-0.01	0.01	0.01	0.01	0.05	0.03
2007-3	0.04	0.01	-0.02	0.03	0.03	0.01	0.02	0.01	-0.05	0.03
2007-4	0.02	0.01	-0.01	0.02	0.04	0.02	-0.02	0.02	-0.01	0.02
2008-1	0.07	0.03	-0.02	0.02	0.07	0.03	-0.01	0.02	-0.07	0.03
2008-2	0.01	0.03	0.10	0.03	-0.00	0.02	0.00	0.02	0.09	0.03
2008-3	-0.10	0.02	-0.08	0.04	-0.01	0.01	-0.09	0.02	-0.00	0.03
2008-4	0.01	0.03	-0.11	0.06	0.23	0.02	-0.16	0.04	-0.10	0.03
2009-1	-0.01	0.05	0.07	0.09	0.00	0.02	-0.02	0.06	0.08	0.05
2009-2	0.05	0.06	0.00	0.05	-0.07	0.03	0.13	0.05	-0.05	0.03
2009-3	0.05	0.05	-0.04	0.05	0.06	0.02	-0.00	0.05	-0.08	0.04
2009-4	-0.04	0.02	-0.03	0.05	-0.03	0.04	-0.01	0.04	0.01	0.05
2010-1	-0.09	0.03	-0.07	0.05	-0.01	0.02	-0.08	0.03	0.01	0.04
2010-2	-0.10	0.02	-0.15	0.04	-0.09	0.02	-0.01	0.03	-0.06	0.02
2010-3	0.12	0.04	0.05	0.04	0.06	0.02	0.07	0.04	-0.08	0.03
2010-4	-0.02	0.04	-0.06	0.04	-0.02	0.03	-0.02	0.03	-0.03	0.03
2011-1	0.08	0.04	0.08	0.05	0.06	0.02	0.03	0.03	-0.00	0.03
2011-2	0.03	0.03	-0.02	0.04	0.04	0.03	-0.01	0.02	-0.05	0.03
2011-3	-0.07	0.03	-0.13	0.05	-0.04	0.02	-0.04	0.03	-0.06	0.03
2011-4	-0.04	0.04	-0.04	0.04	-0.05	0.02	0.00	0.03	0.01	0.03

Table 9: Forecast error decomposition.
Model(right side)= $\alpha_{0,i} + \sum_1^4 \alpha_i \, RSC_{t-i} + \epsilon_{i,t}$

		Dependent Variable					
		$(s_t - f_{i,t\|t-1})/(s_{t-1})$ Forecast error (1)		$(f_{i,t\|t-1} - s_{t-1})/s_{t-1}$ Predicted spot change (2)		$(s_t - s_{t-1})/s_{t-1}$ Realized Spot Change (3)	
Currency: EUR-USD	RSC (t-1)	-0.209	***	0.042		-0.167	***
	RSC(t-2)	-0.206	***	0.056		-0.150	***
	RSC(t-3)	-0.381	***	0.007		-0.374	***
	RSC(t-4)	-0.429	***	-0.045		-0.473	***
	F-statistic	19.67		1.54		32.06	
Currency: EUR-JPY	RSC (t-1)	-0.384	***	0.109	**	-0.275	***
	RSC(t-2)	-0.381	***	-0.026		-0.407	***
	RSC(t-3)	-0.194	***	-0.008		-0.203	***
	RSC(t-4)	-0.214	***	-0.109	**	-0.323	***
	F-statistic	11.34		2.87		16.92	
Currency: EUR-GBP	RSC (t-1)	-0.119		-0.140	***	-0.260	***
	RSC(t-2)	-0.149	*	-0.071	**	-0.220	***
	RSC(t-3)	0.198	**	-0.003		0.195	**
	RSC(t-4)	0.153	*	-0.014		0.139	*
	F-statistic:	4.91		8.31		9.80	
Currency: GBP-USD	RSC (t-1)	0.133	*	0.005		0.138	**
	RSC(t-2)	-0.394	***	-0.030		-0.424	***
	RSC(t-3)	-0.169	**	0.073	**	-0.096	
	RSC(t-4)	-0.108	*	-0.031		-0.140	**1
	F-statistic	14.92		1.08		14.68	
Currency: USD-JPY	RSC (t-1)	-1.034	***	0.178	***	-0.856	***
	RSC(t-2)	-0.900	***	0.148	**	-0.752	***
	RSC(t-3)	-0.312	***	0.063		-0.249	***
	RSC(t-4)	-0.058		-0.031		-0.089	
	F-statistic	68.66		2.62		59.81	

Note: Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Table 10: Forecast error and dummies high and low performance.
Regressors= $\alpha_{0,i} + \sum_1^4 \alpha_i \, RSC_{t-i} + HIGHPERF + LOWPERF + \epsilon_{i,t}$

Dependent Variable: Forecast error	EUR/USD (1)	PVAL	EUR/JPY (2)	PVAL	EUR/GBP (3)	PVAL	GBP/USD (4)	PVAL	USD/JPY (5)
RSC(t-1)	-0.21	0.00 ***	-0.38	0.00 ***	-0.14	0.07 *	0.13	0.04**	-1.02
RSC(t-2)	-0.21	0.00 ***	-0.37	0.00 ***	-0.14	0.07 *	-0.39	0.00***	-0.87
RSC(t-3)	-0.39	0.00 ***	-0.19	0.01 ***	0.19	0.02 **	-0.17	0.01***	-0.29
RSC(t-4)	-0.43	0.00 ***	-0.21	0.00 ***	0.14	0.06 *	-0.11	0.09 *	-0.04
HIGH PERF	-0.01	0.24	0.00	0.87	0.01	0.34	0.00	0.96	0.00
LOW PERF	-0.06	0.00 ***	-0.07	0.00 ***	-0.04	0.00***	-0.05	0.00***	-0.05

Note: Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively. HIGH PERF is a dummy variable indicating the predictors be

Table 11: Dependent variable: Forecast error and dummies high and low performance with interactions.
Regressors= $\alpha_{0,i} + \sum_1^4 \alpha_i \, RSC_{t-i} + HIGHPERF + LOWPERF + \sum_1^4 \theta_i \, RSC_{t-i} * HIGHPERF + \sum_1^4 \lambda_i \, RSC_{t-i} * LOWPERF + \epsilon_{i,t}$

Dependent Variable: Forecast error

	EUR/USD (1)	PVAL	EUR/JPY (2)	PVAL	EUR/GBP (3)	PVAL	GBP/USD (4)	PVAL	USD/JPY (5)
RSC(t-1)	-0.25	0.08*	-0.60	0.00***	-0.12	0.46	-0.08	0.60	-1.44
du20high	-0.01	0.32	0.02	0.24	0.00	0.73	0.01	0.53	0.04
RSC(t-2)	-0.28	0.06*	-0.52	0.00***	0.05	0.83	-0.44	0.00***	-1.34
RSC(t-3)	-0.46	0.00***	-0.30	0.09*	0.29	0.16	-0.35	0.06**	-0.33
RSC(t-4)	-0.52	0.00***	-0.28	0.10	0.07	0.73	-0.19	0.19	-0.27
du20low	-0.06	0.00***	-0.06	0.00***	-0.03	0.08*	-0.05	0.00***	-0.01
HIGH PERFxRSC(t-1)	0.15	0.34	0.33	0.09*	0.09	0.64	0.04	0.79	0.44
HIGH PERFxRSC(t-2)	-0.07	0.64	0.22	0.25	0.05	0.81	0.17	0.32	0.38
HIGH PERFxRSC(t-3)	0.16	0.28	0.11	0.56	0.08	0.67	0.08	0.66	0.01
HIGH PERFxRSC(t-4)	0.14	0.39	-0.06	0.72	0.21	0.31	0.05	0.77	0.03
LOW PERFxRSC(t-1)	0.01	0.96	0.20	0.32	-0.08	0.70	0.26	0.14	0.39
LOW PERFxRSC(t-2)	0.12	0.47	0.12	0.54	-0.25	0.29	0.02	0.93	0.45
LOW PERFxRSC(t-3)	0.04	0.81	0.11	0.55	-0.16	0.50	0.20	0.28	-0.00
LOW PERFxRSC(t-4)	0.08	0.65	0.11	0.55	0.04	0.84	0.09	0.57	0.26

Note: Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively. HIGH PERF is a dummy variable indicating the predictors be

Table 12: Forecast error autoregressice structure
Model(right side)= $\alpha_{0,i} + \sum_1^4 \alpha_i \, FE_{t-i} + \epsilon_{i,t}$

	Forecast err.	p-val								
Dependent Variable: Forecast error										
	EUR/USD (1)	PVAL	EUR/JPY (2)	PVAL	EUR/GBP (3)	PVAL	GBP/USD (4)	PVAL	USD/JPY (5)	PVAL
FE(t-1)	-0.065	0.245	-0.056	0.407	-0.129	0.075*	0.203	0.003***	-0.256	0.000***
FE(t-2)	-0.132	0.018**	-0.157	0.024**	-0.180	0.015**	-0.395	0.000***	-0.256	0.000***
FE(t-3)	-0.303	0.000***	0.054	0.433	0.124	0.094*	-0.076	0.271	0.190	0.001***
FE(t-4)	-0.360	0.000***	-0.044	0.529	0.051	0.485	-0.107	0.111	0.103	0.068**

Note: Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively.

Table 13: Forecast error and dummies high and low performance.
Regressors= $\alpha_{0,i} + \sum_1^4 \alpha_i FE_{t-i} + HIGHPERF + LOWPERF + \epsilon_{i,t}$

Dependent Variable: Forecast error

	EUR/USD (1)	PVAL	EUR/JPY (2)	PVAL	EUR/GBP (3)	PVAL	GBP/USD (4)	PVAL	USD/JPY (5)
FE(t-1)	-0.10	0.05**	-0.07	0.27	-0.16	0.03**	0.17	0.01***	-0.27
FE(t-2)	-0.14	0.01***	-0.15	0.02**	-0.18	0.02**	-0.38	0.00***	-0.24
FE(t-3)	-0.31	0.00***	0.05	0.42	0.12	0.11	-0.09	0.17	0.21
FE(t-4)	-0.37	0.00***	-0.04	0.51	0.04	0.60	-0.11	0.07*	0.15
HIGH PERF	-0.01	0.19	0.00	0.91	0.01	0.28	0.00	0.86	0.01
LOW PERF	-0.06	0.00***	-0.07	0.00***	-0.04	0.00***	-0.05	0.00***	-0.06

Note: Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively. HIGH PERF is a dummy variable indicating the predictors be

Table 14: Forecast error and dummies high and low performance with interactions.
Model(right side)= $\alpha_{0,i} + \sum_1^4 \alpha_i\, FE_{t-i} + HIGHPERF + LOWPERF + \sum_1^4 \theta_i\, FE_{t-i} * HIGHPERF + \sum_1^4 \lambda_i\, FE_{t-i} * LOWPERF + \epsilon_{i,t}$

Dependent Variable: Forecast error

	EUR/USD (1)	PVAL	EUR/JPY (2)	PVAL	EUR/GBP (3)	PVAL	GBP/USD (4)	PVAL	USD/JPY (5)
FE(t-1)	-0.07	0.58	-0.09	0.58	-0.19	0.24	0.10	0.53	-0.30
du20high	-0.01	0.31	-0.00	0.98	0.02	0.26	0.00	0.82	0.00
FE(t-2)	-0.09	0.49	-0.06	0.73	-0.08	0.71	-0.37	0.02**	-0.44
FE(t-3)	-0.37	0.00***	0.11	0.50	-0.00	0.99	-0.10	0.53	0.20
FE(t-4)	-0.40	0.01***	0.03	0.88	-0.12	0.51	-0.19	0.19	-0.06
du20low	-0.06	0.00***	-0.07	0.00***	-0.05	0.01***	-0.05	0.00***	-0.05
HIGH PERFx FE(t-1)	-0.12	0.38	-0.02	0.91	-0.06	0.73	-0.09	0.61	-0.11
HIGH PERFxFE(t-2)	-0.08	0.56	0.02	0.90	-0.13	0.42	0.22	0.18	-0.01
HIGH PERFxFE(t-3)	0.05	0.67	-0.03	0.84	-0.06	0.72	0.03	0.86	-0.30
HIGH PERFx:FE(t-4)	-0.01	0.92	-0.19	0.25	0.14	0.48	0.01	0.96	0.02
LOW PERFxFE(t-1)	-0.01	0.97	0.03	0.85	0.07	0.73	0.12	0.50	0.07
LOW PERFxFE(t-2)	-0.04	0.77	-0.12	0.47	-0.07	0.74	-0.08	0.64	0.24
LOW PERFxFE(t-3)	0.06	0.65	-0.05	0.76	0.16	0.46	0.01	0.96	0.06
LOW PERFxFE(t-4)	0.06	0.72	-0.03	0.89	0.17	0.37	0.08	0.59	0.21

Note: Symbols $***$, $**$, and $*$ indicate significance at the 1%, 5% and 10% level, respectively. HIGH PERF is a dummy variable indicating the predictors be

References

Abarbanell, J. S. and V. L. Bernard (1992). Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior. *The Journal of Finance 47*(3), pp. 1181–1207.

Bacchetta, P. and E. V. Wincoop (2006, 06). Can information heterogeneity explain the exchange rate determination puzzle? *The American Economic Review 96*(3), 552–576.

Bacchetta, P. and E. V. Wincoop (2008, 08). Higher order expectations in asset pricing. *Journal of Money, Credit and Banking 40*(5), 837–866.

Beine, M., A. Benassy-Quere, and R. MacDonald (2007). The impact of central bank intervention on exchange-rate forecast heterogeneity. *Journal of the Japanese and International Economies 21*, 38–63.

Bondt, W. F. M. D. and R. Thaler (1985). Does the stock market overreact? *The Journal of Finance 40*(3), pp. 793–805.

Bondt, W. F. M. D. and R. H. Thaler (1987). Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance 42*(3), pp. 557–581.

Brown, K. C. and W. V. Harlow (1988). Market overreaction: magnitude and intensity. *Journal of Portfolio Management 14*, 6–13.

Cavaglia, S. M. F. G., W. F. C. Verschoor, and C. C. P. Wolff (1994, July). On the biasedness of forward foreign exchange rates: Irrationality or risk premia? *The Journal of Business 67*(3), 321–43.

Cheung, Y.-W. and M. D. Chinn (2001, August). Currency traders and exchange rate dynamics: a survey of the us market. *Journal of International Money and Finance 20*(4), 439–471.

Chinn, M. and J. Frankel (1994, November). Patterns in exchange rate forecasts for twenty-five currencies. *Journal of Money, Credit and Banking 26*(4), 759–70.

Chionis, D. and R. MacDonald (1997). Some tests of market microstructure hypotheses in the foreign exchange market. *Journal of Multinational Financial Management 7*(3), 203 – 229.

Cho, D. W. and P. L. Hersch (1998, January). Forecaster characteristics and forecast outcomes. *Journal of Economics and Business 50*(1), 39–48.

De Bondt, W. F. M. and R. H. Thaler (1990, May). Do security analysts overreact? *American Economic Review 80*(2), 52–57.

Dokko, Y. and R. H. Edelstein (1989). How well do economists forecast stock market prices? a study of the livingston surveys. *The American Economic Review 79*(4), pp. 865–871.

Easterwood, J. C. and S. R. Nutt (1999). Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism? *The Journal of Finance 54*(5), pp. 1777–1797.

Elliott, G. and T. Ito (1999). Heterogeneous expectations and tests of efficiency in the yen/dollar forward exchange rate market. *Journal of Monetary Economics 43*(2), 435 – 456.

Evans, M. D. D. and R. K. Lyons (2002, February). Order flow and exchange rate dynamics. *Journal of Political Economy 110*(1), 170–180.

Frankel, J. A. and K. A. Froot (1987). Using survey data to test standard propositions regarding exchange rate expectations. *The American Economic Review 77*(1), pp. 133–153.

Fujiwara, I., H. Ichiue, Y. Nakazono, and Y. Shigemi (2012). Financial markets forecasts revisited: are they rational, herding or bold? Globalization and Monetary Policy Institute Working Paper 106, Federal Reserve Bank of Dallas.

Harvey, A. C. (1990). *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge University Press.

Ikenberry, D. L. and S. Ramnath (2002). Underreaction to selfselected news events: The case of stock splits. *Review of Financial Studies 15*(2), 489–526.

Ito, T. (1990). Foreign exchange rate expectations: Micro survey data. *The American Economic Review 80*(3), pp. 434–449.

Jongen, R., W. F. Verschoor, C. C. Wolff, and R. C. Zwinkels (2012). Explaining dispersion in foreign exchange expectations: A heterogeneous agent approach. *Journal of Economic Dynamics and Control 36*(5), 719–735.

Jongen, R., W. F. C. Verschoor, C. C. Wolff, and R. C. J. Zwinkels (2008, March). Dispersion of beliefs in the foreign exchange market. *CEPR Discussion Papers* (DP6738).

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. *Transactions of the ASME–Journal of Basic Engineering 82*(Series D), 35–45.

Keane, M. P. and D. E. Runkle (1990). Testing the rationality of price forecasts: New evidence from panel data. *The American Economic Review 80*(4), pp. 714–735.

Lim, T. (2001). Rationality and analysts' forecast bias. *The Journal of Finance 56*(1), 369–385.

Long, J. B. D., A. Shleifer, L. H. Summers, and R. J. Waldmann (1990, August). Noise trader risk in financial markets. *Journal of Political Economy 98*(4), 703–738.

Macdonald, M. and I. W. Marsh (1996). Currency forecasters are heterogeneous: Confirmation and consequences. *Journal of International Money and Finance 15*(5), 665 – 685.

Mankiw, N., D. E. Runkle, and M. D. Shapiro (1984). Are preliminary announcements of the money stock rational forecasts? *Journal of Monetary Economics 14*(1), 15 – 27.

Manzan, S. and F. Westerhoff (2005). Representativeness of news and exchange rate dynamics. *Journal of Economic Dynamics and Control 29*(4), 677 – 689. Bounded rationality, heterogeneity and market dynamics.

Marsh, I. W. and D. M. Power (1996, April). A note on the performance of foreign exchange forecasters in a portfolio framework. *Journal of Banking & Finance 20*(3), 605–613.

Morris, S. and H. S. Shin (2002, December). Social value of public information. *American Economic Review 92*(5), 1521–1534.

Muth, J. (1961). Rational expectations and the theory of price movements. *Econometrica 29*, 315–335.

Pesaran, M. H. (1987). *The Limits to Rational Expectations.* Basil Blackwell, Oxford.