Individual exchange rate forecasts and expected fundamentals*

Christian D. Dick[‡] **Ronald MacDonald**[†] **Lukas Menkhoff**[**]

May 14, 2012

*We thank Martin T. Bohl, Yin-Wong Cheung, Laurence Copeland, Berthold Herrendorf, Karin Loch, Ian Marsh, Patrick Minford, Dieter Nautz and Maik Schmeling as well as participants of the European Economic Association's Annual Meeting 2011 and of several seminars for helpful comments on an earlier version of this paper.

‡Centre for European Economic Research (ZEW) Mannheim, P.O. Box 10 34 43, 68034 Mannheim, Germany, and Department of Economics, Leibniz Universität Hannover; e-mail: dick@zew.de.

†Department of Economics, University of Glasgow, Adam Smith Building, Glasgow G12 8RT, United Kingdom, e-mail: R.MacDonald@lbss.gla.ac.uk

**Department of Economics, Leibniz Universität Hannover, Königsworther Platz 1, 30167 Hannover, Germany, and Centre for European Economic Research (ZEW) Mannheim, Germany; e-mail: menkhoff@gif.uni-hannover.de.

Individual exchange rate forecasts and expected fundamentals

Abstract

This paper demonstrates using a large panel of individual professionals' forecasts that good exchange rate forecasts benefit from the proper understanding of fundamentals, specifically good interest rate forecasts. This relationship is robust to individual fixed effects and further controls. Reassuringly, the relationship is stronger during phases when the impact from fundamentals is more obvious. This occurs when exchange rates substantially deviate from their PPP values, when interest rate differentials are high and when exchange rates are less influenced by strong momentum. Finally, a commonly-shared simple exchange rate model can only produce accurate forecasts if interest rate forecasts are right.

JEL-Classification: F31, F37, E44.

Keywords: Exchange Rate Determination, Individual Expectations, Macroeconomic Fundamentals.

1 Introduction

Exchange rates are among the most important prices in open economies. In contrast, however, to their importance for firms, investors, and policy-makers, there is a considerable lack of understanding on the underlying determinants of exchange rates. At intermediate horizons, such as a month or half a year ahead, exchange rates seem to be hardly explained at all and, in particular, seem to be disconnected from fundamentals (Obstfeld and Rogoff, 2000). This disconnect is surprising, given the fact that foreign exchange markets react to changes in economic fundamentals within minutes (Andersen, Bollerslev, Diebold, and Vega, 2003) and that exchange rates reflect long-term changes in purchasing power (Taylor and Taylor, 2004). At intermediate horizons, however, the relationship between fundamentals and exchange rates seems to be largely unobservable, possibly even non-existent (Frankel and Rose, 1995; Rogoff, 2007). In this paper we suggest a new approach to uncovering potential connections, and provide evidence that fundamentals may indeed shape exchange rates.

Our motivation rests on the notion that the relationship between exchange rates and fundamentals is quite complex, for several reasons. First, the asset market approach to exchange rates emphasizes that *expected* fundamentals can have a greater impact on today's exchange rates than actual observed fundamentals, as emphasized by, for example, Engel and West (2005). Second, it is known that market participants possess and use fundamentals in heterogeneous ways (see Ito, 1990; MacDonald and Marsh, 1996), and that the use of fundamentals may change over time (e.g. Sarno and Valente, 2009). Finally, market participants do not only use fundamentals but also non-fundamentals as information in their decision making (Menkhoff and Taylor, 2007). Each of these sources of complexity may explain why conventional tests of exchange rate models in the spirit of Meese and Rogoff (1983) - regressing exchange rate changes on changes in fundamentals - fail (Cheung, Chinn, and Garcial-Pascual, 2005): the reason is not necessarily the above mentioned "disconnect" but possibly the use of a "false" model, i.e. a model that cannot account well enough for existing complex relations.

In order to circumvent this problem, we propose a research strategy which aims at making potential links between exchange rates and fundamentals visible without requiring an exchange rate model: the basic idea is to use *individual* forecasting data and examine whether there is a positive relationship between good exchange rate forecasting and good forecasting of exchange rate fundamentals by the same individual. This approach relies on survey data, i.e. on *expected* rather than *realized* data. Moreover, we do not make structural assumptions on forecasting *behavior*, but consider forecasting *performance* as an objective criterion. The reliance on performance requires no information on how (time-varying) fundamentals are used.

For our sample of more than 1,050 Germany-based professionals, we find that good US Dollar-Euro forecasts coincide with good interest rate forecasts for the U.S. and the Euro area, which indicates that a good understanding of the determinants of fundamentals helps in understanding exchange rate behavior. If the anticipated formation of exchange rates is supported by knowledge about fundamentals, this ultimately suggests that fundamentals do indeed contribute to shaping exchange rates. This is our main result.

In order to corroborate the relationship between individuals' forecasts of interest rates and exchange rates, we proceed in three steps: First, we use a panel approach that features controls and causality examination. Second, we test an implication of our relation of interest by exploiting the time-varying importance of fundamentals for exchange rates. Third, we test another implication by examining a simple UIP (uncovered interest parity)-like forecasting model. We find in all cases support for our conjecture that good interest rate forecasts are indeed useful for good exchange rate forecasts.

As a first examination we exploit the available panel approach by estimating individual fixed effects. These effects take account of unobserved heterogeneity between professional forecasters and thus control for a general ability to make good forecasts. We find that beyond individual differences in forecasting performance, our relationship of interest remains valid. Next we address a potential endogeneity between interest rates and exchange rates, using an IV approach supporting the claim that there is a causal relation from interest rate forecasts to exchange rate forecasts. Finally, further exploiting more information in the underlying data set, we find that our main result is robust to the consideration of more fundamentals and time-specific effects; the main result also tentatively holds for additional available currencies.

Second, we test an implication of our main result: if good interest rate forecasts support good exchange rate forecasts, this relationship will be stronger when the impact of fundamentals on exchange rates is more obvious. The relationship between fundamentals and exchange rates seems to be time-varying and the literature has provided evidence as to when the relationship may be closer: intuitively, this occurs if there is a consensus about the impact of fundamentals. We examine three indicators of potentially more fundamental impact: i.e. (1) when exchange rates deviate more strongly from their PPP value, (2) when foreign exchange markets are less ruled by a strong trend (less momentum), and (3) when interest rate differentials are rather large (and the high interest currency will depreciate). It transpires that indeed circumstances with potentially stronger fundamental impact seem to increase the benefit of good interest rate forecasts.

Third, we test our relationship of interest by applying it to a simple model of exchange rate determination. This model picks up the UIP relationship in the sense simply that a currency with a relatively increasing expected interest rate is expected to appreciate over the same period (and possibly depreciate later). We find that professionals' forecasts are consistent with this model. Moreover, we find that good, bad and medium forecasters seem to rely on this model. It is revealing, however, that the model's predicted future exchange rate is only correct for the group of good forecasters; the other forecasters appear to use the same model but their worse interest rate expectations do not correctly predict future exchange rates.

We are unaware of researchers using the procedures proposed in this paper before. Nevertheless, this research is based on, and related to, a number of earlier studies which we selectively overview in Section 2. Our study is based on the Centre for European Economic Research's (ZEW, Mannheim) monthly survey among financial market professionals, who give their forecasts about several variables, including exchange rates, interest rates and other macroeconomic fundamentals. As responses are marked by a personal identification number, every single forecast response during the 18-year history of the survey can be related to a concrete individual. We decided to include individuals with a minimum of 10 responses, i.e. considering holidays etc. equal to about one year. This leaves us with more than 1,050 professionals and more than 63,000 responses.

The paper is structured as follows. Section 2 introduces related literature, Section 3 presents data used and Section 4 documents our measurement of forecasting performance. Results are discussed in Section 5. Section 6 presents robustness exercises and Section 7 concludes.

2 Literature

In this section of the paper we provide a selective review of two exchange rate issues in order to position our research: first, we discuss the state of empirical research regarding exchange rate determination, in particular at the medium-term horizon and, second, we review studies concerning individual exchange rate forecasting.

Subsequent to the devastating result of Meese and Rogoff (1983), which showed the failure of exchange rate models in an out-of-sample forecasting context in comparison to a random walk model, the linkage of exchange rates to fundamentals has now been demonstrated to hold at very short and long horizons: at very short-term horizons, exchange rates clearly and systematically react to fundamentals, as many event studies have shown in detail (e.g., Andersen, Bollerslev, Diebold, and Vega, 2003), while at long-term horizons, exchange rates are attracted to the purchasing power parity level and, related to this, seem to be tentatively in line with the monetary model (e.g., Mark, 1995; Taylor and Taylor, 2004). Thus, it is the medium-term horizon where it is most difficult to show a clear relationship between fundamentals and exchange rates (Rogoff, 2007).

There are several approaches which try to obtain new insights in this respect, and there are three that we are particularly close to. First, it has been demonstrated that conventional tests of exchange rate models may fail because coefficients in these models seem to vary over time (e.g., Rossi, 2005). Bacchetta and Van Wincoop (2004) and (2009) argue that market participants attach too much weight to a certain "scapegoat" variable whose expected changes then impact on trading and market outcomes. This excessive focus diminishes the importance of other exchange rate fundamentals. ter Ellen, Verschoor, and Zwinkels (2011) also find evidence for time-varying forecasting strategies. A second approach is the consideration of dispersed heterogeneous information which is incorporated over time into exchange rates (e.g. Bacchetta and Van Wincoop, 2006). Order flow is interpreted as an empirical proxy for dispersed information flows and can indeed explain exchange rate changes over medium-term horizons (Evans and Lyons, 2002). Also the relation of order flow to macroeconomic information has been demonstrated recently (e.g., Evans, 2010). According to the order flow approach, there is private information about how to anticipate and interpret fundamental information which drives a wedge between published fundamentals and exchange rates.

A third approach is that of Engel and West (2005). They highlight the fact that exchange rates, as financial market prices, are determined by expectations about future fundamentals and show that under reasonable assumptions, exchange rates are close to a random walk even when they behave according to conventional exchange rate models. The argument runs that expectations may look far ahead, that such long-horizon expectations about fundamentals may differ markedly from current realizations, and that small changes in long-term expectations, as well as in the corresponding discount factors, can cause major changes in present exchange rates. Due to these characteristics of a financial market price, exchange rates cannot be related to contemporaneous fundamentals. Thus, the Meese and Rogoff-result may occur even if expected fundamentals are indeed the driving forces of exchange rates (see also Engel, Mark, and West, 2007).

These three strands of literature show that the relationship between exchange rates and fundamentals may be time-varying, may be weakened by the role of order flow and may be difficult to detect because expectations about fundamentals dominate realizations.

Due to the important role of individual expectations for our approach we now selectively review respective studies. Ito (1990) is the first to examine a small group of exchange rate forecasters individually, finding that they differ from each other and that part of this difference may be biased by their professional position. Further studies have analyzed heterogeneity (see the survey by Jongen, Wolff, and Verschoor, 2008), focusing on different currencies (MacDonald and Marsh, 1996), on the process of expectation formation (Bénassy-Quéré, Larribeau, and MacDonald, 2003), on individual differences in forecasting performance (Elliot and Ito, 1999) or on individual expectations about fundamentals (Dreger and Stadtmann, 2008).

In order to identify structure within the heterogeneity of forecasts, Frankel and Froot (1990) suggest an interplay of chartists and fundamentalists. The characteristics of these groups are surveyed in Menkhoff and Taylor (2007), and the interplay of these groups and how this impacts market outcome has been modeled, for example, by De Grauwe and Grimaldi (2006). A direct and measurable implication of expectation heterogeneity is examined by Beber, Breedon, and Buraschi (2010) who find, *inter alia,* that heterogeneity has a significant effect on implied volatility, which is a major pricing determinant of currency options.

What we learn from these studies is that there are various dimensions of heterogeneity among individual exchange rate forecasters and that heterogeneity is important for modeling and pricing in foreign exchange. This motivates analyzing individual data and considering potentially rival influences from non-fundamental forces, such as chartism.

Taking the insights from both exchange rate issues together - (i) complex relations between exchange rates and fundamentals at medium-term horizons and (ii) very heterogeneous exchange rate expectations - we prefer to stay agnostic about the specific form of the relationship between exchange rates and fundamentals. Instead, we simply focus on individual performance in forecasting both exchange rates and fundamentals, and then examine the relationship between individual performances regarding exchange rate forecasts and expected fundamentals. This approach takes account of major heterogeneity between forecasters, implicitly considers time-varying relations between exchange rates and fundamentals, allows for the possibility of private information (as in the order flow literature) and for an impact from non-fundamental analysis. As far as we are aware this is the first time that such an approach has been used in the literature.

3 Data

Microdata of forecasts We consider USD/EUR exchange rate forecasts by financial professionals as collected in a unique panel spanning 18 years of individual forecasts made in the context of the Financial Market Survey by the Centre for European Economic Research (ZEW) in Mannheim, Germany. These forecasters work in various areas of the financial industry or in financial departments of industrial companies. The forecasts collected in the ZEW Financial Market Survey have been used in various recent empirical studies in finance and macroeconomics, such as Schmeling and Schrimpf (2011). The reason for the popularity of this data set lies in the relatively high frequency of the survey point (monthly), and the relatively high number of responses per point: the data set comprises 216 survey points from 12.1991 to 11.2009, with an average number of responses of 307; hence, the microeconomic panel is both relatively long and broad, summing up to a total of more than 1,700 forecasters and 66,000 observations. As a meaningful measurement of forecasting performance requires a certain minimum number of responses per forecaster, we omit forecasters with less than 10 USD/EUR forecasts. This reduces the sample to 1,056 forecasters. Table 1 provides more details on the structure of the survey responses. The US Dollar forecasts are of a qualitative nature; i.e., forecasters indicate whether the USD is expected to appreciate, remain unchanged or depreciate compared to the Euro within the subsequent six months.[1]

Table 1 about here

This data set is well suited for the particular research topic of this paper for three reasons: first, and consistent with, for example, Consensus Forecasts, the ZEW Financial Market Survey includes a variety of targeted macroeconomic and financial variables, and the forecasters tend to respond to all of the central questions when they take part (there are only 1.3% missing responses for USD/EUR forecasts, and even less than 0.5% for European interest rate forecasts). This allows us to consider the USD/EUR forecasts in connection with the interest rate forecasts of the identical forecaster at the same point in time, which is the main focus of our study; in addition, we also have simultaneous forecasts with respect to other exchange rates (GBP/EUR, JPY/EUR), inflation rates and economic activity, which we use as control variables in our regressions. Second, we have access to the *individual* forecasters' predictions rather than the consensus forecasts and as the observations are associated with person-specific IDs, we are able to study the heterogeneity in forecasting performance across forecasters. Third, we have exact information about the date on which an individual forecaster replies to the survey, which allows us to relate forecasts to precise exchange rate realizations, such as the reference point of a forecast, or the trend of the last 30 days before the forecast was made.

Exchange rates The period of interest between 12.1991 and 11.2009 includes the transition from national currencies to the Euro. We therefore consider the US Dollar (USD) with respect to the D-Mark (DM, before 01.1999) and the Euro (EUR, after 01.1999). Hence, we convert the DM/USD exchange rates into USD/EUR rates for the period before 01.1999.[2] We consider both

[1]The relevant survey question was (after 01.1999) "*In the medium-term (6 months), the following currencies compared to the Euro will appreciate/stay constant/depreciate.*" or (before 01.1999) "*The exchange rate (D-Mark per one unit foreign currency) of the following currencies will increase/not change/decrease.*".

[2]Please note that in this paper the spot rate S_t and also the forward rate $F_{t,k}$ are given as units of foreign currency per Euro, which implies that $S_{t+1} - S_t > 0$ corresponds to a depreciation of the foreign currency with respect to the Euro. This representation of the USD/EUR rate is consistent with most studies, e.g. Fama (1984), Backus, Gregory, and Telmer (1993) or Burnside, Han, Hirshleifer, and Wang (2010).

spot exchange rates as well as the one-month forward exchange rates on a daily basis. We replace missing exchange rates (e.g. from weekends) with those recorded on the preceding trading day.

4 Forecasting performance

For the measurement of forecasting performance, we follow several authors who have argued that forecasts about marketable assets should be evaluated from an investor's perspective by a zero net investment trading rule (Leitch and Tanner, 1991; Anatolyev and Gerko, 2005; Jordà and Taylor, 2011). Accordingly, we translate the qualitative forecasts of respondents into a long/short position, i.e., we translate an appreciation expectation into a buy etc.

Measuring forecasting performance with respect to exchange rates Regarding foreign exchange, we follow Elliot and Ito (1999) who formulate a trading strategy in which sophisticated investors take a long USD position using the forward market when they expect the US Dollar to appreciate, such that $F_{t,k} > E_{i,t}[S_{t+k}]$, and take a short USD position when they expect the US Dollar to depreciate, such that $F_{t,k} < E_{i,t}[S_{t+k}]$, where $E_{i,t}[S_{t+k}]$ represents the subjective expectation of forecaster i.[3]

The usage of trading rules is easily adaptable in the context of monthly qualitative forecasts. In the underlying survey, the professional forecasters have to respond to the question: do they expect a foreign currency to appreciate or depreciate compared to the Euro with the current *spot* rate as reference point. A natural trading strategy, T_{ind}, triggers a trade in the forward market according to the expected direction of change of spot exchange rates. The one-month forward contract will then be settled one month later in the spot market, and a new trade will be made in the forward market according to the new forecast made in the current month. As forward rates are linked to interest rates differentials through covered interest rate parity, the log returns of the trading rule

[3]Strictly speaking forecasts refer to spot rates but the trading rule also considers interest rate differentials. We show in the robustness section that this slight inconsistency does not drive our results.

take account of refinancing costs.[4] We consider the log returns of T_{ind} based on the prediction of forecaster j, i.e.

$$r_{j,t,t+k} = I_t(s_t > E_{j,t}[s_{t+1}])(f_{t,1} - s_{t+1}) + I_t(s_t < E_{j,t}[s_{t+1}])(s_{t+1} - f_{t,1}) \tag{1}$$

as the performance measure for exchange rate forecasts. $r_{j,t,t+k}$ varies across forecasters and time and may thus be used in the context of panel regressions.

Compared to alternative measures, there are important advantages to using trading rules as a forecast performance measure: first, conventional statistical measures (such as the mean squared error) underlie narrow assumptions about a forecasters' loss function (e.g., quadratic).[5] Second, the trading rule-approach avoids the loss of information by a categorization of continuous realizations of exchange rate movements into an *appreciate*, a *constant* and a *depreciate* range. Third, we are able to compute the average profit and the Sharpe ratio for each forecaster. The latter is relevant in cross sectional analysis as profits from trading strategies typically depend on their risk, which may be different for several forecasters.[6] Sharpe ratios can also be linked to other studies on exchange rate models (Jordà and Taylor, 2009; Rime, Sarno, and Sojli, 2010) or carry trade strategies (Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2010; Menkhoff, Sarno, Schmeling, and Schrimpf, 2011). For example, Jordà and Taylor (2009) compare Sharpe ratios in their analysis of carry trades to the Sharpe Ratio for the S&P 500 of 0.4. For the sake of comparability with our results, we also provide monthly Sharpe ratios in Table 2.

Table 2 about here

It can be seen that the annual Sharpe ratio of the median forecaster amounts to 0.114, which

[4] As the paper aims at comparing forecasting performance rather than establishing evidence for profitable trading strategies for investors, *transaction* costs (e.g., bid/ask spreads) are ignored.

[5] While we argue that trading rules are more appropriate to measure exchange rate forecast performance in our setting, we also apply an error-based concept in the robustness section, and find similar results.

[6] The choice of the neutral ("no change") category provides an opportunity to reduce the risk by following a trading strategy. Furthermore, we are considering an unbalanced panel, such that some forecasters may have been active in phases with higher volatility (and higher profit opportunities at the same time).

is rather low. This indicates that a trading strategy based on some average exchange rate forecast is unlikely to be profitable in practice, in particular as transaction costs are not yet taken into account. However, the annual Sharpe ratio for the forecaster at the 95% percentile amounts to 1.159, which is substantial. Table 2 also shows that Sharpe ratios of greater than 0.4 can be achieved by the forecasts of almost 30% of the forecasters. Overall, these statistics demonstrate the heterogeneity in forecasting performance across the sample, which is central to the strategy followed in our analysis.[7]

Measuring forecasting performance with respect to fundamentals Unlike currencies, macroeconomic fundamentals are not tradeable assets. As performance measures based on trading rules are not available, we rely on a measure of *forecast errors* by comparing forecasts with their respective realizations. For this purpose, the directional forecasts (e.g., the interest rate rises, stays constant, or decreases)[8] are coded for simplicity in $X^e_{i,t+6} \in \{1, 0, -1\}$, an approach also applied by, for example, Souleles (2004). Likewise, the realizations (observed interest rates, inflation rates, growth rates of industrial production) are also categorized into three corresponding groups. It has to be noted, however, that the latter step depends on the choice of threshold values for a no-change category. We choose symmetric threshold values such that, over the entire time span, the share of observations in the no-change category for *realizations* is equally large as the share of *forecasts* in this category.[9] In this setting, forecasters can be wrong to two different extents: they make a *small* error when they predict an unchanged variable, whereas the actual outcome is an increase, but a *severe* error if they predict a decline. We take account of the severity of these errors by computing

[7]Elliot and Ito (1999) present their results in terms of t-values, a performance measure closely related to the Sharpe ratio, which we also report in the Appendix, Table A1.

[8]For economic activity, the Financial Market Survey asks whether the *economic situation* will improve, remain unchanged, will worsen over 6 months.

[9]The share of forecasts in the no-change category is 40 percent for short-term interest rates, 44 percent for industrial production, and 45 percent for inflation in the Eurozone/Germany. The figures are similar for the U.S. for inflation and interest rates; for industrial production, however, the unchanged category contains 53 percent of the observations. Note that we take different threshold values for the Eurozone and the Unites States, respectively. For example, we group realizations into this category if the yearly industrial production growth rates (inflation rates) six months ahead are not more than 2.2 (0.345) percentage points different from the current ones. Short-term interest rates are categorized into this middle category if they have not changed by more than 10.5 percent within a six-month horizon.

absolute forecast errors by $|{}_t\varepsilon_{i,t+6}(X)| = |{}_tX^e_{i,t+6} -_t X_{t+6}|$, which takes on 2 for a severe error, 1 for a small error and 0 for a correct prediction.

Table 3 presents the cross-section of average absolute forecast errors, $|\varepsilon(\bar{X}_{j,t}|$ for different macroeconomic fundamentals, including U.S. and Eurozone interest rates. It can be seen that the forecasters tend to commit less severe forecast errors for the interest and inflation rate in the Eurozone compared to the United States, while this is reverse for industrial production.

Table 3 about here

5 Empirical analysis

This section presents results starting with describing the fundamental relationship between (forecasting performance with respect to) fundamentals and exchange rates (Section 5.1). We then test whether this relation holds in a panel approach (Section 5.2), whether an implication holds (Section 5.3) and whether it can be revealed from forecasters' implicitly expected relation between interest rate and exchange rate forecasts (Section 5.4).

5.1 Exchange rates and fundamentals

This paragraph shows the fundamental relationship that we find throughout various analyses of our data: a positive link between forecast performance for exchange rates and for an important fundamental; namely, interest rates. As introduced above, the measurement units for the respective performance measures are the *average return* of T_{ind} for exchange rate forecasts, and *absolute forecast errors* for interest rate forecasts. Figure 1 illustrates the average perfromance for each of the 1,056 forecasters in our sample with respect to U.S. interest rate forecasts and USD/EUR-forecasts.

Figure 1 about here

Figure 1 shows a negative relationship between the interest rate forecast errors (on the y-axis) and the returns earned from their exchange rate forecasts (on the x-axis), which underlines that performance is positively related across the forecasted variables. In fact, the correlation coefficient of -0.23 is statistically significant at any conventional level. Also a negative, although weaker relationship is found between forecast errors with respect to Eurozone interest rates and U.S. dollar forecast performance; the corresponding correlation coefficient is -0.08, which is significant at the 5% level.

5.2 Panel analysis

While we have demonstrated *correlation* between the performance with respect to interest rate and exchange rate forecasts further analyses are required: (i) to rule out that forecasting ability for both interest rates and exchange rates does not jointly arise because a forecaster is particularly skilled, (ii) to demonstrate that the performance of the interest rate forecasts is *causal* for the performance of the exchange rate forecasts, and (iii) to check that this result is robust for the consideration of alternative fundamental forecasts. This section introduces a panel approach which looks into the individual forecasts rather than the forecaster-specific aggregates and uses fixed effects, instruments, and further control variables to address (i)-(iii), respectively.

The model We conduct fixed effects panel regressions of the individual return of a trading strategy, T_{ind} ($r_{j,t,t+1}$), based on an individual forecast by forecaster j in period t on the absolute error the forecaster makes with respect to the interest rates in the Eurozone ($\varepsilon_{j,t}(i^{EUR})$) or the United States ($\varepsilon_{j,t}(i^{USD})$), as well as on a battery of control variables $\Phi_{j,t}$ and $\Psi_{j,t}$ in different specifications, i.e.

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(i^{EUR})| + \beta_2|\varepsilon_{j,t}(i^{USD})| + \gamma\Phi_{j,t} + \delta\Psi_{j,t} + \epsilon_{j,t}. \tag{2}$$

By following the fixed effects methodology, we rule out that unobserved heterogeneity across forecasters drives our results, such that we can attribute a change in exchange rate forecast performance (compared to an individual forecaster's average performance) to changes in $|\varepsilon_{j,t}(i^{EUR})|$, $\Phi_{j,t}$ or $\Psi_{j,t}$. In line with this idea, the Breusch-Pagan tests reject the null of no individual-specific effects particularly for the simpler specifications (i.e. (i)-(iv) from Table 4). The Hausman tests confirm that a fixed effects estimator should be applied, as random effects are inconsistent for virtually all specifications.[10]

In Eq. 2, we regress the return from a trading strategy (which evaluates the performance of exchange rate forecasts) on a contemporaneous performance measure with respect to interest rates ($\varepsilon_{j,t}(i)$) or, as control variables, with respect to other fundamentals (in $\Phi_{j,t}$). While this setting allows us to focus on the connection between interest rate and exchange rates forecasts, it generates a potential endogeneity problem, as it is not *a priori* clear that interest rate forecast errors cause errors in exchange rate forecasts and not vice versa: for example, if exchange rates and fundamentals are related, there could be a third factor affecting both the USD/EUR exchange rate as well as the interest rate in one of these countries. To eliminate this problem, we rely on IV estimation using the first lagged value of the forecasting errors with respect to interest rates and other fundamentals as external instruments for forecast errors; this IV approach is preferable to an estimator without instruments according to the results from Davidson and MacKinnon (1989)'s test in the majority of specifications.[11]

The effect of interest rate forecasts Table 4 reports the results of the fixed effects regression of the return earned from T_{ind} (i.e., our forecasting performance measure) on the absolute forecast error with respect to interest rates as well as various control variables: *negative* coefficients for the error variables $|\varepsilon(i)|$ indicate that *more severe* errors in the predictions of interest rates are associated with *lower* success in predicting exchange rates.

[10] See Table A2 in the Appendix for detailed results.

[11] See also Table A2 in the Appendix for further details.

Table 4 about here

Specifications (i) and (ii) only consider the influence of absolute interest rate forecast errors on returns, and find a negative and significant relationship. This effect is economically important as, for example, an increase in U.S. interest rate forecast error by one error point is associated with a decrease of the monthly return by 13 basis points. A similar relationship (11 basis points) holds for the forecast error with respect to the Eurozone interest rates.

Controlling for other fundamentals Depending on the specification, the vector of control variables $\Phi_{j,t}$ includes individual forecast errors with respect to other fundamentals than interest rates, i.e. inflation ($|\varepsilon(\pi)|$) and industrial production growth forecast errors $|\varepsilon(y)|$. These control variables are chosen to single out the effect of *interest rate* forecasts while at the same time acknowledging that inflation and economic activity are further important fundamentals to exchange rates.

As columns (iii) and (iv) in Table 4 show, the coefficients for the interest rate forecast errors remain virtually unchanged when further fundamentals are controlled for. The results are also stable and even more pronounced when we additionally control for year dummies in specifications (v) to (vii). We also find a relatively robust negative relationship between forecasting errors made for European inflation rates and exchange rate forecasting performance, while the coefficient estimates for the remaining fundamental forecast errors are mostly insignificant with the exception of U.S. production forecasts - see specifications (iii) to (vii).

5.3 Exchange rate and fundamentals: interactions in different market phases

In the following, we test an implication of our main result, namely that the impact of correctly expected fundamentals on exchange rates depends on *market phases*, which is motivated by the many studies mentioned above finding a time-varying influence of fundamentals on exchange rates (e.g., Rossi, 2005; Bacchetta and Van Wincoop, 2004, 2009). In order to define relevant market phases, we build on insights from the empirical literature on exchange rate behavior, as well as market participants' behavior: (i) Following several studies on PPP (e.g. Taylor, Peel, and Sarno, 2001; Christopoulos and Leon-Ledesma, 2010) we hypothesize that fundamentals are more important for exchange rate forecasts when there is a strong obvious misalignment of the nominal exchange rate from its PPP value. (ii) Traders state that when technical trading is particularly pronounced this reduces the impact of fundamentals on exchange rates (Cheung and Wong, 2000), which is largely consistent with shifts in forecasting approaches (Jongen, Verschoor, Wolff, and Zwinkels, 2012) and with chartist-fundamentalist models (see, for example, De Grauwe and Grimaldi, 2006). Finally, large interest rate differentials may have an impact, as they signal an exchange rate readjustment according to uncovered interest rate parity (or they invite carry trades, which would tend to reduce the role of fundamentals). We define market phases on the basis of the prevailing market conditions.

Defining market phases When the nominal exchange rate deviates strongly from its PPP value, the exchange rate can be expected to revert to its fundamental value. Thus, we capture such *value phases* by a dummy variable labeled FUND_t. More specifically, following the concept of real exchange rates, we compute a ratio of the CPI in Germany compared to the CPI in the United States,[12] i.e. (in logs)

$$q_t = s_t + p_t^{EUR} - p_t^{US}, \tag{3}$$

where p_t represent the CPIs, s_t the log exchange rate and q_t the ratio. If q_t is relatively large (small), the USD is relatively undervalued (overvalued) compared to the EUR in real terms. We take a recursive approach by comparing q_t to its distribution over the preceding ten years at each point in time. FUND_t equals unity if q_t belongs to the bottom or top quartile, and zero otherwise.

We consider the size of the trend of the USD/EUR exchange rate over the previous 30 days as a signal for a prevailing *momentum phase*. Again, we carry out a recursive approach and classify

[12] To avoid a structural break, we take the German CPI as reference base for the entire time span. Using the CPI for the entire Eurozone for the entire time span yields similar results.

past absolute trends into three equally large subgroups: a phase in which the prevailing trend is relatively low ("low-momentum-phase", belonging to the lowest 33 percent during the 10 years prior to the respective date), a "normal momentum phase" and a "high-momentum-phase" (belonging to the top 33 percent).[13] We capture these phases by dummy variables D^L and D^H which are one for low and high momentum phases, respectively, and zero otherwise (the normal momentum phase will be considered the benchmark).

Finally, market conditions may differ in terms of the *interest differential phase*. To take this into account, we measure the absolute size of the differential between U.S. and European short term interest rates, $|i^{USD} - i^{EUR}|$.

The interaction model To investigate how the impact of correctly anticipated fundamentals depends on the market phases introduced above, we consider interaction models following regressions of the type

$$r_{j,t,t+1} = \mu_j + \beta_1 |\varepsilon_{j,t}(i)| + \beta_2 \mathrm{SIG}_{j,t} + \beta_3 \left(|\varepsilon_{j,t}(i)| \times \mathrm{SIG}_{j,t} \right) + \epsilon_{j,t}, \tag{4}$$

where $\mathrm{SIG}_{j,t}$ represents the signal for the respective market phase; we conduct the regressions for $|\varepsilon_{j,t}(i^{EUR})|$ and $|\varepsilon_{j,t}(i^{USD})|$ separately and without instruments. Controlling for different states of the value, momentum or interest rate differential phases, respectively, we focus on the estimate of the marginal effect of an interest rate forecast (error) on the return earned by the exchange rate forecast, i.e. $\frac{\partial r}{\partial |\varepsilon(i)|} = \hat{\beta}_1 + \hat{\beta}_3 \times \mathrm{SIG}_{j,t}$.[14]

Forecasting fundamentals depending on value phases We model interaction effects of the absolute interest rate forecast error in dependence of the value market phase by setting $\mathrm{SIG}_{j,t} =$

[13]As we have the exact date of each individual forecast in our data, we are able to attach such a trend-phase as well as a contemporaneous interest rate differential to every forecast.

[14]The standard error of this marginal effect can be obtained by

$$\left(Var(\hat{\beta}_1) + \mathrm{SIG}_{j,t}^2 Var(\hat{\beta}_3) + 2\mathrm{SIG}_{j,t} Cov(\hat{\beta}_1, \hat{\beta}_3) \right)^{\frac{1}{2}}.$$

FUND_t in Eq. 4. Table 5 shows the coefficient estimates and the computed marginal effects.

Table 5 about here

Table 5, (i)-(ii), shows that the negative marginal effects of an interest rate forecast error are larger when $\text{FUND}_t = 1$, i.e. when the exchange rate deviates substantially from its fundamental value according to PPP: the marginal effect of an error with respect to Eurozone interest rates is almost twice as large in these market phases with fundamental mispricing. The average return from T_{ind} decreases by 20 basis points for each increase in error points with respect to U.S. interest rates when currencies are fundamentally mispriced; in contrast, this effect only amounts to 13 basis points in market phases when exchange rates are more aligned to fundamental values. To illustrate this finding, Figure 2 shows predictions of returns conditional on the forecast error and the degree of deviation of the current nominal exchange rate from its PPP level.

Figure 2 about here

While these findings suggest that it is more important to understand *interest rates* in times in which a severe mispricing of exchange rates calls for value strategies, it is worth noting that a similar effect can be documented for industrial production, whereas there is a mixed pattern for inflation rates, see Table 5, (iii)-(vi).

Forecasting fundamentals based on momentum phases Similarly, we model interaction effects of the absolute interest rate forecast error in dependence of the momentum market phase by setting $\text{SIG}_{j,t} = \left(D^H_{j,t}\ D^L_{j,t}\right)'$ and $\beta_2 = (\beta_{21}\ \beta_{22})$ and $\beta_3 = (\beta_{31}\ \beta_{32})$ in Eq. 4.[15]

Table 6, (i) and (ii), shows that the marginal effects of interest rate forecast errors vary substantially across momentum phases: they matter most when the momentum is not particularly

[15]The marginal effect is now computed by $\frac{\partial r}{\partial|\varepsilon(i)|} = \hat{\beta}_1 + \hat{\beta}_{31} \times D^L + \hat{\beta}_{32} \times D^H$ and its standard error by

$$\left(Var(\hat{\beta}_1) + (D^L)^2 Var(\hat{\beta_{31}}) + (D^H)^2 Var(\hat{\beta_{32}}) + 2(D^L)Cov(\hat{\beta}_1, \hat{\beta_{31}}) + 2(D^H)Cov(\hat{\beta}_1, \hat{\beta_{32}})\right)^{\frac{1}{2}}.$$

pronounced.

Table 6 about here

The marginal effect of a deterioration of a Euro interest rate forecast by one error point corresponds, on average, to a decline of the monthly trading return of 0.213 percentage points when the forecasts were made in normal momentum phases (see (i)). This value is not far away from the marginal effect in low momentum phases (-0.223), but differs substantially from the marginal effects observed in high momentum phases (0.025). While the former two marginal effects are significantly different from zero, this is not the case for the latter. These results indicate that a good prediction of European interest rates helps improve the exchange rate forecasts unless momentum trading dominates markets. To illustrate this issue further, Figure 3 depicts predictions of returns conditional on the forecast error and the momentum phase.

Figure 3 about here

Figure 3(a) shows that returns decrease with increasing Euro interest rate forecast error for both low and normal momentum phases, leading to a positive expected return if the interest rates are predicted correctly, and to a negative expected return if the interest rates are anticipated in a (severely) wrong way. In contrast, the expected return is positive in high momentum phases regardless of the quality of the Euro interest rate forecast. As can be seen from the marginal effects in Table 5, (ii), and from subfigure 3(b), the results are very similar (and maybe even more pronounced) when the relationship between the forecast of the U.S. interest rate and the exchange rate forecasting performance is considered.

For comparison, Table 6 also shows that the marginal effects of the other fundamental forecast errors (w.r.t inflation, industrial production) show a similar pattern across momentum phases but are smaller in absolute value compared to those of the interest rate forecast errors: to mention the most pronounced effect, an increase of one error point with respect to the forecast of the European industrial production (see (v) in Table 6) leads to a return decrease of 0.155 percentage points in low momentum phases.

Forecasting fundamentals and interest differential phases Finally, we also consider interaction models of the absolute forecast error with interest differential phases; hence, we set $\text{SIG}_t = |i_t^{USD} - i_t^{EUR}|$, and we focus on the marginal effects, i.e. $\frac{\partial r}{\partial |\varepsilon_{j,t}(i)|} = \hat{\beta}_1 + \hat{\beta}_3 \times |i_t^{USD} - i_t^{EUR}|$. Table 7 presents the coefficient estimates as well as the marginal effects evaluated at the average absolute interest rate differential over the sample period.

Table 7 about here

For this particular value, there are relatively large negative effects of prediction errors in interest rates forecasts (see (i) and (ii)). Figure 4 shows the state-dependent marginal effects in more detail.

Figure 4 about here

The effects of errors in interest rate forecasts (for both U.S. and EUR interest rates) on exchange rate forecasts are significantly negative; the marginal effects even decrease with increasing interest rate differentials. These results indicate that the ability to predict interest rates is even more pronounced in phases in which interest rate differentials are large in absolute terms. This suggests that large interest rate differentials are rather a sign of a fundamental misalignment (in which fundamental analysis becomes more important) than an opportunity for carry trades.

For comparison, Table 7, (iii)-(vi), also reports similar exercises for the other fundamental forecasts besides interest rates. The findings for interest rate forecasting errors are mainly confirmed by growth forecast errors but not by inflation forecast errors as Figure 4, (c)-(f), illustrates. As for the analysis of value phases, the contribution of good inflation forecasts to good exchange rate forecasts does not fit well into the pattern. One may speculate whether a possible impact of inflation (forecasts) on exchange rates is overruled by very obvious, relatively shorter-term economic forces, i.e. short-term interest rates and business cycle considerations.

5.4 The expected relation between interest rate and exchange rate changes

So far, we have demonstrated that exchange rate forecasting performance depends on the quality of interest rate forecasts. Now we go a step beyond relating performance measures by directly examining the expected relation between interest rate and exchange rate changes. For this exercise, we rely on a core ingredient of a wide class of exchange rate models, i.e., the mechanism that a relative interest rate increase appreciates the respective currency. This mechanism is consistent, for example, with the uncovered interest parity as it describes the expected exchange rate adjustment of an expected interest rate shock; this mechanism is assumed to be present in the Mundell-Fleming framework, and it is consistent with the overshooting exchange rate model and neo-Keynesian macroeconomic models.

In a first step we test whether professionals in our survey do form exchange rate expectations in line with this mechanism. If this mechanism is widely assumed to work, we can test in a second step whether the better input (interest rate forecasts) does indeed contribute to better output (exchange rate forecasts). To test this line of reasoning, consider a simple model which relates expected exchange rate changes to the expected change in Eurozone interest rates relative to the expected change in the U.S. interest rates, i.e.,

$$E_t[\Delta s_{t,t+6}] = \beta_0 + \beta_1[E_t[\Delta i^{EUR}_{t,t+6}] - E_t[\Delta i^{US}_{t,t+6}]] + \epsilon_t \tag{5}$$

If the difference between the expected change in Eurozone interest rates and the expected change in the U.S. interest rates ($E_t[\Delta i^{EUR}_{t,t+6}] - E_t[\Delta i^{US}_{t,t+6}]$) determines expected changes in foreign exchange rates, we would expect the parameter β_1 to be different from zero. We estimate Eq. 5 based on the individual exchange rate and interest rate forecasts with a fixed-effects regression,[16] and report

[16] The forecasters give qualitative information w.r.t. increases or decreases of both U.S. and Eurozone interest rates, which we code 1,0, and -1. For the relative interest rate measure, we take the difference of these forecast. When the expectation is identical for both Eurozone and U.S. interest rates, the differential equals 0. In principle, the differential is given on a scale from -2 to 2. Positive values represent a larger expected increase in Eurozone interest rates compared to the increase in U.S. interest rates.

the coefficient estimates in Table 8, Panel A.

Table 8 about here

As Table 8, (i), demonstrates, $\hat{\beta}_1$ is found to be significantly larger than zero; consequently, the forecasters expect, on average, the USD to depreciate against the Euro ($\Delta s_{t,t+6} > 0$) when the differential of Eurozone interest rates vs. U.S. interest rates increases. As there are more candidate influencing factors beyond interest rates, we also augment Eq. 5 by $E_t[\Delta\pi^{EUR}_{t,t+6}] - E_t[\Delta\pi^{US}_{t,t+6}]$, i.e., the difference in the expected changes in inflation. Table 8, (ii), illustrates that nevertheless, the relative interest rate expectations continue to have a strong effect whereas the inflation differential also has an effect, albeit a smaller one. Hence, we conclude that expected interest rate differentials are indeed a dominant determinant of forecasters' exchange rate expectations, and hence we continue to consider Eq. 5 as a parsimonious representation of the forecasters' model.

To elaborate this in more detail, we analyze whether good forecasters rely on a different model than bad forecasters. To do so, we divide the total set of forecasters into three different groups according to their overall (*ex post*) forecasting performance (measured by average returns of a forecaster j) and reestimate Eq. 5 for these subgroups (high performer, medium performer, and low performer) separately. It can be seen from Table 8, (iii)-(v), that relative interest rate expectations matter regardless of whether we consider low, medium, or high performers, respectively: the coefficient estimates are found to be significantly positive for all groups.

In a second step, we check whether the individual interest rate forecasts are suited to predict *actual* exchange rate changes, given that the forecasters follow a model with the above mentioned structure (i.e., $E_t[\Delta s_{t,t+6}]$ and $E_t[\Delta i^{EUR}_{t,t+6}] - E_t[\Delta i^{US}_{t,t+6}]$ are *positively* related). In particular, we regress ex post exchange rate changes ($\Delta s_{t,t+6}$) on the RHS variables of Eq. 5 and estimate $\hat{\beta}_0$ and $\hat{\beta}_1$ for the groups of low, medium, and high performers separately. Table 8, Panel B, displays the results. Strikingly, the estimates for $\hat{\beta}_1$ are significantly *negative* for the low and medium performers (see (vi)-(vii)): this shows that on average, the USD has *appreciated* after an increase of the differential of Eurozone interest rates change vs. U.S. interest rates change expectations of these groups. This is contrary to the forecasters' models' implication and will lead to misguided forecasts, on average. In contrast, $\hat{\beta}_1$ carries the correct (positive) sign for the group of high performers (see (viii)); more often than not, an increase of the differential of Eurozone interest rates change vs. U.S. interest rates change expectation by this group is associated with USD *depreciation*, as is implied by the forecasters' model.

Overall, the findings in this section provide evidence for the view that the qualitative difference between low and high performers (w.r.t. exchange rate forecasts) is unlikely to be due to differences in the exchange rate forecasting model (rather, the model's structure is in fact similar), but due to differences in the model's central input factor: the quality of individual interest rate forecasts.

6 Robustness

This section documents some of our robustness calculations showing that the main findings are not unique to the USD/EUR exchange rate (Section 6.1) and do not depend on the specific trading rule (Section 6.2) or on the usage of trading rules as a performance measure in general (Section 6.3). Finally, Section 6.4 demonstrates that our main results are robust to the chosen estimator.

6.1 Further currencies

As our panel data set also includes forecasts for the GBP/EUR and JPY/EUR exchange rates, British and Japanese interest rates and further fundamentals, we can extend the analysis above to further currencies. In doing so, we show that the overall relationship between interest rate forecasts and exchange rate forecasts demonstrated above is not unique to the USD/EUR exchange rate. However, relations are more noisy for these minor currencies, probably because professionals focus on the US dollar.

As introduced in Eq. 2, we run fixed effects regressions of the type

$$r_{j,t,t+1} = \mu_j + \beta_1 |\varepsilon_{j,t}(i^{EUR})| + \beta_2 |\varepsilon_{j,t}(i^{\star})| + \gamma \Phi_{j,t} + \delta \Psi_{j,t} + \epsilon_{j,t},$$

i.e., we regress the return of a trading rule based on an individual's forecasts of the GBP/EUR rate (and separately, the JPY/EUR rate) on the forecast error with respect to the European interest rate and the foreign (i.e. British or Japanese) interest rate $i^{\star}$ and corresponding control variables. Table 9 displays the results. Strikingly, the negative and significant coefficients of absolute interest rate forecast errors remain a common feature in all specifications, while there are larger differences across currencies and specifications for the other fundamentals considered control variables.

Table 9 about here

The β coefficients differ in size across currencies, as they are largest for the Japanese, and smallest for the British interest rate forecast errors: an increase of the Japanese interest rate forecast error by one standard deviation (0.5529) decreases the return for the JPY/EUR investment according to T_{ind} by 37 basis points (in (iv)), which is even relatively larger than the documented relationship for the U.S. interest rate and the USD/EUR exchange rate. In contrast, it appears that the influence of a valid Eurozone interest rate forecast is more important than a British interest rate forecast, as a one standard deviation increase in the Eurozone interest rate decreases the return for the GBP/EUR investment according to T_{ind} by 18 basis points, which is in a similar range to the U.S. interest rate for the USD/EUR exchange rate. In contrast, an increase in absolute forecast error with respect to UK interest rates decreases the exchange rate forecast return by only 8 basis points.

6.2 Different specifications of the trading rule

So far, we have used a market-based loss function T_{ind} (see Eq. 1) for the evaluation of an individual's forecasting performance, which we repeat here for convenience:

$$r_{j,t,t+k} = I_t(s_t > E_{j,t}[s_{t+1}])(f_{t,1} - s_{t+1}) + I_t(s_t < E_{j,t}[s_{t+1}])(s_{t+1} - f_{t,1}).$$

This rule implies that the investor uses the forward market when taking a long/short position, which is (through covered interest rate parity) equivalent to borrowing in one currency and investing the same amount in the other currency at market interest rates. While this approach is natural for an investor, it has to be noted that we observe exchange rate forecasts expressed in terms of changes of *spot rates* (and not *forward rates*, which incorporate spot rates and *and* the current levels of refinancing costs (i.e., the interest rate differential). Hence, $E_t[s_{t+1} - f_t^1]$ is not directly observable nor can it be backed out indirectly (due to the directional nature of the considered forecasts). To deal with two potential objections on these grounds, this section presents two alternative trading rules as robustness checks: first, the measured return could be driven by changes in the refinancing costs rather than exchange rates (and hence we replace $f_{t,1}$ in Eq. 1 with s_t for an alternative trading rule $T_{ind}(1)$). Second, trades which are made according to Eq. 1 could be *ex ante* unprofitable if $s_t > E_{j,t}[s_{t+1}]$ but $f_t^1 \leq E_{j,t}[s_{t+1}]$ (and hence we consider a trading rule $T_{ind}(2)$ in which a trade according to Eq. 1 is not made unless either $E_{j,t}[s_{t+1}] > s_t \geq f_t^1$ or $E_{j,t}[s_{t+1}] < s_t \leq f_t^1$ holds). Intuitively, this latter trading rule is more conservative (in which forecasters only trade when forward rates "predict" a different exchange rate change according to UIP than the forecasters' own forecasts), whereas the former trading rule is a gross trading rule which ignores the costs and revenues of borrowing and investing in different currencies. Table 10 presents the estimates.

Table 10 about here

Table 10 confirms the general results from the main part. The alternative trading rule $T_{ind}(1)$ yields results which are closely related to those produced above - it appears that the differences between these two return definitions is mainly captured in the individual fixed effects and year dummies (Panel A). This makes intuitive sense as the considered spot rates and one-month-forward rates are highly correlated ($\rho > 0.99$) at monthly frequency. Moreover, the absolute difference of log USD/EUR spot rates and forward rates is on average (over the sample period) 14 basis points, while the average absolute change of log spot rates from one month to the next amounts to 229 basis points. The results of the alternative trading rule $T_{ind}(2)$ are not as close, but point in the same direction (Panel B).

6.3 An alternative to *trading rules* as measures of forecasting performance

Average absolute forecasting errors This paragraph documents that our findings do not depend on the use of trading rules to measure exchange rate forecast performance; in contrast, the main insights are similar when the analysis is based on absolute forecasting errors $|\varepsilon_{j,t}(FX)|$ instead (computed as above for the interest rate forecasts).[17] These two measures are negatively related, as a *large* error corresponds to *poor* forecasting performance, which implies low returns. In fact, there is a negative correlation coefficient of -0.8 when considering the entire panel of data over time for all forecasters.

An ordered response model When using exchange rate forecast errors, we have to deal with the categorical nature of the dependent variable, i.e., the 0, 1 or 2 score of the forecast error. Ordered probit models provide a common way to compute $P[(|\varepsilon_{j,t}(FX)| = 0)\big||\varepsilon_{j,t}(i)|]$, i.e. the

[17] We group the one-month-ahead realizations of log exchange rate changes into "appreciation", "no-change" and "depreciation" categories. The bounds of the "unchanged" category are chosen symmetrically around zero such that the share of realizations in the no-change category equals the share of expectations in that category: the size of the medium category for the USD/EUR forecasts is 27%, leading to a threshold of $\pm 1.1\%$ for the medium category of realizations. The absolute errors are then obtained by taking the difference, such that a severe error is counted as 2, and a smaller one as 1.

probability of making a correct exchange rate forecast in dependence of $|\varepsilon_{j,t}(i)|$;[18] as we are interested in phase-dependent effects of interest rate forecasts on exchange rate forecasts, we specify the models with interaction terms (as also done in Eq. 4), i.e.

$$\varepsilon^\star = \beta' X = \beta_1 |\varepsilon_{j,t}(i)| + \beta_2 \mathrm{SIG}_{j,t} + \beta_3 \left(|\varepsilon_{j,t}(X)| \times \mathrm{SIG}_{j,t} \right) + \epsilon_{j,t}, \tag{6}$$

where the respondents‘ exchange rate forecast errors $|\varepsilon_{j,t}(FX)|$ are related to the unobserved $\varepsilon^\star$ with the threshold parameters κ_1 and κ_2. $\mathrm{SIG}_{j,t}$ is the short-cut for the variables $|\varepsilon_{j,t}(i)|$ is interacted with; as before, this may be a dummy signalling fundamental mispricing phases, low/high momentum trading phases or the size of interest rate differential.

Results Table 11 displays the results from the ordered probit regressions, where the probability of making a correct forecast $P(|\varepsilon_{j,t}(FX)| = 0)$ is computed by $\Phi(\kappa_1 - \beta' X)$, with $\Phi(\cdot)$ being the cumulative standard normal density.

Table 11 about here

The marginal effects of an interest rate forecast error on the probability of a correct exchange rate forecast are computed by $-\phi(\kappa_1 - \beta' X) \times [\beta_1 + \beta_3 x_1]$ (with $\phi(\cdot)$ being the standard normal density). Table 11 also presents these marginal effects, where columns (i) and (ii) contain the interaction models with momentum signals. The marginal effects of interest rate forecasts observed in the low and normal momentum phases are significantly negative for both the U.S. and Eurozone interest rates (while the effects are more pronounced for the U.S. interest rates), indicating that a worse interest rate forecast decreases the probability of making correct exchange rate forecasts. In high trend phases, these effects are smaller in absolute size or even insignificant, confirming our results from the main section that the relationship between interest rates and exchange rate forecasting performance breaks down when the signals for momentum strategies are strong. Columns (iii)

[18] For brevity, we focus on $P[(|\varepsilon_{j,t}(FX)| = 0) \big| |\varepsilon_{j,t}(i)|]$. The argumentation could obviously also be made on $P[(|\varepsilon_{j,t}(FX)| = 2) \big| |\varepsilon_{j,t}(i)|]$, i.e. the probability of making a severe error. Those results would tell the same story.

and (iv) show the results from the interaction models including the interest rate differential phase, taking two different levels of absolute interest rate differentials as illustrative examples. As in the baseline analysis above, it can be seen that higher forecast errors decrease the probability of making a good exchange rate forecast and that this effect is more pronounced when interest rate differentials are larger. Columns (v) and (vi) show that the probability of making a correct USD forecast decreases more strongly with more severe interest rate errors when the exchange rate deviates substantially from its fundamentally fair value according to PPP.

6.4 Different estimators

As described in more detail in Section 5.2, we conduct panel IV fixed effects regressions. Our main result, i.e. a significantly negative relationship between short term interest forecast errors on exchange rate forecasting performance, however, is also found when using pooled OLS with (Table A3) or without (Table A4) instruments or fixed effects without instruments (Table A5). We also demonstrate that our results are qualitatively unaffected by autocorrelation in the panel. To show this, we report the estimates from the fixed effects estimation technique put forth by Baltagi and Wu (1999) to deal with AR(1) disturbances (Table A6). Moreover, we obtain qualitatively similar results when we consider an alternative IV strategy (Table A7): instead of using lagged values, we use the absolute forecast errors with respect to the interest rates in the *UK* and in *Japan* as exogenous instruments for the forecast errors with respect to the *US* and the *Eurozone*. Likewise, we use the absolute forecast errors with respect to the inflation rate and industrial production in these countries as instruments for the US and Eurozone inflation and industrial production, respectively.[19]

[19]These instruments are valid for two reasons: first, it can be shown from our data that skills in predicting these macroeconomic series are correlated across countries: for example, the cross-sectional correlation between average absolute errors with respect to Eurozone and UK interest rates is 0.51. In the panel context, there still remains a positive correlation of absolute forecast errors with respect to these two series of 0.25. Secondly, there is no theoretical reason to believe that errors in predicting the macroeconomic circumstances in Japan should have a systematic impact on the USD/EUR exchange rate predictions which is not yet covered by the forecast error with respect to the fundamentals in the United States or the Eurozone; hence, the instruments are exogenous.

7 Conclusions

The research reported in this paper suggests an affirmative answer to the question of whether exchange rates are related to economic fundamentals at medium-term horizons, such as a month ahead or longer. As is now widely accepted, it is difficult to obtain a conclusive set of results from conventional tests of exchange rate models at this horizon (Cheung, Chinn, and Garcial-Pascual, 2005; Engel and West, 2005) and so in this paper we propose another route.

The starting point of our research is the hypothesis that expected fundamentals determine exchange rates. Accordingly, we rely on a large data set of individual expectations on fundamentals and exchange rates. Analyzing these expectations shows enormous heterogeneity, a fact that is well documented in the literature and it demonstrates therefore that in this sense our data are conventional. In order to learn about the formation of exchange rates, we make use of the heterogeneity with respect to forecasting performance. Given the supposition that individuals who can forecast exchange rates should have a correct understanding about exchange rate determinants, we investigate whether the quality of fundamental forecasts is related to the ability to predict exchange rates. As interest rates can be seen as the most important determinant of exchange rates over medium-term horizons, we analyze the connection between interest rate and exchange rate forecast performance. We find that good exchange rate forecasting performance is robustly related to good interest rate forecasts. This main result also holds when we consider individual fixed effects in the panel approach, controlling for general exchange rate forecasting ability, when we use an IV approach to test causality and when we control the main relation for further potential determinants.

While our results indicate that there is an important role for interest rate forecasts in general, we also investigate in what respect the importance of fundamentals varies over market phases, i.e. value, momentum or interest differential phases. We find evidence that signals for momentum strategies make fundamental considerations dispensable, while good fundamental forecasts of interest rates and economic growth become even more important when exchange rates substantially deviate from their PPP value or when interest rate differentials are high.

Finally, we leave our otherwise agnostic perspective on exchange rate models and test a simple, UIP-inspired relation between expected relative interest rate changes and exchange rate changes. We find that most forecasters seem to share such a kind of understanding, but that only good exchange rate forecasters also had those interest rate expectations which leads to the correct exchange rate forecast.

Overall, we provide evidence based on a large sample of professional forecasters that their forecasting performance at the one month horizon is positively related to their performance in forecasting short term interest rates. This robust relationship suggests that understanding fundamentals helps to understand exchange rates. We also find, however, that this determination is potentially rivaled by other time-varying influences, such as stronger trends in exchange rates which may lead to a non-fundamentally motivated momentum trading. This rivalry may be one of the reasons why it is so difficult to reveal the impact of fundamentals on exchange rates in conventional tests.

References

Anatolyev, S., and A. Gerko (2005): "A Trading Approach to Testing for Predictability," *Journal of Business and Economic Statistics*, 23(4), 455–461.

Andersen, T. G., T. Bollerslev, F. X. Diebold, and C. Vega (2003): "Micro Effects of Macro Announcements: Real-time Price Discovery in Foreign Exchange," *American Economic Review*, 93, 38–62.

Bacchetta, P., and E. Van Wincoop (2004): "A Scapegoat Model of Exchange-Rate Fluctuations," *American Economic Review Papers and Proceedings*, 94(3), 114–118.

——— (2006): "Can Information Heterogeneity Explain the Exchange Rate Determination Puzzle?," *American Economic Review*, 96, 552–576.

——— (2009): "On the Unstable Relationship between Exchange Rates and Macroeconomic Fundamentals," *NBER Working Paper 15008*.

Backus, D. K., A. W. Gregory, and C. I. Telmer (1993): "Accounting for Forward Rates in Markets for Foreign Currency," *Journal of Finance*, 48, 1887–1908.

Baltagi, B., and P. Wu (1999): "Unequally Spaced Panel Data Regressions with AR (1) Disturbances," *Econometric Theory*, 15(6), 814–823.

Beber, A., F. Breedon, and A. Buraschi (2010): "Differences in Beliefs and Currency Risk Premia," *Journal of Financial Economics*, 98(3), 415–438.

Bénassy-Quéré, A., S. Larribeau, and R. MacDonald (2003): "Models of Exchange Rate Expectations: How Much Heterogeneity?," *Journal of International Financial Markets, Institutions and Money*, 13(2), 113–136.

Breusch, T. S., and A. R. Pagan (1980): "The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics," *Review of Economic Studies*, 47(1), pp. 239–253.

Burnside, C., M. Eichenbaum, I. Kleshchelski, and S. Rebelo (2010): "Do Peso Problems Explain the Returns to the Carry Trade?," *Review of Financial Studies*, forthcoming.

Burnside, C., B. Han, D. Hirshleifer, and T. Y. Wang (2010): "Investor Overconfidence and the Forward Premium Puzzle," *Review of Economic Studies*, forthcoming.

Cheung, Y.-W., M. D. Chinn, and A. Garcial-Pascual (2005): "Empirical Exchange Rate Models of the Nineties: Are Any Fit to Survive?," *Journal of International Money and Finance*, 24(7), 1150–1175.

Cheung, Y.-W., and C. Y.-P. Wong (2000): "A Survey of Market Practitioners' Views on Exchange Rate Dynamics," *Journal of International Economics*, 51, 401–419.

Christopoulos, D., and M. Leon-Ledesma (2010): "Smooth Breaks and Non-Linear Mean Reversion: Post-Bretton Woods Real Exchange Rates," *Journal of International Money and Finance*, 29(6), 1076–1093.

Davidson, R., and J. MacKinnon (1989): "Testing for Consistency Using Artificial Regressions," *Econometric Theory*, 5(3), 363–384.

De Grauwe, P., and M. Grimaldi (2006): "Exchange Rate Puzzles: A Tale of Switching Attractors," *European Economic Review*, 50(1), 1–33.

Dreger, C., and G. Stadtmann (2008): "What Drives Heterogeneity in Foreign Exchange Rate Expectations: Insights from a New Survey," *International Journal of Finance and Economics*, 13, 360–367.

Elliot, G., and T. Ito (1999): "Heterogeneous Expectations and Tests of Efficiency in the Yen/Dollar Forward Exchange Rate Market," *Journal of Monetary Economics*, 43, 435–456.

Engel, C., N. Mark, and K. West (2007): "Exchange Rate Models are not as Bad as you Think," *NBER Macroeconomics Annual*, 22, 381–441.

Engel, C., and K. West (2005): "Exchange Rates and Fundamentals," *Journal of Political Economy*, 113(3), 485–517.

Evans, M. (2010): "Order Flows and the Exchange Rate Disconnect Puzzle," *Journal of International Economics*, 80(1), 58–71.

Evans, M., and R. Lyons (2002): "Order Flow and Exchange Rate Dynamics," *Journal of Political Economy*, 110(1), 170–180.

Fama, E. F. (1984): "Forward and Spot Exchange Rates," *Journal of Monetary Economics*, 14, 319–338.

Frankel, J., and A. Rose (1995): "Empirical Research on Nominal Exchange Rates," *Handbook of International Economics*, 3, 1689–1729.

Frankel, J. A., and K. A. Froot (1990): "Chartists, Fundamentalists, and Trading in the Foreign Exchange Market," *American Economic Review*, 80(2), 181–185.

Ito, T. (1990): "Foreign Exchange Rate Expectations: Micro Survey Data," *American Economic Review*, 80(3), 434–449.

Jongen, R., W. F. Verschoor, C. Wolff, and R. Zwinkels (2012): "Explaining Dispersion in Foreign Exchange Expectations: A Heterogeneous Agent Approach," *Journal of Economic Dynamics and Control*, 36, 719–735.

Jongen, R., C. Wolff, and W. F. Verschoor (2008): "Foreign Exchange Expectations: Survey and Synthesis," *Journal of Economic Surveys*, 22(1), 140–165.

Jordà, O., and A. M. Taylor (2009): "The Carry Trade and Fundamentals: Nothing to Fear than FEER Itself," *NBER Working Paper 15518.*

——— (2011): "Performance Evaluation of Zero Net-Investment Strategies," *NBER Working Paper 17150.*

Leitch, G., and J. Tanner (1991): "Economic Forecast Evaluation: Profits versus the Conventional Error Measures," *American Economic Review*, 81, 580–590.

MacDonald, R., and I. W. Marsh (1996): "Currency Forecasters are Heterogeneous: Confirmation and Consequences," *Journal of International Money and Finance*, 15(1), 665–685.

Mark, N. (1995): "Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictability," *American Economic Review*, 85(1), 201–218.

Meese, R., and K. Rogoff (1983): "Empirical Exchange Rate Models of the Seventies: Do they Fit out of Sample?," *Journal of International Economics*, 14(1-2), 3–24.

Menkhoff, L., L. Sarno, M. Schmeling, and A. Schrimpf (2011): "Carry Trades and Global Foreign Exchange Volatility," *Journal of Finance*, 67, 681–718.

Menkhoff, L., and M. P. Taylor (2007): "The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis," *Journal of Economic Literature*, 45, 936–972.

Obstfeld, M., and K. Rogoff (2000): "The Six Major Puzzles in International Macroeconomics: Is There a Common Cause?," *NBER Macroeconomics Annual 2000*, 15, 339–390.

Rime, D., L. Sarno, and E. Sojli (2010): "Exchange Rate Forecasting, Order Flow and Macroeconomic Information," *Journal of International Economics*, 80(1), 72–88.

Rogoff, K. S. (2007): "Comment on: "'Exchange Rate Models are Not as Bad as you Think"' by Charles Engel, Nelson C. Mark, and Kenneth D. West," *NBER Macroeconomics Annual 2007*, 22, 443–452.

Rossi, B. (2005): "Testing Long-Horizon Predictive Ability with High Persistence, and the Meese-Rogoff Puzzle," *International Economic Review*, 46(1), 61–92.

Sarno, L., and G. Valente (2009): "Exchange Rates and Fundamentals: Footloose or Evolving Relationship?," *Journal of the European Economic Association*, 7(4), 786–830.

Schmeling, M., and A. Schrimpf (2011): "Expected Inflation, Expected Stock Returns, and Money Illusion: What Can we Learn From Survey Expectations," *European Economic Review*, forthcoming.

Souleles, N. S. (2004): "Expectations, Heterogeneous Forecast Errors, and Consumption: Micro Evidence from the Michigan Consumer Sentiment Surveys," *Journal of Money, Credit, and Banking*, 36(1), 39–72.

Taylor, A. M., and M. P. Taylor (2004): "The Purchasing Power Debate," *Journal of Economic Perspectives*, 18(4), 135–158.

Taylor, M., D. Peel, and L. Sarno (2001): "Nonlinear Mean-Reversion in Real Exchange Rates: Toward a Solution to the Purchasing Power Parity Puzzles," *International Economic Review*, 42(4), 1015–1042.

ter Ellen, S., W. F. Verschoor, and R. Zwinkels (2011): "Dynamic Expectations Formation in the Foreign Exchange Market," *Erasmus School of Economics Working Paper*.

Table 1: Structure of survey responses

This table reports the number of participants and observations with different minimum number of USD/EUR forecasts. (While the entire database consists of 1747 forecasters with USD/EUR forecasts, we consider those forecasters who responded at least 10 times to the survey in the remainder of this analysis.)

Min # of responses	# of forecasters	% of all participants	# of observations
1	1,747	100.00	64,813
10	1,056	60.45	63,222
25	763	43.40	59,511
50	519	29.52	50,705
100	208	11.83	28,310
150	62	3.53	11,333
200	11	0.63	2,264

Table 2: Average exchange rate forecasting performance in the cross section: Mean returns and Sharpe ratios of T_{ind}

This table reports statistics on the cross section of forecasters with respect to the average performance of a forecaster over time when she follows the trading rule T_{ind} according to her forecasts. Panel A includes the performance measures for the 95-percentile, median and 5-percentile forecaster, sorted by mean returns and Sharpe ratios, respectively. These values are compared to the average value T_0 of a simulation experiment which repeats 10,000 purely random (coin toss) strategies (an investor buys or sells USD against the Euro in the forward market according to a coin toss, and settles her position one month later). Panel B reports the number and percentage share of forecasters with Sharpe ratios within specific intervals.

Panel A	Percentile of forecasters	Mean return	Sharpe ratio
T_{ind}	X_{95}	0.746	1.159
	X_{50}	0.076	0.114
	X_{05}	-0.673	-0.856
T_0	Average	-0.002	-0.001
Panel B	**Sharpe ratio**	**# of forecasters**	**in %**
T_{ind}	x<-1.0	40	3.8
	-1.0<x <0.4	131	12.3
	-0.4<x<0.4	580	54.4
	0.4<x<1.0	235	22.0
	1.0<x	80	7.5

Table 3: Macroeconomic fundamentals: average absolute forecast errors

This table reports the distribution of forecasts (median and quartiles) of the average absolute forecast errors $|\varepsilon_i(X)|$ across the cross section with respect to different macroeconomic variables X, i.e. the short term interest rate i, the inflation rate π, and the yearly growth rate of the industrial production y. A severe forecast error (wrong direction of change) is counted as 2, a small forecast error (e.g., constant instead of increase or decrease) is counted as 1.

	$\|\varepsilon_i(i)\|$ Eurozone	$\|\varepsilon_i(i)\|$ USA	$\|\varepsilon_i(\pi)\|$ Eurozone	$\|\varepsilon_i(\pi)\|$ USA	$\|\varepsilon_i(y)\|$ Eurozone	$\|\varepsilon_i(y)\|$ USA
X_{25}	0.58	0.65	0.53	0.58	0.62	0.48
X_{50}	0.71	0.77	0.63	0.69	0.73	0.57
X_{75}	0.83	0.90	0.73	0.79	0.84	0.68

Table 4: Panel Fixed Effects Regression

This table reports the results of panel regressions with individual fixed effects of the trading rule T_{ind}'s period forecast return, $r_{j,t,t+1}$ (based on the USD/EUR forecast of the forecaster j in t), on the absolute forecast error made for European and U.S.-American interest rates ($|\varepsilon_{j,t}(i^{EUR})|$ and $|\varepsilon_{j,t}(i^{USD})|$, respectively) as well as a battery of control variables $\Phi_{j,t}$ and $\Psi_{j,t}$, i.e.

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(i^{EUR})| + \beta_2|\varepsilon_{j,t}(i^{USD})| + \gamma\Phi_{j,t} + \delta\Psi_{j,t} + \epsilon_{j,t}.$$

Depending on the specification (i) to (vii), $\Phi_{j,t}$ includes forecast errors with respect to other fundamentals than interest rates, i.e. inflation ($|\varepsilon(\pi)|$) and industrial production growth forecast errors $|\varepsilon(y)|$. We use lagged values as external instruments for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$. $\Psi_{j,t}$ represents purely exogenous control variables such as year specific dummy variables. Significance: ***:1%, **: 5%, *: 10%.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
$\lvert\varepsilon_{j,t}(i^{EUR})\rvert$	-0.107		-0.105		-0.184		-0.159
	***(0.031)		***(0.031)		***(0.039)		***(0.041)
$\lvert\varepsilon_{j,t}(i^{USD})\rvert$		-0.134		-0.148		-0.162	-0.123
		***(0.036)		***(0.038)		***(0.054)	**(0.057)
$\lvert\varepsilon_{j,t}(\pi^{EUR})\rvert$			-0.095		-0.145		-0.190
			**(0.044)		***(0.052)		***(0.056)
$\lvert\varepsilon_{j,t}(\pi^{USD})\rvert$				0.177		0.021	0.082
				***(0.045)		(0.056)	(0.060)
$\lvert\varepsilon_{j,t}(y^{EUR})\rvert$			-0.040		0.088		0.116
			(0.065)		(0.085)		(0.096)
$\lvert\varepsilon_{j,t}(y^{USD})\rvert$				-0.066		-0.170	-0.201
				(0.056)		***(0.060)	***(0.069)
$\bar{\mu}$	0.182	0.213	0.269	0.137	0.421	0.450	0.594
	***(0.025)	***(0.031)	***(0.058)	**(0.057)	***(0.094)	***(0.095)	***(0.111)
Year dummies	NO	NO	NO	NO	YES	YES	YES
$N \times T$	51,512	50,793	51,155	50,084	51,155	50,084	49,872
R^2_B	0.003	0.008	0.001	0.012	0.130	0.121	0.089
R^2_O	0.001	0.002	0.001	0.001	0.021	0.023	0.021
R^2_W	0.001	0.002	0.001	0.002	0.018	0.019	0.017

Table 5: Interaction model: signals for value trade phases

This table reports the results of a panel regression with individual fixed effects of the trading rule T_{ind}'s period forecast return, $r_{j,t,t+1}$ (based on the forecast of the forecaster j in t), on a fundamental forecast error (in absolute terms) $|\varepsilon_{j,t}(X)|$, a dummy variable FUND_t taking on unity if the exchange rate strongly deviates from its PPP value and zero otherwise, and an interaction of the these two variables, i.e.,

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(X)| + \beta_2\text{FUND}_t + \beta_3\left(|\varepsilon_{j,t}(X)| \times \text{FUND}_t\right) + \epsilon_{j,t}.$$

Depending on the specification (i) to (vi), X represents the interest rates i, the industrial production growth rate (yoy) y and the inflation rate π projections for the U.S. and the Eurozone, respectively, made by j in t. Clustering-robust standard errors (by observational unit) are provided in parentheses. We also report the covariance between $\hat{\beta}_1$ and $\hat{\beta}_4$ or $\hat{\beta}_1$ and $\hat{\beta}_5$, respectively. The table also provides the marginal effects of a fundamental forecast error in both value phases ($F_t = 1$) and non-value phases ($F_t = 0$). Significance: ***:1%, **: 5%, *: 10%.

	(i)- $X: i_{EUR}$	(ii)- $X: i_{USD}$	(iii)- $X: \pi_{EUR}$	(iv)- $X: \pi_{USD}$	(v)- $X: y_{EUR}$	(vi)- $X: y_{USD}$
$\|\varepsilon_{j,t}(X)\|$	-0.085	-0.129	-0.080	0.261	-0.055	-0.022
	***(0.028)	***(0.037)	***(0.028)	***(0.027)	**(0.028)	(0.030)
F_t	-0.048	-0.065	-0.186	0.153	-0.103	-0.124
	(0.032)	(0.040)	***(0.034)	***(0.039)	***(0.036)	***(0.032)
$\|\varepsilon_{j,t}(X)\| \times F_t$	-0.061	-0.070	0.104	-0.354	-0.030	-0.003
	*(0.032)	*(0.041)	***(0.035)	***(0.036)	(0.033)	(0.036)
$\bar{\mu}$	0.220	0.279	0.226	-0.036	0.217	0.193
	***(0.024)	***(0.0335)	***(0.025)	(0.029)	(0.028)	(0.025)
$N \times T$	63,693	62,940	63,675	62,832	63,760	63,070
R^2_{corr}	0.002	0.003	0.001	0.003	0.002	0.001
$Cov(\hat{\beta}_1, \hat{\beta}_3)$	-0.0008	-0.0013	-0.0008	-0.0008	-0.0008	-0.0009
$\left.\frac{\partial r}{\partial\|\varepsilon_{j,t}(X)\|}\right\|_{F_t=0}$	-0.085	-0.129	-0.080	0.261	-0.055	-0.022
	***(0.028)	***(0.037)	***(0.028)	***(0.028)	**(0.028)	(0.030)
$\left.\frac{\partial r}{\partial\|\varepsilon_{j,t}(X)\|}\right\|_{F_t=1}$	-0.147	-0.199	0.025	-0.094	-0.085	-0.025
	***(0.017)	***(0.018)	(0.019)	***(0.094)	***(0.018)	(0.021)

Table 6: Interaction model: signals for momentum trade phases

This table reports the results of a panel regression with individual fixed effects of the trading rule T_{ind}'s period forecast return, $r_{j,t,t+1}$ (based on the forecast of the forecaster j in t), on a fundamental forecast error (in absolute terms) $|\varepsilon_{j,t}(X)|$, a trend-phase dummy (for low and high trend phases, D^L and D^H) and an interaction of the forecast error with the trend-phase, i.e.,

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(X)| + \beta_{21}D^L_{j,t} + \beta_{22}D^H_{j,t} + \beta_{31}\left(|\varepsilon_{j,t}(X)| \times D^L_{j,t}\right) + \beta_{32}\left(|\varepsilon_{j,t}(X)| \times D^H_{j,t}\right) + \epsilon_{j,t}.$$

Note that the "normal" trend phase is taken as reference. Depending on the specification (i) to (vi), X represents the interest rates i, the industrial production growth rate (yoy) y and the inflation rate π projections for the U.S. and the Eurozone, respectively, made by j in t. Clustering-robust standard errors (by observational unit) are provided in parentheses. We also report the covariance between $\hat{\beta}_1$ and $\hat{\beta}_4$ or $\hat{\beta}_1$ and $\hat{\beta}_5$, respectively. $\frac{\partial r}{\partial|\varepsilon_{j,t}(X)|}$ represents the marginal effects of a fundamental forecast error on $r_{j,t,t+1}$. Significance: ***:1%, **: 5%, *: 10%.

	(i)- $X: i_{EUR}$	(ii)- $X: i_{USD}$	(iii)- $X: \pi_{EUR}$	(iv)- $X: \pi_{USD}$	(v)- $X: y_{EUR}$	(vi)- $X: y_{USD}$
$\lvert\varepsilon_{j,t}(X)\rvert$	-0.214	-0.208	0.070	0.048	-0.118	-0.063
	***(0.026)	***(0.030)	**(0.028)	*(0.026)	***(0.028)	**(0.028)
$D^L_{j,t}$	-0.120	0.010	0.010	-0.092	-0.094	-0.150
	***(0.032)	(0.036)	(0.033)	***(0.034)	***(0.033)	***(0.032)
$D^H_{j,t}$	-0.233	-0.276	-0.053	-0.074	-0.189	-0.121
	***(0.037)	***(0.039)	(0.034)	*(0.038)	***(0.036)	***(0.033)
$\lvert\varepsilon_{j,t}(X)\rvert \times D^L_{j,t}$	-0.009	-0.177	-0.197	-0.040	-0.037	0.044
	(0.036)	***(0.041)	***(0.038)	(0.036)	(0.039)	(0.038)
$\lvert\varepsilon_{j,t}(X)\rvert \times D^H_{j,t}$	0.240	0.268	-0.013	0.012	0.183	0.099
	***(0.037)	***(0.038)	(0.040)	(0.038)	***(0.041)	**(0.042)
$\bar{\mu}$	0.304	0.316	0.109	0.120	0.232	0.193
	***(0.023)	***(0.026)	***(0.020)	***(0.023)	***(0.022)	***(0.021)
$N \times T$	63,693	62,940	63,675	62,832	63,760	63,070
R^2_{corr}	0.003	0.005	0.001	0.006	0.002	0.001
$Cov(\hat{\beta}_1, \hat{\beta}_4)$	-0.0007	-0.0009	-0.0008	-0.0007	-0.0008	-0.0008
$Cov(\hat{\beta}_1, \hat{\beta}_5)$	-0.0007	-0.0008	-0.0008	-0.0006	-0.0009	-0.0008
$\frac{\partial r}{\partial\lvert\varepsilon_{j,t}(X)\rvert}$ (Low momentum phase)	-0.224	-0.385	-0.127	0.007	-0.155	-0.020
	***(0.026)	***(0.028)	***(0.028)	(0.025)	***(0.026)	(0.026)
$\frac{\partial r}{\partial\lvert\varepsilon_{j,t}(X)\rvert}$ (Normal momentum phase)	-0.214	-0.208	0.070	0.048	-0.118	-0.063
	***(0.026)	***(0.030)	**(0.028)	*(0.026)	***(0.028)	**(0.028)
$\frac{\partial r}{\partial\lvert\varepsilon_{j,t}(X)\rvert}$ (High momentum phase)	0.026	0.060	0.058	0.060	0.065	0.036
	(0.026)	**(0.027)	**(0.028)	**(0.029)	(0.027)	(0.033)

Table 7: Interaction model: interest rate differential phases

This table reports the results of a panel regression with individual fixed effects of the trading rule T_{ind}'s period forecast return, $r_{j,t,t+1}$ (based on the forecast of the forecaster j in t), on a fundamental forecast error (in absolute terms) $|\varepsilon_{j,t}(X)|$, the absolute differential between the U.S. and Euro interest rates, $|i_t^{USD} - i_t^{EUR}|$, and an interaction of the these two variables, i.e.,

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(X)| + \beta_2|i_t^{USD} - i_t^{EUR}| + \beta_3\left(|\varepsilon_{j,t}(X)| \times |i_t^{USD} - i_t^{EUR}|\right) + \epsilon_{j,t}.$$

Depending on the specification (i) to (vi), X represents the interest rates i, the industrial production growth rate (yoy) y and the inflation rate π projections for the U.S. and the Eurozone, respectively, made by j in t. Clustering-robust standard errors (by observational unit) are provided in parentheses. We also report the covariance between $\hat{\beta}_1$ and $\hat{\beta}_4$ or $\hat{\beta}_1$ and $\hat{\beta}_5$, respectively. The table also provides the marginal effects of a fundamental forecast error on $r_{j,t,t+1}$ evaluated at the average absolute interest rate differential between 1991.12 and 2009.11, $\overline{|i_t^{USD} - i_t^{EUR}|} = 2.84118$. Significance: ***:1%, **: 5%, *: 10%.

	(i)- $X : i_{EUR}$	(ii)- $X : i_{USD}$	(iii)- $X : \pi_{EUR}$	(iv)- $X : \pi_{USD}$	(v)- $X : y_{EUR}$	(vi)- $X : y_{USD}$
$\|\varepsilon_{j,t}(X)\|$	-0.083	-0.113	-0.195	-0.067	0.119	0.149
	**(0.033)	***(0.035)	***(0.033)	*(0.036)	***(0.035)	***(0.037)
$\|i_t^{USD} - i_t^{EUR}\|$	-0.047	-0.048	-0.142	-0.109	0.010	-0.003
	***(0.018)	***(0.019)	***(0.016)	***(0.016)	(0.018)	(0.017)
$\|\varepsilon_{j,t}(X)\| \times \|i_t^{USD} - i_t^{EUR}\|$	-0.040	-0.056	0.120	0.068	-0.124	-0.112
	**(0.017)	***(0.019)	***(0.018)	***(0.020)	***(0.019)	***(0.020)
$\bar{\mu}$	0.269	0.323	0.321	0.239	0.131	0.112
	***(0.032)	***(0.034)	***(0.027)	***(0.028)	***(0.032)	***(0.030)
$N \times T$	63,693	62,940	63,675	62,832	63,760	63,070
R^2_{corr}	0.002	0.004	0.002	0.001	0.002	0.002
$Cov(\hat{\beta}_1, \hat{\beta}_3)$	-0.0005	-0.0006	-0.0005	-0.0006	-0.0006	-0.0006
$\left.\frac{\partial r}{\partial\|\varepsilon_{j,t}(X)\|}\right\|_{\overline{\|i_t^{USD}-i_t^{EUR}\|}}$	-0.196	-0.271	0.146	0.126	-0.234	-0.169
	***(0.025)	***(0.029)	***(0.026)	***(0.028)	***(0.027)	***(0.028)

Table 8: Exchange rate forecasting models and their usage to predict actual exchange rate changes

This table summarizes our analysis explaining the forecasters' exchange rate models (Panel A) and relating these models to actual exchange rate changes (Panel B). To explain expected exchange rate changes in Panel A, we conduct fixed-effects regressions of the type

$$E_{t,j}[\Delta s_{t,t+6}] = \beta_0 + \beta_1[E_{t,j}[\Delta i^{EUR}_{t,t+6}] - E_{t,j}[\Delta i^{US}_{t,t+6}]] + \epsilon_{t,j}$$

where $\Delta s_{t,t+6}$ represents a in exchange rates, and $E_{t,j}[\Delta i^{EUR}_{t,t+6}] - E_{t,j}[\Delta i^{US}_{t,t+6}]$ the difference between the expected change in Eurozone interest rates and the expected change in the U.S. interest rates. A second specification (ii) augments the RHS by $E_{t,j}[\Delta \pi^{EUR}_{t,t+6}] - E_{t,j}[\Delta \pi^{US}_{t,t+6}]$, while (iii)-(v) display the estimated coefficients when low performers (w.r.t exchange rate forecasts), medium performers and high performers are considered separately.
The regressions in Panel B replace expectations on the LHS of the regression equation with actual changes; (vi)-(viii) display the coefficient estimates for low, medium and high performers, respectively.
For brevity, Diff(Δi) is a shortcut for $[E_{t,j}[\Delta i^{EUR}_{t,t+6}] - E_{t,j}[\Delta i^{US}_{t,t+6}]$, and Diff($\Delta \pi$) for $E_{t,j}[\Delta \pi^{EUR}_{t,t+6}] - E_{t,j}[\Delta \pi^{US}_{t,t+6}]$. Standard errors are provided in parentheses. Significance: ***:1%, **: 5%, *: 10%.

	Panel A- LHS: $E^j[\Delta FX]$					Panel B - LHS: ΔFX		
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
	all	*all*	*low p.*	*medium p.*	*high p.*	*low p.*	*medium p.*	*high p.*
Diff(Δi)	0.181	0.158	0.186	0.207	0.143	-0.675	-0.243	0.518
	***(0.004)	***(0.004)	***(0.007)	***(0.006)	***(0.007)	***(0.068)	***(0.058)	***(0.068)
Diff($\Delta \pi$)		0.067						
		***(0.005)						
const	0.026	0.037	-0.137	0.005	0.204	-0.120	0.249	1.034
	***(0.003)	***(0.003)	***(0.006)	(0.005)	**(0.005)	***(0.048)	(0.048)	(0.054)
$N \times T$	62,082	61,489	17.494	25,160	19,428	17,556	25,446	19,533
N	1053	1052	351	352	350	351	352	350
$R^2_{overall}$	0.08	0.09	0.09	0.09	0.05	0.00	0.00	0.01
R^2_{within}	0.04	0.04	0.05	0.05	0.02	0.01	0.00	0.00
$R^2_{between}$	0.44	0.41	0.44	0.44	0.31	0.04	0.03	0.10

Table 9: Robustness: GBP/EUR and JPY/EUR exchange rates

This table reports the results of panel regressions with individual fixed effects of the trading rule T_{ind}'s period forecast return, $r_{j,t,t+1}$ (based on the GBP/EUR and JPY/EUR forecast of the forecaster j in t), on the absolute forecast error made for European, British and Japanese interest rates ($|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{GBP})|$ and $|\varepsilon_{j,t}(i^{JPY})|$, respectively) as well as a battery of control variables $\Phi_{j,t}$ and $\Psi_{j,t}$, i.e.

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(i^{EUR})| + \beta_2|\varepsilon_{j,t}(i^{EUR})| + \gamma\Phi_{j,t} + \delta\Psi_{j,t} + \epsilon_{j,t}.$$

Depending on the specification (i) to (viii), $\Phi_{j,t}$ includes forecast errors with respect to other fundamentals than interest rates, i.e. inflation ($|\varepsilon(\pi)|$) and industrial production growth forecast errors $|\varepsilon(y)|$. We use lagged values as external instruments for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{GBP})|$, $|\varepsilon_{j,t}(i^{JPY})|$, and $\Phi_{j,t}$. $\Psi_{j,t}$ represents year specific dummy variables as purely exogenous control variables. Significance: ***:1%, **: 5%, *: 10%.

	(i): GBP/EUR	(ii): GBP/EUR	(iii): GBP/EUR	(iv): GBP/EUR	(v): JPY/EUR	(vi): JPY/EUR	(vii): JPY/EUR	(viii): JPY/EUR
$\lvert\bar{\varepsilon}(i_{EUR})\rvert$	-0.194		-0.264		-0.157		-0.235	
	***(0.021)		***(0.026)		***(0.031)		***(0.038)	
$\lvert\bar{\varepsilon}(i_{GBP})\rvert$		-0.068		-0.125				
		**(0.028)		***(0.033)				
$\lvert\bar{\varepsilon}(i_{JPY})\rvert$						-0.786		-0.671
						***(0.071)		***(0.091)
$\lvert\bar{\varepsilon}(\pi_{EUR})\rvert$	-0.040		-0.073		0.199		0.240	
	(0.029)		**(0.034)		***(0.043)		***(0.050)	
$\lvert\bar{\varepsilon}(\pi_{GBP})\rvert$		0.028		-0.041				
		(0.034)		(0.041)				
$\lvert\bar{\varepsilon}(\pi_{JPY})\rvert$						0.082		0.292
						(0.065)		***(0.079)
$\lvert\bar{\varepsilon}(y_{EUR})\rvert$	-0.059		-0.160		0.378		0.147	
	(0.043)		***(0.057)		***(0.063)		*(0.083)	
$\lvert\bar{\varepsilon}(y_{GBP})\rvert$		-0.061		0.102				-0.049
		(0.049)		*(0.059)				(0.072)
$\lvert\bar{\varepsilon}(y_{JPY})\rvert$						0.027		
						(0.054)		
const.	0.262	0.125	0.705	0.454	-0.130	0.465	0.181	0.974
	***(0.038)	***(0.038)	***(0.062)	***(0.067)	**(0.057)	***(0.056)	*(0.094)	***(0.144)
Year dummies	NO	NO	YES	YES	NO	NO	YES	YES
N	51,175	46,531	51,175	46,531	51,161	38,703	51,258	38,703
R^2	0.001	0.001	0.009	0.019	0.001	0.002	0.015	0.003

Table 10: Robustness: Panel Fixed Effects Regression with alternatively specified trading rules

We consider the forecast returns obtained by alternative trading rules $T_{ind}(1)$ and $T_{ind}(2)$, which are given by

$$r^{(1)}_{j,t,t+k} = I_t(s_t > E_{j,t}[s_{t+1}])(s_t - s_{t+1}) + I_t(s_t < E_{j,t}[s_{t+1}])(s_{t+1} - s_t)$$

and

$$r^{(2)}_{j,t,t+k} = I_t(f^1_t \geq s_t > E_{j,t}[s_{t+1}])(f_{t,1} - s_{t+1}) + I_t(f^1_t \leq s_t < E_{j,t}[s_{t+1}])(s_{t+1} - f_{t,1}),$$

respectively. This table presents the results of panel fixed-effects regressions of $r^{(1)}_{j,t,t+k}$ (for $T_{ind}(1)$) and $r^{(2)}_{j,t,t+k}$ (for $T_{ind}(2)$) on the absolute forecast error made for European and U.S.-American interest rates ($|\varepsilon_{j,t}(i^{EUR})|$ and $|\varepsilon_{j,t}(i^{USD})|$) as well as for the respective inflation rates ($|\varepsilon_{j,t}(\pi)|$) and industrial production growth rates ($|\varepsilon_{j,t}(y)|$) and on year dummies. Panel A represent the coefficient estimates for $T_{ind}(1)$, Panel B for $T_{ind}(2)$. We use lagged values as external instruments for the errors on the RHS. Significance: ***:1%, **: 5%, *: 10%.

	Panel A: $T_{ind}(1)$		**Panel B:** $T_{ind}(2)$	
	(i)	(ii)	(iii)	(iv)
$\lvert\varepsilon_{j,t}(i^{EUR})\rvert$	-0.180		-0.042	
	***(0.039)		*(0.023)	
$\lvert\varepsilon_{j,t}(i^{USD})\rvert$		-0.164		-0.120
		***(0.054)		***(0.031)
$\lvert\varepsilon_{j,t}(\pi^{EUR})\rvert$	-0.135		-0.266	
	***(0.051)		***(0.030)	
$\lvert\varepsilon_{j,t}(\pi^{USD})\rvert$		0.022		-0.093
		(0.056)		***(0.032)
$\lvert\varepsilon_{j,t}(y^{EUR})\rvert$	0.088		-0.255	
	(0.085)		***(0.050)	
$\lvert\varepsilon_{j,t}(y^{USD})\rvert$		-0.149		-0.073
		**(0.059)		**(0.035)
$\bar{\mu}$	0.409	0.437	0.859	0.734
	***(0.096)	*(0.094)	***(0.056)	***(0.055)
Year dummies	YES	YES	YES	YES
$N \times T$	51,155	50,084	51,182	50,109
R^2_B	0.095	0.096	0.206	0.224
R^2_O	0.021	0.022	0.048	0.056
R^2_W	0.019	0.020	0.037	0.049

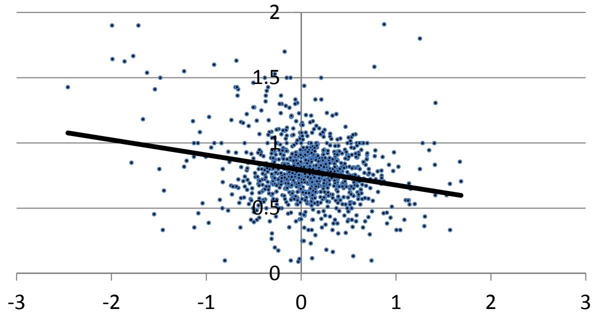
Table 11: Robustness: absolute forecast errors

This table reports the results from an ordered-probit regression of the type $\varepsilon^\star = \beta' X = \beta_1 |\varepsilon_{j,t}(i)| + \beta_2 \mathrm{SIG}_1 + \beta_3 (|\varepsilon_{j,t}(X)| \times \mathrm{SIG}_t) + \epsilon_{j,t}$ where the respondents‘ exchange rate forecast errors $|\varepsilon_{j,t}(FX)|$ are related to the unobserved $\varepsilon^\star$ with the threshold parameters κ_1 and κ_2. $|\varepsilon_{j,t}(i)|$ represents the absolute interest rate forecast error, SIG_t is a short-cut for the variables that $|\varepsilon_{j,t}(i)|$ is interacted with, e.g. the dummy variables for a fundamental mispricing according to PPP ($F_t = 1$ if mispriced), low or high trend phases D^L and D^h, respectively, or the interest rate differential $|i_t^{USD} - i_t^{EUR}|$.

Marginal effects of an interest rate forecast error on the probability of making a correct exchange rate forecast ($\left.\frac{\partial P(|\varepsilon(FX)|=0)}{\partial|\varepsilon_{j,t}(X)|}\right|_{\varepsilon_{j,t}(X)=1}$) are computed by $-\phi(\kappa_1 - \beta' X) \times [\beta_1 + \beta_3 \mathrm{SIG}_t]$, whereas the corresponding standard errors are obtained by the delta method. Standard errors are provided in parentheses. Significance: ***:1%, **: 5%, *: 10%.

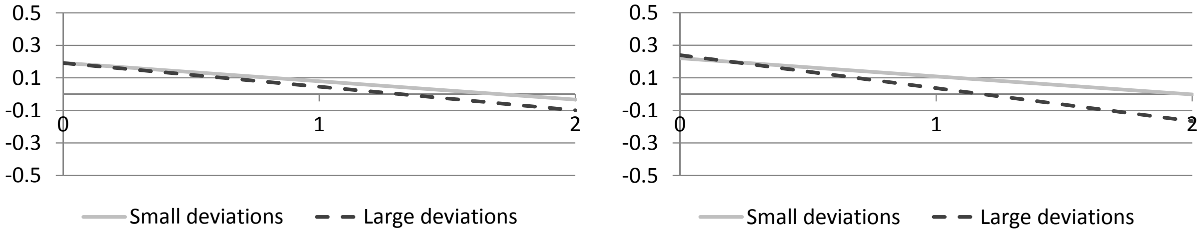
	(i) EUR	(ii) USD	(iii) EUR	(iv) USD	(v) EUR	(vi) USD
$\|\varepsilon_{j,t}(i)\|$	0.070	0.148	0.030	0.077	0.033	0.103
	***(0.011)	***(0.012)	**(0.012)	***(0.013)	**(0.013)	***(0.014)
$D^L_{j,t}$	0.050	0.035				
	***(0.015)	**(0.017)				
$D^H_{j,t}$	0.113	0.143				
	***(0.016)	***(0.018)				
$\|\varepsilon_{j,t}(i)\| \times D^L_{j,t}$	0.001	0.021				
	(0.016)	(0.017)				
$\|\varepsilon_{j,t}(i)\| \times D^H_{j,t}$	-0.082	-0.116				
	***(0.016)	***(0.017)				
$\|i_t^{USD} - i_t^{EUR}\|$			0.010	0.004		
			(0.007)	(0.007)		
$\|\varepsilon_{j,t}(i)\| \times \|i_t^{USD} - i_t^{EUR}\|$			0.012	0.030		
			*(0.007)	***(0.007)		
F_t					0.013	0.013
					(0.014)	(0.016)
$\|\varepsilon_{j,t}(i)\| \times F_t$					0.013	0.019
					(0.015)	(0.016)
κ_1	-0.300	-0.235	-0.332	-0.280	-0.342	-0.282
	***(0.011)	***(0.012)	***(0.013)	***(0.014)	***(0.011)	***(0.014)
κ_2	0.737	0.804	0.704	0.756	0.694	0.756
	***(0.011)	***(0.012)	***(0.013)	***(0.014)	***(0.011)	***(0.014)
$N \times T$	63,055	62,552	63,055	62,552	63,055	62,552
R^2_{corr}	0.001	0.002	0.001	0.003	0.000	0.002
$\left.\frac{\partial P(\|\varepsilon(FX)\|=0)}{\partial\|\varepsilon(i)\|}\right\|_{\varepsilon(i)=1}$ (Low trend)	-0.026 ***(0.004)	-0.061 ***(0.004)				
$\left.\frac{\partial P(\|\varepsilon(FX)\|=0)}{\partial\|\varepsilon(i)\|}\right\|_{\varepsilon(i)=1}$ (Normal trend)	-0.027 ***(0.004)	-0.055 ***(0.004)				
$\left.\frac{\partial P(\|\varepsilon(FX)\|=0)}{\partial\|\varepsilon(i)\|}\right\|_{\varepsilon(i)=1}$ (High trend)	0.004 (0.004)	-0.012 ***(0.004)				
$\left.\frac{\partial P(\|\varepsilon(FX)\|=0)}{\partial\|\varepsilon(i)\|}\right\|_{\varepsilon(i)=1,\|i_t^{USD}-i_t^{EUR}\|=0.1}$			-0.011 **(0.005)	-0.030 ***(0.005)		
$\left.\frac{\partial P(\|\varepsilon(FX)\|=0)}{\partial\|\varepsilon(i)\|}\right\|_{\varepsilon(i)=1,\|i_t^{USD}-i_t^{EUR}\|=2.84188}$			-0.023 ***(0.004)	-0.059 ***(0.004)		
$\left.\frac{\partial P(\|\varepsilon(FX)\|=0)}{\partial\|\varepsilon(i)\|}\right\|_{\varepsilon(i)=1,\|F=0}$					-0.012 **(0.005)	-0.038 ***(0.005)
$\left.\frac{\partial P(\|\varepsilon(FX)\|=0)}{\partial\|\varepsilon(i)\|}\right\|_{\varepsilon(i)=1,\|F=1}$					-0.017 ***(0.005)	-0.045 ***(0.005)

Figure 1: Illustration of the link of average forecast performance, sorted by forecaster



This scatter plot illustrates the relationship between interest rate forecasts errors (w.r.t U.S. interest rates) and the performance of exchange rate predictions on the level of individual forecasters, i.e., we compute averages of these measures over time for each individual forecaster. Absolute forecast errors ($|\varepsilon_i(i)|$) are displayed at the y-axis, average returns based on T_{ind} on the x-axis.

Figure 2: Expected effects of fundamental forecast errors under different exchange rates value phases

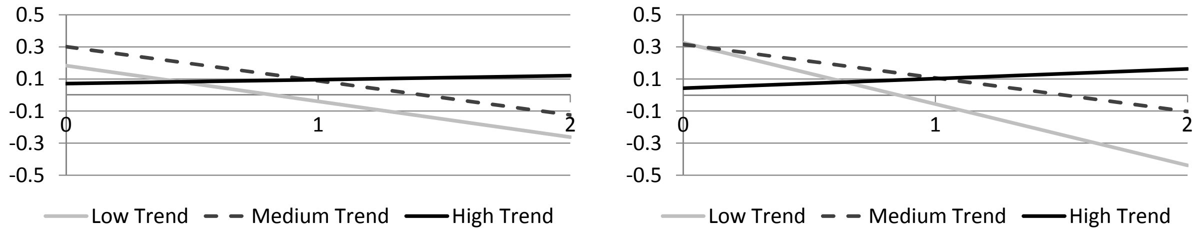


(a) i_{EUR} (b) i_{USD}

This figure depicts predictions of the average returns conditional on 1) the forecast quality of an interest rate forecast and 2) the value phase based on the fixed effects panel regression

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(i)| + \beta_2\text{FUND}_t + \beta_3\left(|\varepsilon_{j,t}(i)| \times \text{FUND}_t\right) + \epsilon_{j,t}.$$

The x-axis shows the absolute forecast error (0 for no error, 2 for a severe error), while the y-axis displays the returns. In each graph, there is a different line for each a value phase in which the exchange rate strongly deviates from the PPP value, and a market phase with small deviations from PPP.



(c) i_{EUR} (d) i_{USD}

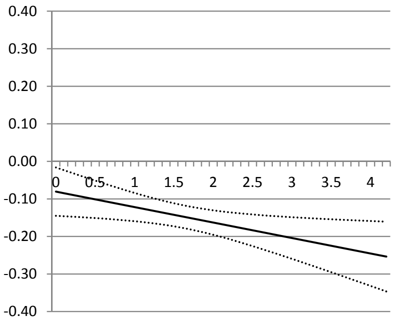
This figure depicts predictions of the average returns conditional on 1) the forecast quality of an interest rate forecast and 2) the momentum phase based on the fixed effects panel regression

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(i)| + \beta_2 D^L_{j,t} + \beta_3 D^H_{j,t} + \beta_4\left(|\varepsilon_{j,t}(i)| \times D^L_{j,t}\right) + \beta_5\left(|\varepsilon_{j,t}(i)| \times D^H_{j,t}\right) + \epsilon_{j,t}.$$

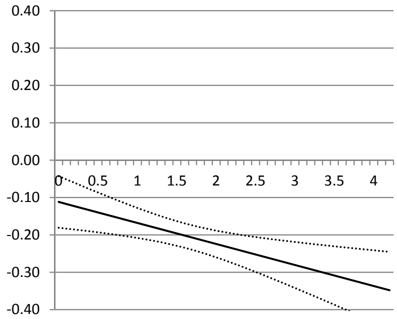
The x-axis shows the absolute forecast error (0 for no error, 2 for a severe error), while the y-axis displays the returns. In each graph, there is a different line for each the low momentum phase, normal momentum phase and the high momentum phase.

Figure 3: Expected effects of fundamental forecast errors under different momentum phases

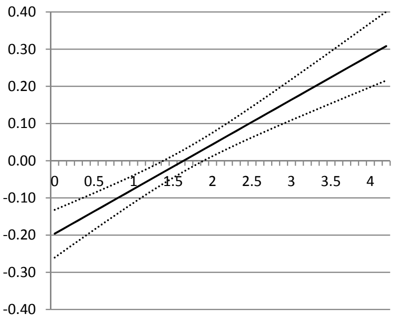
Figure 4: Marginal effects of forecast errors depending on absolute size of the interest rate differential



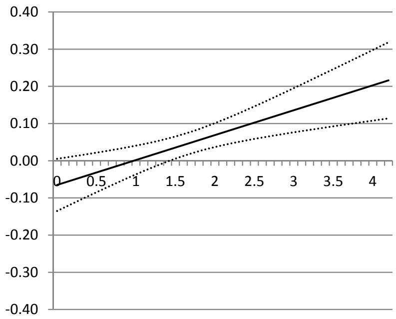
(a) i_{EUR}



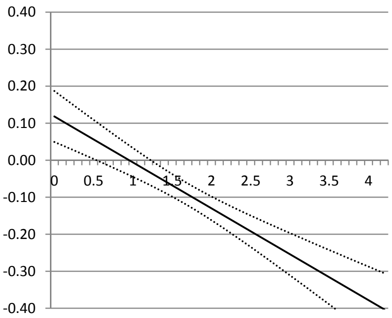
(b) i_{USD}



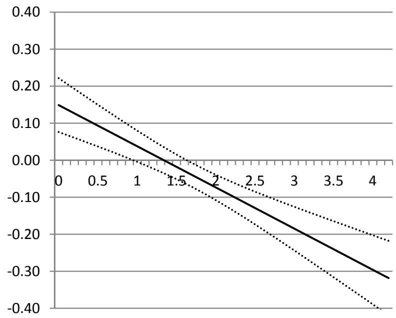
(c) π_{EUR}



(d) π_{USD}



(e) y_{EUR}



(f) y_{USD}

This figure displays how marginal effects of a fundamental forecast error point (zero for a correct forecast, 2 for a forecast of the wrong direction of change) on the return from a trading strategy using exchange rate forecasts depend on the absolute level of the interest rate differential between U.S. and EUR interest rates. The marginal effects are based on an interaction model, i.e.

$$r_{j,t,t+1} = \mu_j + \beta_1 |\varepsilon_{j,t}(X)| + \beta_2 |i_t^{USD} - i_t^{EUR}| + \beta_3 \left(|\varepsilon_{j,t}(X)| \times |i_t^{USD} - i_t^{EUR}| \right) + \epsilon_{j,t},$$

where the marginal effects $\frac{\partial r}{\partial |\varepsilon_{j,t}(X)|} = \beta_1 + \beta_3 \times |i_t^{USD} - i_t^{EUR}|$ depend on the absolute interest rate differential. The y-axis show the marginal effects, the x-axis the size of the interest rate differential $|i_t^{USD} - i_t^{EUR}|$. The dotted lines are the 95% confidence bounds.

Appendix

A.1 Data appendix

Exchange Rates To obtain a long-time series of daily exchange rates (from 01.1976 to 07.2010), we follow Burnside, Eichenbaum, Kleshchelski, and Rebelo (2010), drawing on a set of spot rates and forward rates denominated in terms of FCU/GBP. We then convert Pound quotes into Euro quotes by dividing the GBP/FCU quote by the EUR/GBP quote.[20] These data are taken from Datastream, and were originally collected by WM Company/Reuters. The mnemonics of the considered spot rates are DMARKER (used until 12.1998), ECURRSP (since 01.1999), JAPAYEN, SWISSFR, USDOLLR. The mnemonics of the considered forward rates are DMARK1F (until 01.1998), UKEUR1F (since 01.1999), JAPYN1F, SWISF1F, USDOL1F (all until 01.2007), and UKJPY1F, UKCHF1F, and USGBP1F (after 01.2007). In order to transform the GBP-denominated exchange rates with respect to the DM or Euro, we also make use of the spot rates DMARKER and ECURRSP, respectively. The spot and the forward rates are both midquotes sampled at the same point in time.

Interest Rates We use the same the data sources used by Burnside, Eichenbaum, Kleshchelski, and Rebelo (2010) and download three-month interbank interest rates for Germany (until 12.1998), the Eurozone (starting 01.1999), the United States, the United Kingdom, Japan and Switzerland from Datastream. These data were originally collected by the Financial Times and ICAP. The mnemonics are ECWGM3M, ECJAP3M, ECSWF3M, ECUKP3M, ECUSD3M, ECEUR3M.

[20] *Spot* rates which measure directly the foreign value of the Euro/the D-Mark (without making a transformation from GBP) are also available on a daily basis from other sources. To make sure that our results on the forecasting performance of forecasters do not depend on this transformation, we compare our spot rate data with these directly obtained exchange rates. In particular, these are the D-Mark quotes from the historical database of the Frankfurt Stock Exchange provided by the Deutsche Bundesbank, as well the Euro rates downloadable in Datastream (mnemonics EMJPYSP. EMUSDSP,EMCHFSP, EMGBPSP). All those spot rates have a correlation with those from our data sample of > 0.999.

Table A1: Average exchange rate forecasting performance in the cross section: t-values of T_{ind}

Elliot and Ito (1999) present their results in terms of t-values, a performance measure closely related to the Sharpe ratio, where the mean returns are divided by their standard errors instead of the standard deviation. We report statistics about these t-values in the cross section of forecasters underneath. The table reports the t-values and the associated mean returns for the individual trading strategies. It displays the respective values for the 95%, 90%, 50%, 5% and 1% percentile forecaster, sorted by t-values. These values are compared to simulated values, i.e. the average value T_0 from 10,000 purely random (coin toss) strategies (an investor buys or sells USD against the Euro in the forward market according to a coin toss, and settles her position one month later).

		t-values	Mean
T_{ind}	X_{99}	2.845	1.087
	X_{95}	2.108	0.387
	X_{90}	1.711	0.432
	X_{50}	0.210	0.149
	X_{05}	-1.447	-0.266
	X_{01}	-2.214	-0.422
T_0	Average	-0.010	-0.002

As the t-values of a purely random strategy can be approximated by a standard normal distribution, the t-values computed for the individual forecasters can be directly compared to critical values for two-sided tests of the hypothesis that an individual's average profit equals zero. For example, a t-value of 2.108 (which can be observed for the forecaster at the 95% percentile) points to a significantly positive average return, as this value is above the critical value of 1.96 at the 5% significance level. In contrast, the forecaster at the 5% percentile has a t-value of -1.447, which is consistent with the hypothesis of zero average profits at the 5% significance level (and does *not* imply that this particular forecaster makes predictions which are significantly *worse* then those from a random strategy at the 5% significance level.

A.2 Further analyses

Table A2: Diagnostics

This table reports the diagnostics about the correct estimator for our panel regression of interest,

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(i^{EUR})| + \beta_2|\varepsilon_{j,t}(i^{USD})| + \gamma\Phi_{j,t} + \delta\Psi_{j,t} + \epsilon_{j,t}.$$

We proceed in three steps. In a first step, we conduct Breusch and Pagan (1980)-tests to determine for each specification reported in Table 4 whether or not individual-specific effects are present. Under the null, individual-specific effects are absent. In a second step, we compare the fixed effects and random effects estimators by the means of Hausman tests. If the null can be rejected, there are systematic differences between the coefficient estimates, indicating that random effects does not estimate consistently and hence, fixed effects should be used. Ultimately, we perform regressions in which we take the lagged variables to instrument for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$ and make use of Davidson and MacKinnon (1989)'s test of the null hypothesis that OLS can consistently estimate the model (i.e. there is no need to instrument for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$).

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
Breusch/Pagan LM	5.60	3.83	3.08	3.97	0.01	0.00	0.02	0.02	0.01
df	1	1	1	1	1	1	1	1	1
p-value	***0.018*	**0.050*	**0.079*	***0.046*	*0.920*	*0.987*	*0.900*	*0.898*	*0.914*
Hausman									
$(\beta^{FE}-\beta^{RE})'[V_{\beta^{FE}}-V_{\beta^{RE}}](\beta^{FE}-\beta^{RE})$	5.23	6.48	80.02	22.58	43.76	26.79	46.95	45.82	46.98
df	1	1	3	3	21	21	24	25	26
p-value	***0.022*	***0.011*	****0.000*	****0.000*	****0.003*	*0.178*	****0.003*	****0.007*	****0.007*
Davidson-MacKinnon									
F-Statistic	0.09	1.02	1.82	6.93	3.20	2.08	3.53	3.619	3.478
p-value	*0.761*	*0.313*	*0.142*	****0.000*	***0.022*	*0.100*	****0.002*	****0.001*	****0.002*

Table A3: Panel Pooled OLS Regression, no instruments

This table reports the results of panel pooled OLS regressions of the trading rule T_{ind}'s period forecast return, $r_{j,t,t+1}$ (based on the forecast of the forecaster j in t), on the absolute forecast error made for European and U.S.-American interest rates ($|\varepsilon_{j,t}(i^{EUR})|$ and $|\varepsilon_{j,t}(i^{USD})|$, respectively) as well as a battery of control variables $\Phi_{j,t}$ and $\Psi_{j,t}$, i.e.

$$r_{j,t,t+1} = \beta_0 + \beta_1|\varepsilon_{j,t}(i^{EUR})| + \beta_2|\varepsilon_{j,t}(i^{USD})| + \gamma\Phi_{j,t} + \delta\Psi_{j,t} + \epsilon_{j,t}.$$

Depending on the specification (i) to (ix), $\Phi_{j,t}$ includes forecast errors with respect to other fundamentals than interest rates, i.e. inflation ($|\varepsilon(\pi)|$) and industrial production growth forecast errors $|\varepsilon(y)|$. Unlike in Table 4, we do not use instruments for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$. $\Psi_{j,t}$ represents purely exogenous control variables such as year specific dummy variables. Significance: ***:1%, **: 5%, *: 10%.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
$\|\varepsilon_{j,t}(i^{EUR})\|$	-0.129		-0.130		-0.160		-0.131
	***(0.015)		***(0.015)		***(0.016)		***(0.016)
$\|\varepsilon_{j,t}(i^{USD})\|$		-0.191		-0.192		-0.171	-0.146
		***(0.017)		***(0.017)		***(0.019)	***(0.019)
$\|\varepsilon_{j,t}(\pi^{EUR})\|$			0.008		-0.035		-0.034
			(0.015)		**(0.017)		**(0.017)
$\|\varepsilon_{j,t}(\pi^{USD})\|$				0.056		-0.034	-0.026
				***(0.015)		**(0.016)	*(0.015)
$\|\varepsilon_{j,t}(y^{EUR})\|$			-0.105		-0.030		-0.021
			***(0.016)		*(0.016)		(0.016)
$\|\varepsilon_{j,t}(y^{USD})\|$				-0.023		-0.072	-0.064
				(0.017)		***(0.017)	***(0.017)
β_0	0.185	0.244	0.255	0.220	0.645	0.649	0.775
	***(0.015)	***(0.016)	***(0.021)	***(0.021)	***(0.234)	***(0.239)	***(0.242)
Year dummies	NO	NO	NO	NO	YES	YES	YES
$N \times T$	63,693	62,940	63,414	62,401	63,414	62,401	62,257
R^2	0.001	0.003	0.002	0.003	0.026	0.026	0.027

Table A4: Panel Pooled OLS Regression, with instruments

This table reports the results of panel pooled OLS regressions of the trading rule T_{ind}'s period forecast return, $r_{j,t,t+1}$ (based on the forecast of the forecaster j in t), on the absolute forecast error made for European and U.S.-American interest rates ($|\varepsilon_{j,t}(i^{EUR})|$ and $|\varepsilon_{j,t}(i^{USD})|$, respectively) as well as a battery of control variables $\Phi_{j,t}$ and $\Psi_{j,t}$, i.e.

$$r_{j,t,t+1} = \beta_0 + \beta_1|\varepsilon_{j,t}(i^{EUR})| + \beta_2|\varepsilon_{j,t}(i^{USD})| + \gamma\Phi_{j,t} + \delta\Psi_{j,t} + \epsilon_{j,t}.$$

Depending on the specification (i) to (ix), $\Phi_{j,t}$ includes forecast errors with respect to other fundamentals than interest rates, i.e. inflation ($|\varepsilon(\pi)|$) and industrial production growth forecast errors $|\varepsilon(y)|$. We use lagged values as external instruments for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$. $\Psi_{j,t}$ represents purely exogenous control variables such as year specific dummy variables. Significance: ***:1%, **: 5%, *: 10%.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
$\|\varepsilon_{j,t}(i^{EUR})\|$	-0.056		-0.056		-0.140		-0.114
	**(0.028)		**(0.028)		***(0.037)		***(0.038)
$\|\varepsilon_{j,t}(i^{USD})\|$		-0.134		-0.143		-0.156	-0.128
		***(0.034)		***(0.035)		***(0.053)	**(0.053)
$\|\varepsilon_{j,t}(\pi^{EUR})\|$			-0.060		-0.148		-0.180
			(0.042)		***(0.048)		***(0.051)
$\|\varepsilon_{j,t}(\pi^{USD})\|$				0.198		0.025	0.082
				***(0.040)		(0.047)	*(0.050)
$\|\varepsilon_{j,t}(y^{EUR})\|$			-0.162		0.043		0.065
			***(0.051)		(0.068)		(0.075)
$\|\varepsilon_{j,t}(y^{USD})\|$				-0.038		-0.150	-0.162
				(0.054)		**(0.060)	**(0.066)
β_0	0.145	0.213	0.298	0.103	-0.032	0.018	0.108
	***(0.023)	***(0.029)	***(0.050)	**(0.052)	(0.080)	(0.075)	(0.088)
Year dummies	NO	NO	NO	NO	YES	YES	
$N \times T$	50,793	51,512	51,155	50,084	51,155	50,084	49,872
R^2	0.000	0.002	0.001	.	0.022	0.023	0.022

Table A5: Panel Fixed Effects Regression, no instruments

This table reports the results of panel regressions with individual fixed effects of the trading rule T_{ind}'s period forecast return, $r_{j,t,t+1}$ (based on the forecast of the forecaster j in t), on the absolute forecast error made for European and U.S.-American interest rates ($|\varepsilon_{j,t}(i^{EUR})|$ and $|\varepsilon_{j,t}(i^{USD})|$, respectively) as well as a battery of control variables $\Phi_{j,t}$ and $\Psi_{j,t}$, i.e.

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(i^{EUR})| + \beta_2|\varepsilon_{j,t}(i^{USD})| + \gamma\Phi_{j,t} + \delta\Psi_{j,t} + \epsilon_{j,t}.$$

Depending on the specification (i) to (ix), $\Phi_{j,t}$ includes forecast errors with respect to other fundamentals than interest rates, i.e. inflation ($|\varepsilon(\pi)|$) and industrial production growth forecast errors $|\varepsilon(y)|$. $\Psi_{j,t}$ represents purely exogenous control variables such as year specific dummy variables. Unlike in Table 4, we do not use instruments for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$. Significance: ***:1%, **: 5%, *: 10%.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
$\lvert\varepsilon_{j,t}(i^{EUR})\rvert$	-0.139		-0.140		-0.169		-0.141
	***(0.015)		***(0.015)		***(0.016)		***(0.016)
$\lvert\varepsilon_{j,t}(i^{USD})\rvert$		-0.182		-0.184		-0.171	-0.145
		***(0.017)		***(0.017)		***(0.019)	***(0.019)
$\lvert\varepsilon_{j,t}(\pi^{EUR})\rvert$			-0.002		-0.033		-0.032
			(0.016)		*(0.017)		*(0.017)
$\lvert\varepsilon_{j,t}(\pi^{USD})\rvert$				0.044		-0.035	-0.028
				***(0.015)		**(0.016)	*(0.016)
$\lvert\varepsilon_{j,t}(y^{EUR})\rvert$			-0.074		-0.022		-0.013
			***(0.016)		(0.016)		(0.017)
$\lvert\varepsilon_{j,t}(y^{USD})\rvert$				-0.030		-0.073	-0.067
				*(0.017)		***(0.018)	***(0.017)
$\bar{\mu}$	0.192	0.237	0.246	0.225	0.714	0.694	0.837
	***(0.011)	***(0.014)	***(0.018)	***(0.020)	***(0.248)	***(0.252)	***(0.255)
Year dummies	NO	NO	NO	NO	YES	YES	YES
$N \times T$	63,693	62,940	63,414	62,401	63,414	62,401	62,257
R^2_B	0.006	0.050	0.032	0.056	0.177	0.179	0.171
R^2_O	0.001	0.003	0.002	0.003	0.026	0.026	0.027
R^2_W	0.001	0.002	0.002	0.002	0.023	0.023	0.025

Table A6: Panel Fixed Effects Regression with AR(1) correction, no instruments

This table reports the results of panel regressions with individual fixed effects of the trading rule T_{ind}'s period forecast return, $r_{j,t,t+1}$ (based on the forecast of the forecaster j in t), on the absolute forecast error made for European and U.S.-American interest rates ($|\varepsilon_{j,t}(i^{EUR})|$ and $|\varepsilon_{j,t}(i^{USD})|$, respectively) as well as a battery of control variables $\Phi_{j,t}$ and $\Psi_{j,t}$, i.e.

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(i^{EUR})| + \beta_2|\varepsilon_{j,t}(i^{USD})| + \gamma\Phi_{j,t} + \delta\Psi_{j,t} + \epsilon_{j,t}.$$

Depending on the specification (i) to (ix), $\Phi_{j,t}$ includes forecast errors with respect to other fundamentals than interest rates, i.e. inflation ($|\varepsilon(\pi)|$) and industrial production growth forecast errors $|\varepsilon(y)|$. $\Psi_{j,t}$ represents purely exogenous control variables such year specific dummy variables. Unlike in Table 4, we do not use instruments for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$. We control for first-order autocorrelation by the fixed-effects method proposed by Baltagi and Wu (1999). Significance: ***:1%, **: 5%, *: 10%.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
$\|\varepsilon_{j,t}(i^{EUR})\|$	-0.152		-0.152		-0.172		-0.147
	***(0.017)		***(0.017)		***(0.018)		***(0.018)
$\|\varepsilon_{j,t}(i^{USD})\|$		-0.178		-0.178		-0.165	-0.139
		***(0.017)		***(0.017)		***(0.018)	***(0.019)
$\|\varepsilon_{j,t}(\pi^{EUR})\|$			0.002		-0.017		-0.014
			(0.017)		(0.017)		*(0.018)
$\|\varepsilon_{j,t}(\pi^{USD})\|$				0.006		-0.045	-0.041
				***(0.017)		***(0.017)	**(0.017)
$\|\varepsilon_{j,t}(y^{EUR})\|$			-0.080		-0.038		-0.029
			***(0.017)		**(0.017)		(0.017)
$\|\varepsilon_{j,t}(y^{USD})\|$				-0.062		-0.081	-0.072
				***(0.018)		***(0.018)	***(0.019)
$\bar{\mu}$	0.228	0.262	0.286	0.295	0.824	0.814	0.806
	***(0.014)	***(0.015)	***(0.018)	***(0.019)	***(0.108)	***(0.107)	***(0.107)
Year dummies	NO	NO	NO	NO	YES	YES	YES
$N \times T$	62,625	61,874	62,346	61,338	62,346	61,338	61,195
R^2_B	0.001	0.020	0.011	0.015	0.163	0.170	0.161
R^2_O	0.001	0.002	0.002	0.002	0.025	0.025	0.026
R^2_W	0.001	0.002	0.002	0.002	0.015	0.015	0.016
DW (Bhargava et al.)	1.64	1.64	1.63	1.63	1.67	1.66	1.66
DW (Baltagi/Wu)	1.86	1.87	1.87	1.87	1.90	1.90	1.90

Table A7: Panel Fixed Effects Regression, alternative instruments

This table reports the results of panel regressions with individual fixed effects of the trading rule T_{ind}'s period forecast return, $r_{j,t,t+1}$ (based on the forecast of the forecaster j in t), on the absolute forecast error made for European and US-American interest rates ($|\varepsilon_{j,t}(i^{EUR})|$ and $|\varepsilon_{j,t}(i^{USD})|$, respectively) as well as a battery of control variables $\Phi_{j,t}$, i.e.,

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(i^{EUR})| + \beta_2|\varepsilon_{j,t}(i^{EUR})| + \gamma\Phi_{j,t} + \delta\Psi_{j,t} + \epsilon_{j,t}.$$

Depending on the specification (i) to (ix), $\Phi_{j,t}$ includes forecast errors with respect to other fundamentals than interest rates, i.e. inflation ($|\varepsilon(\pi)|$) and industrial production growth forecast errors $|\varepsilon(y)|$. $\Psi_{j,t}$ represents year specific dummy variables.
Unlike in Table 4, we use *alternative* instruments for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$, which are correlated with these variables but uncorrelated with the unexplained portion of Eq. 2. Doing so, we make use of the facts that: (i) our dataset covers a broader set of countries than the US and the Eurozone, i.e. the UK and Japan; and that, (ii), skills in predicting macroeconomic series persist across countries. We thus employ the absolute forecast errors with respect to the interest rates in the *UK* and in *Japan* as exogenous instruments for the forecast errors with respect to the *US* and the *Eurozone*. Likewise, we use the absolute forecast errors with respect to the inflation rate and industrial production in these countries as instruments for the US and Eurozone inflation and industrial production, respectively. These instruments are valid for two reasons: first, it can be shown from our data that skills in predicting these macroeconomic series are correlated across countries: for example, the cross-sectional correlation between average absolute errors with respect to Eurozone and UK interest rates is 0.51. In the panel context, there still remains a positive correlation of absolute forecast errors with respect to these two series of 0.25. Secondly, there is no theoretical reason to believe that errors in predicting the macroeconomic circumstances in Japan should have a systematic impact on the USD/EUR exchange rate predictions which is not yet covered by the forecast error with respect to the fundamentals in the United States or the Eurozone; hence, the instruments are exogenous.
Significance: ***:1%, **: 5%, *: 10%.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$\|\varepsilon_{j,t}(i^{EUR})\|$	-0.409		-0.446		-0.980	
	***(0.057)		***(0.064)		***(0.080)	
$\|\varepsilon_{j,t}(i^{USD})\|$		-0.514		-0.374		-0.830
		***(0.066)		***(0.081)		***(0.103)
$\|\varepsilon_{j,t}(\pi^{EUR})\|$			-0.010		0.219	
			(0.088)		**(0.102)	
$\|\varepsilon_{j,t}(\pi^{USD})\|$				-0.338		0.197
				***(0.104)		*(0.108)
$\|\varepsilon_{j,t}(y^{EUR})\|$			-0.072		0.164	
			***(0.076)		*(0.087)	
$\|\varepsilon_{j,t}(y^{USD})\|$				-0.270		-0.282
				**(0.125)		***(0.109)
$\bar{\mu}$	0.373	0.484	0.769	0.773	1.178	1.051
	***(0.042)	***(0.053)	***(0.100)	***(0.100)	***(0.306)	***(0.303)
Year dummies	NO	NO	NO	NO	YES	YES
$N \times T$	58,102	58,088	51,746	51,849	51,826	51,826