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Abstract

This paper provides novel evidence on exchange rate expectations of both chartists and fundamentalists separately. These groups indeed form expectations differently. Chartists change their expectations more often; however, all professionals' expectations vary considerably as they generally follow strong exchange rate trends. In line with non-linear exchange rate-modeling, professionals expect mean reversion only if exchange rates deviate strongly from PPP. Chartists survive in currency markets since they forecast just as accurately as fundamentalists. Unexpectedly from an efficient market viewpoint, chartists even outperform fundamentalists at short horizons. Overall, these findings clearly support the chartist-fundamentalist approach.

JEL-Code: F310, G150, D840.

Keywords: exchange rate formation, expectation formation, heterogeneous agent models, forecasting performance.

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1 Introduction

There is ample research on the way exchange rate expectations are formed, stimulated in particular by Frankel and Froot (1987). There is also a great number of studies systematically documenting characteristics of chartists and fundamentalists in foreign exchange, starting with Taylor and Allen (1992). However, up until now there has been no direct evidence combining these two strands of literature: How do professionals, who tell us that they are chartists or fundamentalists, each form their exchange rate expectations?

This is an important question from at least three perspectives. First, the so-called chartist-fundamentalist models of exchange rates make assumptions about the behavior of these two groups (e.g., Frankel and Froot, 1990; De Grauwe and Grimaldi, 2006; Manzan and Westerhoff, 2007). We examine whether chartists and fundamentalists really behave as they are assumed to do in this line of research. Second, models of heterogeneous agents have been shown to be able to replicate the characteristics of unstable financial markets (Day and Huang, 1990; Farmer and Joshi, 2002). These models argue that instability arises from the expectation formation of a non-fundamentally-oriented group of traders, a notion which corresponds to our group of chartists. Hence, we examine whether the decision making of this group contributes to financial instability. Third, the existence of various groups in financial markets implicitly assumes that all these groups operate successfully in the long run. In this respect, the efficient market hypothesis states that chartism-inspired behavior will not be competitive in the longer run (Fama, 1991). To complement the abundance of studies testing the profitability of hypothetical chartist trading rules (e.g., Park and Irwin, 2007; Neely, Weller, and Ulrich, 2010), we examine whether actual expectations of chartists provide a basis for profitable trading strategies to the same degree as expectations of fundamentalists.

All examinations presented here are the first to systematically connect information about individual exchange rate expectations with the respective professionals' preferred kind of information, i.e. charts or fundamentals. This connection enables us to directly test the real world behavior of chartists and fundamentalists, and thus to complement existing indirect evidence derived from simulation studies (e.g., Föllmer, Horst, and Kirman, 2005; Tramontana, Westerhoff, and Gardini, 2010), experiments (Sonnemans, Hommes, Tuinstra, and Van De Velden, 2004) or explanations of forecast dispersion (Jongen, Verschoor, Wolff, and Zwinkels, 2012). Our findings clearly support the common core of the chartist-fundamentalist models: forecasters who rely heavily on charts do indeed form exchange rate expectations more in line with trends than fundamentalists and they reinforce existing trends, which may destabilize foreign exchange markets. Finally, challenging the efficient market hypothesis (Fama, 1991, 1998), chartist behavior is individually rational as these forecasts are at least as good as those of the peer group.

This study is based on the Financial Market Survey conducted on a monthly basis by the Centre for European Economic Research (ZEW) in Mannheim, Germany, on several hundred professional forecasters. This survey regularly asks professionals about their individual US-dollar / Euro expectations, starting in January 1999. We combine these answers with information about the respective individuals' self-assessment of the use of charts and fundamentals, which has been carried out three times, in 2004, 2007 and 2011. Overall, our sample comprises almost 400 forecasters which provide an unbalanced panel with more than 30,000 observations over up to 153 months, up to and including September 2011. We classify forecasters into the categories of chartists, fundamentalists, and a third one, which we call intermediates.

Our study makes use of these data in three steps, analyzing actual forecasting behavior, forecasting dynamics and forecasting performance: (1) Regarding forecasting behavior, we test the revealed behavior of chartists and fundamentalists, as inspired by chartist-fundamentalist models. In line with earlier literature (e.g., Menkhoff and Taylor, 2007), we use the terms of charts and technical analysis as synonyms. We find that chartists tend to follow trends more often than fundamentalists. (2) Regarding forecasting dynamics, chartists tend to revise the direction of their exchange rate forecasts more frequently than fundamentalists, confirming a standard assumption in heterogeneous agents' models (e.g., Brock and Hommes, 1998; Farmer and Joshi, 2002). The choice of forecasting tools is influenced by recent experience: when exchange rates exhibit trends, the professionals (chartists and fundamentalists) tend to switch towards chartism; in contrast, the professionals move away from chartism when the exchange rate deviates substantially from its longer-term average (the purchasing power parity, PPP). (3) Regarding forecasting performance, professionals, such as chartists, will only survive in competitive foreign exchange markets if they perform well. We find that chartists are indeed equally good forecasters as fundamentalists. When differentiating between forecasting horizons, chartists perform relatively better at shorter horizons, whereas fundamentalists are at least as good at longer horizons. This fits well with the chartists' (fundamentalists') preference for short (long) horizons (Taylor and Allen, 1992).

All these findings correspond to the core assumptions of chartist-fundamentalist models or with the stylized facts about expectation formation and the use of charts and fundamentals, respectively. Detailed references to this literature are discussed in the following section. In this sense, we provide supportive evidence complementing earlier approaches, which often relied on indirect tests. On closer examination, however, we also obtain evidence that is less conclusive regarding some specific assumptions. The most important issue in this respect seems to be our intuition that the switching between chartism and fundamentalism is largely an opportunistic shift of weight that forecasters give to these tools (different from De Grauwe and Grimaldi, 2006; Manzan and Westerhoff, 2007), whereas their general preferences for either charts or fundamentals seem to be quite stable over time. Moreover, chartists are neither less profitable than fundamentalists as modeled by Day and Huang (1990), nor more profitable as modeled by De Grauwe and Grimaldi (2006, p.29), and switching between strategies is not related to exchange rate volatility (ibid, p.26).

The paper is structured as follows: Section 2 briefly discusses relevant literature in order to embed our study in earlier work and to carve out our own contribution. Section 3 reports the comprehensive dataset. Section 4 presents results of our research in several steps (Sections 4.1 to 4.3), Section 5 contains robustness tests. Conclusions are drawn in Section 6.

2 Literature and hypotheses

This section shows the relation of our research to three strands of earlier literature, of which we can only cover a selection. There are studies which have influenced and shaped the *chartist-fundamentalist models*. More generally, studies modeling the interaction of *heterogeneous agents* often focus on the forecasting dynamics of groups, which may lead to price instability. Finally, our work is related to studies about the *performance* of chartist and fundamentalist trading.

Chartist-fundamentalist models. These models have been stimulated by observations which motivate to model foreign exchange markets where both, chartists and fundamentalists, co-exist and interact (Frankel and Froot (1990), subsequently refined by De Grauwe and Grimaldi (2006)).[1] The basic idea is that there are these two groups in the market who follow different investment strategies. Chartists usually dominate the market with their trend-following behavior, which generates its own kind of risk for fundamentalists. However, when exchange rate misalignment becomes more and more obvious, the relative attractiveness of fundamentalism increases, and more market participants follow fundamentals. This mechanism limits the power of chartism and reduces the deviation of exchange rates from their fundamental equilibrium rate.[2] We use professional forecasters' self-assessment regarding their forecasting tools to classify them as chartists, fundamentalists, or intermediates. Next, we test whether chartists' and fundamentalists' forecasting behavior does differ as expected. Simplifying the variety of technical trading rules (see, e.g. Neely

[1]Standard economic models with representative agents cannot adequately explain exchange rate formation (e.g., Meese and Rogoff, 1983; Cheung, Chinn, and Garcia-Pascual, 2005). Empirically, there is a high degree of heterogeneity among foreign exchange professionals, as found by Frankel and Froot (1990) or Ito (1990) and later reconfirmed by, e.g., MacDonald and Marsh (1996). A crucial characteristic of heterogeneity is the formation of exchange rates following bandwagon expectations over short horizons and regressive expectations over longer horizons (Frankel and Froot, 1987). This finding already contains the core ingredient of chartist-fundamentalist models, i.e. the co-existence of trend-following and mean-reverting expectations (for a survey, see Jongen, Verschoor, and Wolff (2008), for non-linear extensions see (e.g., Menkhoff, Rebitzky, and Schröder, 2008; Reitz, Rülke, and Stadtmann, 2012). Finally, dealers say that that they use primarily charts at shorter horizons and rely more on fundamentals at longer horizons (Taylor and Allen, 1992), a robust result which also extends to fund managers (see survey by Menkhoff and Taylor, 2007).

[2]This also provides a motivation for foreign exchange interventions (e.g., Beine, De Grauwe, and Grimaldi, 2009). It should be noted that De Grauwe and Grimaldi (2006) define chartists as being unaware of fundamental information. In contrast, Manzan and Westerhoff (2007) assume, that fundamentalists do not consider technical analysis.

and Weller, 2011), we investigate whether chartists can in fact be characterized by a strong use of trend-following strategies (Rötheli, 2011), i.e. a use that is stronger than for fundamentalists (*Hypothesis 1*).

The characterization of chartists needs to be complemented by a characterization of fundamentalists. Fundamental models basically assume mean-reverting forecasting behavior towards purchasing power parity. Thus, we investigate whether the orientation at PPP is more pronounced for fundamentalists (*Hypothesis 2*). This hypothesis has been tested in a simpler way, i.e. neglecting *chartists*, for an earlier sample of the ZEW data with a supportive result (Menkhoff, Rebitzky, and Schröder, 2008).

Heterogeneous agents models. A core element of chartist-fundamentalist models in foreign exchange is the dynamics between groups.[3] Brock and Hommes (1997, 1998) explicitly model a switching mechanism where agents alter their strategy when they realize that an alternative strategy has performed better than their original one. In the field of exchange rate modeling, De Grauwe and Grimaldi (2006) incorporate this notion to a switching between chartists and fundamentalists.[4]

These models provide further testable hypotheses. First, various heterogeneous agents' models assume that the existence of non-fundamentally-driven behavior of a group of agents introduces instability to the respective system, in our case the exchange rate (see Brock and Hommes, 1998; Farmer and Joshi, 2002). This idea has previously been formalized by DeLong, Shleifer, Summers, and Waldmann (1989), albeit in a different way. These agents' willingness to frequently switch their positions is a source of instability. Applied to our case, one would expect that chartists show

[3]Such heterogeneity is modeled via segmented investors (Day and Huang, 1990; Chiarella, Dieci, and Gardini, 2002) or via segmented markets (Westerhoff, 2004). The results of these simulation studies are largely consistent with stylized facts (King, Osler, and Rime, 2012), observations in experimental asset markets (see, e.g., Sonnemans, Hommes, Tuinstra, and Van De Velden, 2004; Haruvy, Lahav, and Noussair, 2007; Bloomfield, Tayler, and Zhou, 2009; Hommes, 2011) and models from behavioral finance, such as Barberis, Shleifer, and Vishny (1998). Finally, heterogeneous agents have been usefully linked to the dispersion of expectations in foreign exchange (Menkhoff, Rebitzky, and Schröder, 2009; Jongen, Verschoor, Wolff, and Zwinkels, 2012).

[4]On expectations see Jongen, Verschoor, Wolff, and Zwinkels (2012). Modifications to this switching mechanism include the consideration of contagion (Lux, 1998) or the consideration of expected profitability (Dieci and Westerhoff, 2010).

instable behavior by switching between appreciation and depreciation expectations (motivating long and short positions in a currency) more frequently than fundamentalists (*Hypothesis 3*).

Next, as switching is motivated by profitability considerations (Brock and Hommes, 1997), Lux (1998) and De Grauwe and Grimaldi (2006) propose that chartist trading rules are adopted when momentum trading has been profitable in the preceding period (*Hypothesis 4*). Turning to fundamentalists' behavior, recent empirical exchange rate modeling suggests a non-linear response of exchange rates to changes in fundamentals (e.g. Dumas, 1993; Taylor, Peel, and Sarno, 2001; De Grauwe and Grimaldi, 2006). This implies that a greater deviation from the fundamental value clearly decreases the perceived risk of following a fundamental strategy (e.g., Bauer, De Grauwe, and Reitz, 2009), and that the switching mechanism in this model induces a shift from chartist to fundamentalist strategies (*Hypothesis 5*).

Performance of chartist trading. Independently of these research issues, there is a growing body of studies finding profitability of chartist trading in foreign exchange (e.g. Okunev and White, 2003; Qi and Wu, 2006; Park and Irwin, 2007; Neely, Weller, and Ulrich, 2010). A shortcoming of these studies is that they can only analyze the performance of *simulated* trading rules and do not calculate real-world returns. Moreover, a *comparative* analysis of forecasting performance by chartists and fundamentalists has been almost completely neglected by previous empirical studies. An exception is Goodman (1979), who finds favorable results for chartists, although for a small sample. This lack of consideration in empirical research is surprising, as theoretical models disagree about whether chartists are inferior (Day and Huang, 1990) or superior (De Grauwe and Grimaldi, 2006) to fundamentalists. In functioning markets professionals should only consider *useful* information such that neither chartists nor fundamentalists should be systematically superior, an idea we will analyze on the basis of our data (*Hypothesis 6*).[5]

[5] However, there are two caveats to be made: first, we sometimes reduce chartism to *momentum trading* which underestimates its potential profitability among the major exchange rates (Pukthuanthong, Levich, and Thomas III, 2007; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012). Second, it seems interesting to control results for the attractively high returns from carry trades (see survey by Burnside, 2011).

Overall, we examine six hypotheses derived from a wide range of literature. The starting assumption on the existence of chartists and fundamentalists only provides the foundations for our research. Hypotheses 1 and 2 analyze forecasting behavior, Hypotheses 3 to 5 analyze forecasting dynamics and Hypothesis 6 addresses forecasting performance. Hypotheses 2 and 6 have been tested before with smaller samples; regarding the remaining hypotheses, our study covers new ground.

3 Data

We consider a unique panel of individual exchange rate forecasts made by close to 400 German professional forecasters contributing to the Financial Market Survey conducted by the Centre for European Economic Research (ZEW) in Mannheim, Germany. The database has been used for recent research (e.g., Schmeling and Schrimpf, 2011) due to its length (monthly observations starting in 1991) and breadth (an average of about 300 forecasters respond each month).

Microdata of the USD/EUR forecast. The data are particularly interesting for our research questions, as we are able to connect the forecasts to additional information on the preferred FX forecasting tools of as many as 396 of the participating professional forecasters. We are not only able to follow an individual forecaster's expectations with respect to the USD/EUR rate over time, but are also able to link these expectations to the forecaster's stated use of fundamental analysis, technical analysis and the analysis of order flows, respectively. This kind of information has been surveyed at three different points in time, in 2004.01, 2007.04 and 2011.09, and some of the forecasters have responded to more than one of these "surveys of methods". For our analysis, we focus on the USD/EUR forecasts after the introduction of the Euro in 1999.01, and we generally consider only those forecasters from whom we have collected additional information on forecasting tools. Thus, we analyze a panel consisting of a total of 33,861 observations over 153 months (until 2011.09). Some robustness checks are based on the entire panel of forecasters during this time period, which comprises 744 forecasters and a total of 44,950 observations. We do not consider forecasters who have responded to the survey less than 10 times.

The exchange rate forecasts are directional in nature, meaning we have information on whether a forecaster expects the USD to appreciate, remain constant or depreciate against the Euro. Each forecast is associated with a time stamp indicating the exact day on which the forecast was made. This allows us to track the circumstances (such as prevailing trends) around each forecast.

The use of charts by forecasters. The surveys of methods in 2004.01, 2007.04 and 2011.09 ask the forecasters to attach percentage values to their use of fundamental analysis, technical analysis and the analysis of order flows (see Table 1). The table reveals that, on average, the proportion of analytical tools remains relatively constant. Analysts attribute an average share of almost sixty percent to fundamental analysis, and below thirty percent to technical analysis. We therefore concentrate on fundamental and technical analysis in the remainder of this paper.

[Table 1 about here]

Due to this information, we can compare our sample of forecasters to other populations of foreign exchange professionals. Menkhoff and Taylor (2007, Table 3) refer to surveys of foreign exchange dealers and international fund managers (also from Germany), who give charts a weight of 35-45 percent and 36 percent, respectively. This indicates that the professional forecasters covered here think more in line with fund managers than dealers which seems to reflect their analytical stance. In this sense the sample fits to the rising importance of asset managers in foreign exchange at the cost of interbank dealers (King, Osler, and Rime, 2012). It is notable, however, that algorithmic trading - a sophisticated form of chartist behavior as one referee says - has recently increased and may thus shift the balance towards chartism (King and Rime, 2010; Boehmer, Fong, and Wu, 2012). Whatever the ”market shares” of chartists and fundamentalists in current markets may be, we just characterize behavior of these two groups.

Chartists and fundamentalists. To obtain groups of forecasters with diverging forecasting techniques, we define the groups of chartists and fundamnetalists in a pragmatic way as follows. There are two criteria forecasters need to meet in order to be classified as *chartists*: first, they assign a relatively larger weight to technical analysis than to fundamental analysis (or order flow analysis); and second, their weighting of technical analysis is at least at the 40 percent level. In order to obtain groups of similar size and thus to make the distinction clear, we define *fundamentalists* as forecasters who assign a weight of at least 80 percent to fundamental analysis. The remaining forecasters are called *intermediates*. We compute the average response for those forecasters who have responded to the special questions more than once.

[Table 2 about here]

Table 2 shows that our chosen groups of forecasters represent a relatively selective sample: only 60 and 65 forecasters are classified as chartists and fundamentalists, respectively, while the vast majority of the total of 396 forecasters, i.e. 271 persons, are classified as intermediate. The fundamentalists attach a weight of only just below 8 percent to chartist strategies, which is much lower than the 56 percent stated by chartists. In contrast, the group of chartists attaches an average weight of 30 percent to fundamental information, which is much lower than the fundamentalists' 89 percent. Hence, the two groups, fundamentalists and chartists, differ substantially in terms of the forecasting methods used, while the group of intermediates comprises all remaining forecasters. Overall, the data support the existence of chartists and fundamentalists, and thus the basic assumption motivating this research.

Note the asymmetry between chartists' and fundamentalists' use of the other group's forecasting technique: the group of chartists makes substantial use of fundamental information, while the group of fundamentalists does not use technical information in the same way. This result follows mainly from our definition of the two groups, which is asymmetric, and should not be interpreted as a particular group behavior.[6]

Persistence. A final issue in the data section is data reliability. Since professionals are asked three times about the analytical tools they use to forecast exchange rates, we can compare each individual's persistence in answers. The respective Panels A and B in Table 3 show that the great majority of respondents continue to use the tools they had used before. Over a period of four and a half years covered by Panel A, 91 of 135 respondents are classified on the diagonal, i.e. 67 percent stay within the same group. Even more revealing may be the fact that only 1 out of 38 chartists and fundamentalists switches positions. The numbers are slightly less advantageous over the seven-year period covered by Panel B (62 percent and 3 out of 43). These observations strongly indicate that the classification into chartists and fundamentalists is quite persistent at the individual level, even though professionals adjust weights between their analytical tools over time.

[Table 3 about here]

Exchange rates and inflation data. We use the USD/EUR exchange rate based on the series XUDLERD issued by the Bank of England on a daily basis. This time series has the advantage of also comprising a synthetically-computed exchange rate for the time before 1999.01, which we need, for example, for the computation of long-run averages. We replace missing exchange rates (e.g. from weekends) with those recorded on the preceding trading day. When computing the profits from trading rules involving both spot and forward rates, we use data from Thomson Financial Datastream.[7] We consider the Consumer Price Index in the Eurozone and the United States obtained from Datastream where necessary.[8]

[6]In this sense, these findings are consistent with Manzan and Westerhoff (2007) who postulate that both fundamentalists and chartists share fundamental information, whereas De Grauwe and Grimaldi (2006) assume that chartists do not have any insights into fundamental behavior. However, our results indicate that most professionals also believe that there is information in technical analysis, not just chartists as supposed by Manzan and Westerhoff (2007).

[7]Datastream Mnemonics: TDEUR1F, TDEUR2F, TDEUR6F, TDEUR1Y, TDEUR2Y, TDEUR3Y, TEUSDSP.

[8]Datastream Mnemonics: USCONPRCE, EMCONPRCF.

4 Empirical results

This section sets out the results of our examination of exchange rate expectations of chartists and fundamentalists in three steps. First, we show results for forecasting behavior (Section 4.1), then results for forecasting dynamics (Section 4.2) and finally results for forecasting performance (Section 4.3).

4.1 Results on forecasting behavior

We make use of the professionals' self-assessment to compare the observed behavior of chartists and fundamentalists. For each of these groups, we analyze the role of trend-following behavior as well as PPP orientation.

Trend-following behavior. Virtually all chartist-fundamentalist models define chartists as being primarily trend-followers. In this paragraph, we investigate whether chartists' predictions tend to be more in line with trend-following strategies compared to those made by fundamentalists (see *Hypothesis 1*). Our results confirm this conjecture.

In particular, we consider a set of simple momentum-based strategies according to which forecasters could extrapolate a prevailing trend (over the past 10, 30, 60, 90 and 180 days) to make a forecast. We concede that this is a simplification of true behavior and thus is a noisy measure of chartist behavior. Nevertheless, this procedure can be empirically implemented. These rules predict a further appreciation (depreciation) of the USD if the USD has gained (lost) value compared to the EUR in the past DD days, such that

$$E[\Delta s_{t,t+h}] = \phi^{(k,DD)} \Delta s_{t-DD,t} \text{ with } \phi^{(k,DD)} > 0. \tag{1}$$

As we know from Section 3 that chartists also use fundamental prediction tools in addition to chartist rules, it is unlikely that their forecasts will correspond to those from Eq. (1) on every occasion. Compared to fundamentalists' predictions, however, one could still expect a higher correlation between chartists' predictions and trend-following behavior. To analyze this, we summarize the degree to which the FX forecasts of an individual forecaster i are in line with chartist behavior by computing the percentage share of forecasts by forecaster i made into the same direction as the forecast made according to Eq. (1), such that

$$\mathrm{SHARE}_i^{DD} = \frac{\text{number of forecasts by } i \text{ in line with trend-following strategy}}{\text{number of all forecasts by } i} \tag{2}$$

where DD captures the number of days for which a potential trend is measured. A share of unity indicates that a forecaster's predictions are in line with a forecasting rule which extrapolates the trend over the previous DD days in all time periods. Hence, SHARE_i^{DD} represents a measure of *revealed* association of a forecaster's predictions with simple momentum rules, and it can be easily compared with the *self-assessed* preferences of forecasting tools by the respective forecaster i: in this vein, Table 4 summarizes the correlation coefficients of SHARE_i^{DD} with the percentage figure attributed by i to fundamental and technical analysis, respectively.

[Table 4 about here]

Table 4, Panel A, shows that SHARE_i^{DD} decreases with a declining preference for fundamental analysis, and increases with the preference for technical analysis. As the correlation coefficients decrease in absolute value for trend periods longer than 30 days, we conclude that the distinction between chartists and fundamentalists is particularly pronounced for shorter trend periods, i.e. trends which are not necessarily well explained by fundamentals. Table 5 compares the average SHARE^{DD} for the groups of chartists and fundamentalists.

[Table 5 about here]

Table 5, Panel A, reconfirms that the association of individual forecasts with the extrapolation of trends tends to be higher among chartists, and lower among fundamentalists. The t-test comparing these two groups indicates that this difference is statistically significant, at least as far as the trends on a 10, 30 or 60-day horizon are concerned. On the basis of simple technical rules, these findings generally demonstrate that *revealed* trend-following and the *stated* preference for technical analysis are tentatively linked. This result is consistent with *Hypothesis 1*, and also ultimately underlines the usefulness of the self-assessment in the surveys of methods.

While the above results on average hold across prevailing trends of different magnitudes (which also include very small past changes in exchange rates), we also take a closer look at how the average SHARE^{30} evolves depending on different strengths of the trend. To do so, we sort the (absolute) 30-day trends according to their magnitude and classify them into percentiles. We compute the average SHARE^{30} for each percentile (and separately for chartists and fundamentalists), and plot it in Figure 1. In addition, we fit third order polynomials to obtain a smoothed representation for chartists and fundamentalists, which are included in Figure 1 by dashed lines.

[Figure 1 about here]

Figure 1 illustrates that (i) forecasters are more sensitive to momentum when past exchange rate trends have been strong (we will discuss this idea in more depth in the next section) and that (ii) the group of fundamentalists behaves differently from chartists to some extent: The dashed line for chartists increases almost monotonically with the absolute trend (at least for percentiles higher than 0.25), whereas there is a U-shaped relationship for fundamentalists. The latter observation suggests that fundamentalists require particularly strong trends to follow them.

PPP orientation. The purchasing power parity is the most prominent fundamental concept in theoretical exchange rate determination, in particular at horizons of six months and longer (see Cheung and Chinn, 2001; Cheung, Chinn, and Marsh, 2004). Hence, we investigate to what extent chartists and fundamentalists make use of this idea when predicting exchange rates. We do not find that PPP orientation is more pronounced for fundamentalists (see *Hypothesis 2*), but we are able to demonstrate that PPP orientation increases non-linearly with increasing fundamental misalignment.

To determine whether or not an exchange rate is in line with fundamentals, we consider the real exchange rate

$$q_t = s_t + ln(CPI_t^{EUR}) - ln(CPI_t^{US}) \tag{3}$$

and compute, for each point in time t, the average real exchange rate $\bar{q}_t$ over the previous 10 years. A forecast with PPP orientation is then made on the basis of

$$E\Delta s_{t,t+k} = \phi^{(PPP)}(\bar{q}_t - q_t) \text{ with } \phi^{(PPP)} > 0 \tag{4}$$

Similarly to the measure SHARE_t^{DD} introduced in Eq. (2), we summarize the degree to which the FX forecasts of an individual forecaster i are in line with PPP orientation by computing the percentage share of forecasts made in the same direction as the forecast made by Eq. (4),

$$\text{SHARE}_i^{PPP} = \frac{\text{number of forecasts by } i \text{ in line with PPP orientation}}{\text{number of all forecasts by } i} \tag{5}$$

Table 4 and 5 (in both tables: Panel B) inform about the relative importance of PPP orientation for the considered groups. The correlation coefficient between SHARE_i^{DD} and the stated preference for fundamental (or technical) analysis is not significantly different from zero. Moreover, on average, 33 percent of all forecasts made by chartists and fundamentalists are made into the direction which can be interpreted as being in line with PPP orientation. This does not reveal any meaningful difference between chartists and fundamentalists (see also Cheung, Chinn, and Marsh, 2004). One reason for this result may be the fact that fundamentalists consider economic fundamentals in more complex ways than assumed in our simplified model.

To see how PPP orientation differs depending on the degree of fundamental misalignment, we sort the periods of survey responses into percentiles according to absolute size of $|\bar{q}_t - q_t|$, and present the averages separately for each of these percentiles in Figure 2. We also fit a third order polynomial to obtain a smoother representation of the considered SHARE^{PPP} for chartists and fundamentalists, separately.

[Figure 2 about here]

Figure 2 shows that the orientation at PPP (SHARE^{PPP}) dramatically increases with increasing misalignment of interest rates. This holds qualitatively true for chartists and fundamentalists. For fundamentalists, this effect appears to be more pronounced, as the dashed lines suggest. Overall, the steep increase of SHARE^{PPP} in percentiles higher than 0.5 is consistent with the view of a non-linear influence of PPP on exchange rate movements (e.g., Taylor, Peel, and Sarno, 2001). The fact that chartists and fundamentalists exhibit similar behavior in that respect (with an only gradual difference between chartists and fundamentalists) underlines that fundamental analysis is also present in the information set of our group of chartists, a result which again reconfirms the stated preferences by this group.

4.2 Results on forecasting dynamics

This section looks at changes in forecasting behavior in two ways. First, we analyze the probability that professionals will switch the *direction* of their exchange rate expectations. Second, we analyze *transitions* from chartist to fundamentalist behavior (and vice versa) by studying the dynamics of the proportion of forecasts in our panel that are in line with trend-following behavior (as a measure of chartist behavior).

Forecasting instability. It is frequently believed and modeled (see Brock and Hommes, 1998; Farmer and Joshi, 2002; Westerhoff, 2004) that technical traders typically provide less stable predictions than fundamentalists and thus contribute to volatility (see our *Hypothesis 3*). As we discuss in more detail below, our evidence supports this idea.

We measure the switching probability of an individual forecaster through the relative frequency with which a forecaster changes the direction of his USD/EUR forecast within two subsequent survey months, that is we count the number of such switches from a depreciation to an appreciation expectation or inversely, and divide it by the number of total possible switches. In a cross-sectional comparison, it becomes apparent that the switching probability is negatively correlated to the stated use of fundamental information, and positively correlated to the stated use of technical information (see Table 6, Panel A).

[Table 6 about here]

In addition, Table 6, Panel B, reports the cross-sectional averages of the individual switching probabilities for chartists and fundamentalists, respectively. It shows that the individual switching probabilities are, on average, about 14 percent for chartists, but only about 9 percent for fundamentalists.

These probability figures refer to month-to-month changes, and the impact of their difference becomes more visible when translated into probabilities of changes from an annual perspective (see Figure 3): based on a binomial distribution where p equals the monthly switching probability, the probability of no change (only one change or less) in forecasts over the course of one year declines from 0.32 (0.71) for chartists to 0.17 (0.49) for fundamentalists. This pattern reconfirms that chartists tend to switch more frequently from a long to a short position forecast and vice versa than fundamentalists. This lends support to *Hypothesis 3*.

[Figure 3 about here]

Explaining the dynamics. The change of expectations may be induced by a switch of strategies, for example by shifts from fundamental to chartist strategies or vice versa. Reasons for such shifts are at the core of *Hypotheses 4* and *5*. This paragraph describes the dynamics of the forecasters' alignment with trend-following forecasting.

In particular, we reconsider the chartist forecasting rule introduced by Eq. (1). Unlike in our analysis above, we now concentrate on the time series dimension and compute, for each period, the proportion of forecasts in the panel of forecasters which points into the same direction as the 30-day chartists forecasting rule, such that

$$\text{SHARE}_t^{30} = \frac{\text{number of forecasters in period } t \text{ in line with trend-following strategy}}{\text{number of all forecasters in period } t} \tag{6}$$

Figure 4 illustrates how SHARE_t^{30} fluctuates over time, separately for each of the groups of chartists and fundamentalists. The two graphs show that there are substantial short-term fluctuations in SHARE_t^{30}. Due to the short-term nature of these changes their effect will be rather on short-term volatility and not on medium-term swings and misalignments of exchange rates.

[Figure 4 about here]

In the following paragraphs, we investigate external circumstances influencing forecasters' decisions to turn to chartist forecasting rules, i.e. the factors determining *changes in* the proportion of forecasts in line with trend-following forecasting rules, by time series regressions of the type

$$\Delta\text{SHARE}_t^{30} = a_0 + a_1 \Delta\text{SHARE}_{t-1}^{30} + a_2 \Delta X_t + e_t \tag{7}$$

$\Delta\text{SHARE}_t^{30}$ denotes the change in the proportion of forecasts made in t which point into the same direction as a trading rule following the trend over the previous 30 days; $\Delta\text{SHARE}_{t-1}^{30}$ denotes a lagged dependent variable; and ΔX_t represents the changes in several control variables. These control variables are discussed in more detail below. Due to potential overlaps (the forecasts are made on a six-month horizon, whereas we sample on a monthly basis), we use Newey-West standard errors with a lag length of five months.

Switching due to success of past momentum strategies. Based on the framework outlined above, we test whether the proportion of forecasters who make use of trend-following strategies reacts to the past performance of such strategies (*Hypothesis 4*). We find evidence in favor of this idea.

In our main operationalization, we assume that investors look back at the previous month's exchange rate movements, and interpret the presence of a strong trend as a signal for the profitability of momentum strategies (ignoring the fact that following a momentum strategy could also lead to losses). This approach (an investment into the currency which has ex post appreciated in the previous 30 days) can be formalized by

$$r_t^{expost(30)} = |f_{t-1}^1 - s_t| \tag{8}$$

where f_{t-1}^1 and s_t represent the (log) forward and spot rates in $t-1$ and t, respectively.

We include changes in returns, i.e. $\Delta r_t^{expost(30)} = r_t^{expost(30)} - r_{t-1}^{expost(30)}$ into the regression equation (7) as a variable of interest. Given *Hypothesis 4*, we expect to find significantly positive coefficients. Table 7, (i), displays the results.

[Table 7 about here]

It transpires that the coefficients for $\Delta r_t^{expost(30)}$ are statistically significantly positive at the one-percent significance level. The adj. R^2 amounts to 18.5 percent, which is higher than the 11.8 percent obtained by (unreported) pure AR(1) regressions. Hence, the inclusion of past returns adds explanatory power. This result demonstrates that forecasters indeed take into account the magnitude of the most recent trends, and switch to chartist rules after relatively large trends. In fact, the described relationship is also economically significant: when the change in the return from holding the appreciating currency amounts to 2.1 percentage points (which corresponds to one standard deviation of Δr_t^{expost}), the percentage share of survey participants who follow chartist strategies increases by an average of 5.4 percentage points, which corresponds to 35 percent of the standard deviation of monthly changes of that proportion. Overall, forecasters tend to enter the camp of chartists directly after large trends and they do not wait another month to see whether the adoption of a momentum strategy has been profitable in the preceding period.

One caveat has to be expressed, however. For a stricter interpretation of *Hypothesis 4*, one could also assume that forecasters closely observe whether a past momentum strategy -which has been chosen based on the information set in the preceding period- has been profitable, or if it has led to losses (a possibility which we have ignored in our approach above). Here, the profitability which matters is the most recent monthly return of an investment decision which was made one month earlier according to Eq. (1) based on the trend observed at that time, such that

$$r_t^{TR30} = I_{t-1}(s_{t-1} > E_{t-1}^{(1)}[s_t])(f_{t-1}^1 - s_t) + I_{t-1}(s_{t-1} < E_{t-1}^{(1)}[s_t])(s_t - f_{t-1}^1) \tag{9}$$

where I_{t-1} is an indicator variable for a decision made in the previous period and $E_{t-1}^{(1)}[s_t]$ represents the forecast made on the basis of Eq. (1). When we include $\Delta r_t^{TR30} = r_t^{TR30} - r_{t-1}^{TR30}$ on the RHS of Eq. (7), the coefficient for Δr_t^{TR30} is not significantly different from zero (see Table 7, (ii)). Thus, according to this result it is not the behavior described in Eq. (9) which drives forecasting dynamics. Our findings rather indicate that forecasters adopt chartist rules when the presence of trends suggests it might be profitable to follow them.

Switching due to deviations from fundamentals. Most chartist-fundamentalist models with switching behavior imply that chartist strategies become less important when exchange rates deviate substantially from fundamentals (*Hypothesis 5*). Our data confirms this; in particular, our findings corroborate the non-linearity of this relationship which is frequently included in these models.

To illustrate this point, we consider the real exchange rate to be misaligned when its deviation from the average value, $|q_t - \bar{q}_t|$ (see Eq. (3)) is high. As several exchange rate models suggest that the relationship between fundamentals and exchange rate is non-linear (Dumas, 1993; Taylor, Peel, and Sarno, 2001; Obstfeld and Rogoff, 2000), we also consider the squared distance $|q_t - \bar{q}_t|^2$, which attaches greater weight to observations for which the misalignments are more pronounced. In particular, in the framework of the time series regression given in Eq. (7), we analyze whether shocks to these deviations ($\Delta|q_t - \bar{q}_t|$) or squared deviations ($\Delta|q_t - \bar{q}_t|^2$) exert influence on the change of the use of chartist rules.

[Table 7 about here]

Table 7, (iii) and (iv), displays the results. The coefficient for $\Delta|q_t - \bar{q}_t|$ is negative, but not significantly different from zero, indicating that the absolute deviation between fundamental values and exchange rate rules does *not* affect the use of chartist rules. In contrast, the coefficient for $\Delta|q_t - \bar{q}_t|^2$ is significantly smaller than zero, which indicates that shocks to the deviation of exchange rates from fundamental values do matter when the deviation is sufficiently large. This result is in line with the earlier finding in Menkhoff, Rebitzky, and Schröder (2008) which is derived using a different method.

It is worth noting that these results do not depend on the way we compute q_t and $\bar{q}_t$. We also consider the fundamental value to simply be represented by the moving average of the exchange rate over the previous ten years, and impose that exchange rates are assumed to mean-revert when they have deviated from this value. The results we find when measuring the deviation by $|s_t - \bar{s}_t|$ or $|s_t - \bar{s}_t|^2$ respectively, are very similar.

Overall, this picture corresponds to the notion of non-linearity of the relationship between exchange rates and fundamentals, and confirms *Hypothesis 5*, albeit with the restriction that only pronounced misalignments will have a (negative) impact on the adoption of chartist rules.

Dynamics under high or low fundamental misalignment. To look further into the details of the non-linear influence of fundamental misalignment on the forecasting dynamics, we reconsider

Hypotheses 4 and 5 and analyze the influence of $\Delta r_t^{expost(30)}$ and $\Delta|q_t - \bar{q}_t|$ on forecasting behavior under different conditions. More specifically, we distinguish states with high and low deviations of the exchange rate from its fundamental value. We find the effects of *Hypothesis 4* (switch to trend-following after good performance in the recent past) to be particularly pronounced when fundamental misalignment is low, whereas the effects of *Hypothesis 5* (fundamental misalignment reduces trend-following) are only valid when fundamental misalignment is large.

For this analysis, we classify all periods in which $|q_t - \bar{q}_t|$ is smaller than its median $X_{50}(|q_t - \bar{q}_t|)$ as *low deviations states*, and the periods with $|q_t - \bar{q}_t| > X_{50}(|q_t - \bar{q}_t|)$ as *high deviations states*. We estimate the dynamic relationship in Eq. (7) for both states separately, such that

$$\Delta\text{SHARE}_t^{30} = \begin{cases} a_{01} + a_{11}\Delta\text{SHARE}_{t-1}^{30} + a_{21}\Delta X_t + e_t & \text{if } |q_t - \bar{q}_t| < X_{50}(|q_t - \bar{q}_t|) \\ a_{02} + a_{12}\Delta\text{SHARE}_{t-1}^{30} + a_{22}\Delta X_t + e_t & \text{if } |q_t - \bar{q}_t| > X_{50}(|q_t - \bar{q}_t|) \end{cases}$$

As covariates, we consider the change in the absolute return of a momentum strategy over the last 30 days, $\Delta r_t^{expost(30)}$, as well as the change in the deviation from PPP, $\Delta|q_t - \bar{q}_t|$. Table 8, Panel A, displays the results.

[Table 8 about here]

Table 8, (i) and (iv), show that the coefficient for $\Delta r_t^{expost(30)}$ is not significantly different from zero at any conventional significance levels in the high deviation states, whereas it is strongly significant at the 1% level in the low deviation states. The *economic* significance of the estimates points in the same direction: as can be derived from Panel B, an increase of $\Delta r_t^{expost(30)}$ by one standard deviation in the low (high) deviation states leads to an increase of $\Delta\text{SHARE}_t^{30}$ by more than one third (less than one fourth) standard deviation. Thus, the effects of *Hypothesis 4* matter more when fundamental misalignment is small.

Unexpectedly, Table 8, specification (ii), demonstrates that $\Delta|q_t - \bar{q}_t|$ even carries a positive sign for the low deviation states, although without contributing too much to explanatory power.

Reassuringly, specification (iv) shows a negative sign of $\Delta|q_t - \bar{q}_t|$ for the high deviation states. For the latter, the R^2 of the corresponding specification is much larger than for the former. This sign-switching pattern explains why $\Delta|q_t - \bar{q}_t|$ does not enter significantly in our analysis in the previous paragraph (see Table 7), and why only $\Delta|q_t - \bar{q}_t|^2$ reveal the effects as postulated by *Hypothesis 5*. Thus, changes in fundamental misalignment only determine the forecasters' behavior when the level of fundamental misalignment is already large - a notion which corresponds to the non-linear relationship in many models.

Switching of chartists and fundamentalists. In this paragraph, we only consider those forecasters who have been classified as fundamentalists and chartists, respectively, and compute $\Delta\text{SHARE}_t^{30}$ for each of these two groups separately. We then conduct the regressions introduced by Eq. (7). Table 9 presents the results for chartists and fundamentalists, respectively.

[Table 9 about here]

Overall, the time series analysis based on these two groups reconfirms the findings made above: both groups tend to adopt chartist forecasting roles when the observed trends have increased in the previous months, and tend to abandon these rules when there are pronounced fundamental misalignments. The negative coefficient for the AR(1) term is more pronounced for chartists than for fundamentalists, which reconfirms that chartists switch their strategies more frequently than fundamentalists. This observation is also in line with the chartists' self-assessment, in which they state that they also rely on alternative approaches. Moreover, the negative coefficient of the squared distance from the PPP value is more pronounced for fundamentalists, indicating that this group is particularly sensitive to severe misalignments of the exchange rate from its fundamental value. This finding is also in line with intuition.

4.3 Results on forecasting performance

As discussed above, the profitability of chartists' and fundamentalists' predictions is controversial. We investigate whether both chartist and fundamentalist investors can survive in the market, i.e. whether neither of our groups is superior in terms of forecasting performance (*Hypothesis 6*). We illustrate that this generally holds true, although chartists appear to be superior as far as very short horizons are concerned.

In order to assess the performance of forecasters we use two measures. First, we compute the average return of a trading strategy for each individual forecaster's FX predictions. Second, we take the same data as input but use a risk-adjustment, here the Sharpe ratio. Both ideas imply that the forecaster targets an investment into a currency on a fixed horizon (either holding a long or a short position); we thus use these measures to capture *trading* performance.[9]

For both measures, we follow the concept introduced in Dick, MacDonald, and Menkhoff (2011) and translate the individual forecasts into trading strategies, taking a long position on the USD (in the forward market) when they expect the USD to appreciate, and a short position when they expect the opposite. Each position will be closed in the spot market at the end of the investment period of k months. As the forecasters are asked to provide a forecast looking six months into the future, it is natural to focus on investments with a six-month horizon ($k = 6$), but we will also consider different investment horizons, i.e. one-, two-, three-, twelve-, 24, and 36-month horizons. Formally, the trading rule is given by

$$r_{t,t+k}^{TR_{IND,k}} = I_t(s_t > E_t^{(IND)}[s_{t+k}])(f_{t,k} - s_{t+k}) + I_t(s_t < E_t^{(IND)}[s_{t+k}])(s_{t+k} - f_{t,k}) \qquad (10)$$

where s_t denotes the log exchange rate of one Euro expressed in USD in month t, $f_{t,k}$ denotes the log k-month forward rate in month t and $E_t^{(IND)}$ represents an individual expectation of forecaster i. For each forecaster, we compute the average monthly return of such trading strategies over time as

[9] In the later robustness Section 5, we also compute absolute average forecast errors for each forecaster.

well as the annualized Sharpe ratios. Table 10 shows the averages for the groups of fundamentalists and chartists, respectively.

[Table 10 about here]

Taking a first look at investments with a six-month horizon, it becomes apparent that chartists and fundamentalists are not systematically different in terms of their forecasting performance: chartists are slightly superior in terms of average returns (Panel A), whereas fundamentalists exhibit slightly larger Sharpe ratios (Panel B), but these findings are far from being significantly different. Note that the annualized average Sharpe ratio is not impressive for any of these two groups, and given the fact that we have not taken transaction costs into account, our results do not indicate that it is profitable to trade according to the average chartist's or average fundamentalist's implicit trading rule.

This latter result does not change when we take investment horizons into consideration that are longer or shorter than six months. However, we do observe gradual changes in the relative average performance of chartists and fundamentalists: in fact, Table 10 suggests that chartists' forecasts lead to more profitable trading strategies than fundamentalists' forecasts when their forecasts are translated into investments over the one-month-horizon. For investments over horizons longer than two months, we do not find significant differences between the forecasting performance of chartists and fundamentalists.

Overall, it is apparent that chartists perform significantly better than fundamentalists in very short horizon trading strategies, whereas forecasts made by fundamentalists become better at intermediate- and long-term horizons. This corroborates the idea that fundamentalists and chartists forecast on different horizons (e.g. Taylor and Allen, 1992). For longer horizons fundamentalists and chartists appear to be similarly profitable, which supports *Hypothesis 6* and underlines the efficiency of FX markets in this important respect.

5 Robustness

This section sets out the results of seven kinds of robustness tests we have performed in short form only, whereas full test results are described in the Appendix. In general, our findings are qualitatively robust to the modifications tested.

(i) We test and find that our sample of forecasts which includes only those professionals who give a self-assessment of their preferred forecasting tool is indeed representative for the larger sample of all forecasters.

(ii) The empirical classification of chartists and fundamentalists follows the intuition of chartist-fundamentalist models. As it is in the last instance arbitrary we also reproduce our main results with three alternative classifications, two of them using broader definitions and one using a narrower definition. As to be expected, broadening groups reduces the difference between groups whereas working with a more narrow definition leads to problems of small sample size. Thus, statistical significance of some results becomes a bit weaker but overall results remain robust.

(iii) When testing for the role of trend following (see Table 5), a natural concern is whether results may be driven by PPP-orientation and vice versa. We test this by cross-tabulation where we distinguish between four phases, i.e. small-strong trends and low-high PPP deviation. Results remain robust under all circumstances, i.e. chartists follow trends stronger than fundamentalists but this difference becomes insignificant when PPP-deviation is high.

(iv) It is known that practitioners consider carry trade strategies or may generally follow a kind of PPP-strategy which impact forecasters' switching into momentum strategies (see Table 7). Thus we control for these alternative determinants of trading behavior, but results remain unaffected.

(v) It has been mentioned in the literature that volatility may influence choice of trading strategies. The argument runs that volatility signals uncertainty and that in this case professionals may refrain from (uncertain) fundamental orientation and instead rely more on chartist trading.

Accordingly we control for this effect when explaining the switching into momentum strategies (Table 7) but it does not explain behavior beyond the earlier considered variables.

(vi) Again referring to the switching into momentum strategies, we rerun regressions with a somewhat different specification, i.e. an autoregressive term. However, this does not have an important effect.

(vii) Performance calculations may be biased by the specific measure. Thus we also use a measure of forecast accuracy instead of the trading rule. Again, results remain unchanged.

6 Conclusions

The formation of exchange rates, and thus the formation of respective expectations, is a complex phenomenon as the limited understanding of this process indicates. One source of complexity is the existence of quite heterogeneous agents, in particular their reliance on either "charts" or "fundamentals" when forming expectations. There is ample evidence showing that these two forms of analysis are indeed of great importance for practitioners (Menkhoff and Taylor, 2007). This has created a motivation to construct models of heterogeneous agents in foreign exchange markets relying on these two forms of analysis. The resulting interplay of chartists and fundamentalists provides useful stylized facts. However, models of this kind rely on plausible but rather untested assumptions about the behavior of heterogeneous agents in foreign exchange. This study provides novel evidence about the role of chartists and fundamentalists in the process of exchange rate formation.

We provide clear support for the core assumptions of chartist-fundamentalist models, such as formulated by De Grauwe and Grimaldi (2006), Bauer, De Grauwe, and Reitz (2009) or Dieci and Westerhoff (2010). In particular, we find that (1) chartists and fundamentalists do indeed form different exchange rate expectations; chartists' expectations are more in line with trends while fundamentalists consider mean reversion slightly more. (2) Chartists change their forecast direction more often than fundamentalists and in this sense contribute to instability. However, despite the differences between chartists and fundamentalists, there are strong common changes in expectations, in particular when exchange rates deviate strongly from long-run averages. (3) Chartists' exchange rate expectations are as good as fundamentalists' or the market average, and they are even better for short horizons, so that chartists can survive in the market. This does not support the conventional understanding of efficient financial markets, as described in Fama (1991).

All these findings are derived from a new perspective clearly supporting the appropriateness of the chartist-fundamentalist model in foreign exchange. To the best of our knowledge, this research is the first to systematically link data about expectation formation with self-stated preferences for charts or fundamentals. We thus provide more direct evidence on chartist-fundamentalist approaches than earlier studies, which rely on either only parts of this information (exchange rate expectations or the use of analytical tools), or on simulations of artificial markets, or on experiments.

Nevertheless, some caveats remain: Regarding our research, the evidence is based on forecasters who are not themselves investors, so that answers may be biased, for example by favoring longer horizons than foreign exchange traders. Regarding the chartist-fundamentalist models, these are highly stylized and reduce market behavior in drastic ways: for instance, chartist behavior is more than trend-following and fundamental behavior reaches beyond PPP-orientation. This may be considered more explicitly in future research.

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Table 1: Weighting of forecasting tools

This table reports the self-assessment of professional forecasters with respect to their preferred forecasting tools. In surveys of methods in 2004/01, 2007/04, and 2011/09 the forecasters are asked to attach weights to technical analysis (Tech.), fundamentalist analysis (Fund.) and the analysis of order flow (OF), depending on their usage of these techniques for their FX predictions. This table reports the cross-sectional mean as well as the standard deviation of these figures.

	Jan 2004			April 2007			Sept. 2011		
	Fund.	Tech.	OF	Fund.	Tech.	OF	Fund.	Tech.	OF
Mean	60.0	29.9	10.1	57.4	28.7	13.9	57.4	27.4	15.2
SD	21.6	19.8	11.9	20.6	17.3	12.9	22.0	18.0	14.1
N	237	237	237	247	247	247	198	198	198

Table 2: Groups

This table reports characteristics of the defined groups of fundamentalists, chartists, and intermediates. Based on the self-assessed usage of forecasting tools in the surveys of methods, we classify forecasters as *chartists* when they put a stronger weight on chartist than on fundamental information, unless the weight on chartist information is below 40 percent. To keep groups similarly large, we define forecasters to be *fundamentalist*s when they attach a weight of at least 80 percent to fundamental analysis. The table displays the mean, standard deviation, minimum and maximum weight (in percent) for fundamental and technical analysis, respectively, for all groups separately.

		Fundamental analysis				Technical analysis			
	N	Mean	SD	Min	Max	Mean	SD	Min	Max
fundamentalists	66	88.6	8.4	80.0	100.0	7.2	7.7	0.0	20.0
intermediates	269	58.2	12.1	20.0	78.3	27.3	10.3	0.0	50.0
chartists	61	30.2	10.3	0.0	45.0	56.0	11.7	40.0	92.5

Table 3: Changes of preferences over time

These tables illustrate how preferences with respect to forecasting tools (fundamental or technical analysis) change over time. We use the identical classification rules described in Table 2 for each of the three surveys of methods separately and consider those forecasters who have responded to at least two of these. The contingency tables show the transition of forecasters w.r.t. these groups from one survey of methods to another one (Panel A: from April 2007 to Sept. 2011; Panel B: from Jan. 2004 to Sept. 2011). The figures in the tables refer to the number of forecasters. The Pearson X^2 tests against the H_0 that the classification of a forecaster based on one survey of methods is independent from the classification in the other survey of methods. (***: 1%, **: 5%, *: 10% significance level).

Panel A		Apr. 2007			
		fundamentalists	intermediates	chartists	Σ
Sept. 2011	fundamentalists	14	15	1	30
	intermediates	8	68	6	82
	chartists	0	14	9	23
	Σ	22	97	16	135
Pearson X_4^2	***44.36				

Panel B		Jan. 2004			
		fundamentalists	intermediates	chartists	Σ
Sept. 2011	fundamentalists	12	8	1	21
	intermediates	11	39	8	58
	chartists	2	5	7	14
	Σ	25	52	16	93
Pearson X_4^2	***23.92				

Table 4: Self-assessment and revealed behavior, correlations

This table reports Pearson correlation coefficients. Panel A shows the correlation of the individual percentage share of forecasts made in line with the momentum strategy SHARE_i^{DD} (where DD denotes the days of the considered trend, i.e. 10, 30, 60, 90, and 180 days) with the individual survey response concerning the weights (in percent) attributed to fundamental and technical analysis, respectively. Panel B shows the correlation of the individual percentage share of forecasts made in line with the PPP with the individual survey response about the weights (in percent) attributed to fundamental and technical analysis, respectively. (***: 1%, **: 5%, *: 10% significance level).

	Panel A					**Panel B**
	SHARE_i^{10}	SHARE_i^{30}	SHARE_i^{60}	SHARE_i^{90}	SHARE_i^{180}	SHARE_i^{PPP}
fund. analysis (in %)	***-0.14	***-0.17	***-0.16	*-0.09	-0.08	-0.07
techn. analysis (in %)	**0.13	**0.14	**0.11	0.05	0.03	0.07

Table 5: Revealed behavior for different groups, averages

Panel A reports the average individual percentage share of forecasts made in line with the momentum strategy SHARE^{DD} (where DD denotes the days of the considered trend, i.e. 10, 30, 60, 90, and 180 days) for the groups of chartists, fundamentalists and intermediates. Panel B reports the average individual percentage share of forecasts made in line with PPP. The last row displays the results of t-statistic, where the H_0 corresponds to equal means between chartists and fundamentalists. (***: 1%, **: 5%, *: 10% significance level).

	Panel A					**Panel B**
	SHARE^{10}	SHARE^{30}	SHARE^{60}	SHARE^{90}	SHARE^{180}	SHARE^{PPP}
fundamentalists	0.34	0.34	0.35	0.37	0.37	0.33
intermediates	0.38	0.38	0.39	0.39	0.39	0.36
chartists	0.39	0.40	0.40	0.40	0.41	0.33
t-test fund. vs. chart.	**2.46	**2.72	**2.48	1.41	1.23	0.02

Table 6: Switching probability, correlations and mean

Panel A reports Pearson correlation coefficients for the correlation of the individual probability of switching the direction of an USD/EUR forecast from one month to the next with the individual survey response about the weights (in percent) attributed to fundamental and technical analysis, respectively. Panel B reports the average individual probability of switching the direction of an USD/EUR forecast from one month to the next for the groups of chartists, fundamentalists and intermediates. The last row displays the results of t-statistic, where the H_0 corresponds to equal means between chartists and fundamentalists. (***: 1%, **: 5%, *: 10% significance level).

Panel A	Correlation with switching probability
fundamental analysis (in %)	***-0.15
technical analysis (in %)	***0.15
Panel B	Mean switching probability, by group
fundamentalists	0.09
intermediates	0.11
chartists	0.14
t-test fund. vs. chartists	2.24**

Table 7: Explaining switching into momentum strategies, time series regressions

This table reports the results of a regression of the type

$$\Delta\text{SHARE}_t^{30} = a_0 + a_1\Delta\text{SHARE}_{t-1}^{30} + a_2\Delta X_t + e_t$$

where $\Delta\text{SHARE}_t^{30}$ denotes the change in the proportion of forecasts made in t which point in the same direction as a trading rule following the trend over the previous 30 days, $\Delta\text{SHARE}_{t-1}^{30}$ a lagged dependent variable and ΔX_t represents the changes in several control variables. These control variables include the ex-post return of a strategy which has followed the trend of the previous 30 days, $r_t^{expost(30)}$, the previous month's return of a momentum-strategy chosen on the basis of the trend the month before, $r_t^{TR(30)}$, the deviation of the real exchange rate from its moving average of the preceding 10 years, $|q_t - \bar{q}_t|$, and the square of this distance, $(q_t - \bar{q}_t)^2$. In addition, we include $\Delta\text{SHARE}_t^{PPP}$ and $\Delta\text{SHARE}_t^{CT}$, which denote the change in the proportion of forecasts made in t which point into the same direction as a PPP-oriented (carry-trade oriented) forecast as further control variables. Due to potential time overlaps (the forecasts are made on a six-month horizon, whereas we sample on a monthly basis), we use Newey-West standard errors with a lag length of five months. Standard errors are provided in parentheses. (***: 1%, **: 5%, *: 10% significance level).

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
$\Delta\text{SHARE}_{t-1}^{30}$	-0.360	-0.347	-0.355	-0.387	-0.393	-0.398	-0.392
	***(0.100)	***(0.106)	***(0.095)	***(0.090)	***(0.089)	***(0.083)	***(0.090)
$\Delta r_t^{expost(30)}$	2.709				2.716	2.516	2.706
	***(0.959)				***(0.800)	***(0.832)	***(0.819)
$\Delta r_t^{TR(30)}$		-0.333					
		(0.731)					
$\Delta\|q_t - \bar{q}_t\|$			-0.819				
			(0.938)				
$\Delta(q_t - \bar{q}_t)^2$				-5.885	-5.802	-5.865	-5.782
				***(1.969)	***(1.967)	***(1.710)	***(1.910)
ΔSHARE^{PPP}						0.547	
						**(0.274)	
ΔSHARE^{CT}						-0.065	
						(0.256)	
$\sigma^{(30)}$							0.287
							(2.288)
const.	-0.001	-0.001	-0.000	0.000	0.000	0.001	0.000
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
T	151	151	150	150	150	150	150
R^2	0.20	0.13	0.13	0.21	0.28	0.31	0.28
adj. R^2	0.19	0.12	0.12	0.20	0.27	0.28	0.26

Table 8: PPP deviations and switching into momentum strategies

Taking the median as the threshold, we distinguish states with high and low deviation of the exchange rate from the PPP-mean-reverting value $|q_t - \bar{q}_t|$. In the following, $\Delta\text{SHARE}_t^{30}$ denotes the change in the proportion of forecasts made in t which point in the same direction as a trading rule following the trend over the previous 30 days, and $\Delta r_t^{expost(30)}$ denotes the change in the ex-post return of a strategy which has followed the trend of the previous 30 days.
Similarly to the analysis in Table 7, we conduct time series regressions for the states of high or low deviation separately, i.e.,

$$\Delta\text{SHARE}_t^{30} = \begin{cases} a_{01} + a_{11}\Delta\text{SHARE}_{t-1}^{30} + a_{21}\Delta X_t + e_t & \text{if } |q_t - \bar{q}_t| < X_{50}(|q_t - \bar{q}_t|) \\ a_{02} + a_{12}\Delta\text{SHARE}_{t-1}^{30} + a_{22}\Delta X_t + e_t & \text{if } |q_t - \bar{q}_t| > X_{50}(|q_t - \bar{q}_t|) \end{cases}$$

$\Delta\text{SHARE}_{t-1}^{30}$ is included as lagged dependent variable and ΔX_t represents the changes in the control variables (i.e. $\Delta r_t^{expost(30)}$ and $\Delta|q_t - \bar{q}_t|$).
Panel A displays the estimates. Due to potential time overlaps (the forecasts are made on a six-month horizon, whereas we sample at monthly frequency), we use Newey-West standard errors with a lag length of five months. Standard errors are provided in parentheses. (***: 1%, **: 5%, *: 10% significance level).

	Lower PPP Deviation			Higher PPP Deviation		
Panel A	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$\Delta\text{SHARE}_{t-1}^{30}$	-0.282	-0.310	-0.287	-0.395	-0.457	-0.470
	***(0.052)	***(0.051)	***(0.058)	***(0.131)	***(0.098)	***(0.090)
$\Delta r_t^{expost(30)}$	2.344		2.141	3.306		3.110
	***(0.734)		***(0.772)	(2.119)		*(1.566)
$\Delta\|q_t - \bar{q}_t\|$		2.081	1.869		-4.352	-4.283
		***(0.540)	***(0.445)		***(1.119)	***(1.135)
const.	0.002	0.006	0.007	-0.001	0.012	0.010
	(0.009)	(0.011)	(0.010)	(0.013)	(0.015)	(0.015)
T	74	74	74	75	75	75
R^2	0.21	0.23	0.32	0.20	0.36	0.41
adj. R^2	0.19	0.21	0.29	0.18	0.34	0.38

Panel B shows the mean and standard deviation of ΔSHARE^{30}, $\Delta r_t^{expost(30)}$, and $\Delta|q_t - \bar{q}_t|$ (i.e. of the monthly changes of the introduced variables) for both states separately.

	All		Lower PPP Deviation		Higher PPP Deviation	
Panel B	Mean	SD	Mean	SD	Mean	SD
ΔSHARE^{30}	-0.0004	0.2069	0.0014	0.1540	-0.0005	0.2500
$\Delta r_t^{expost(30)}$	0.0000	0.0206	-0.0006	0.0226	0.0003	0.0184
$\Delta\|q_t - \bar{q}_t\|$	0.0004	0.0276	-0.0020	0.0284	-0.0027	0.0268

Table 9: Explaining switching into momentum strategies, time series regressions by groups

This table reports the results of a regression of the type described in Table 7. The regressions are conducted separately for chartists and fundamentalists. (***: 1%, **: 5%, *: 10% significance level).

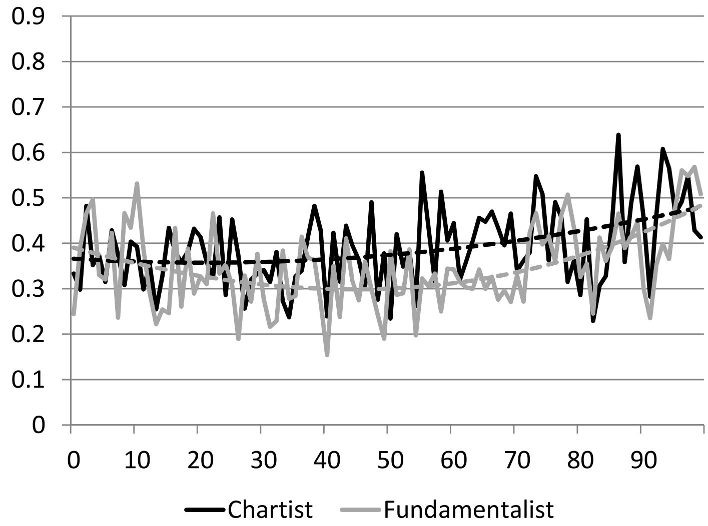
	Fundamentalists	Chartists
ΔSHARE^{30}	-0.397	-0.483
	***(0.072)	***(0.064)
$\Delta r_t^{expost(30)}$	1.745	2.444
	**(0.806)	***(0.801)
$\Delta\lvert q_t - \bar{q}_t\rvert$		
$\Delta(q_t - \bar{q}_t)^2$	-6.710	-4.858
	***(2.023)	***(1.766)
ΔSHARE^{PPP}	0.398	-0.137
	**(0.162)	(0.174)
ΔSHARE^{CT}	-0.244	0.120
	(0.149)	(0.169)
const.	-0.000	-0.000
	(0.017)	(0.009)
T	150	150
R^2	0.28	0.32
adj. R^2	0.25	0.29

Table 10: Performance of trading rules, averages by groups

This table reports the cross-sectional averages (separately for fundamentalists, chartists and intermediates) of the average monthly return (Panel A) and the annualized Sharpe Ratio (Panel B) from trading strategies based on individual forecasts. These trading strategies translate an appreciation (depreciation) expectation into a long (short) position, taken in the forward market; the positions will be closed k months later in the spot market. We consider investments on different horizons, i.e. 1, 2, 3, 6, 12, 24 and 36 months. The last row displays the results of t-statistic, where the H_0 corresponds to equal means between chartists and fundamentalists. (***: 1%, **: 5%, *: 10% significance level).

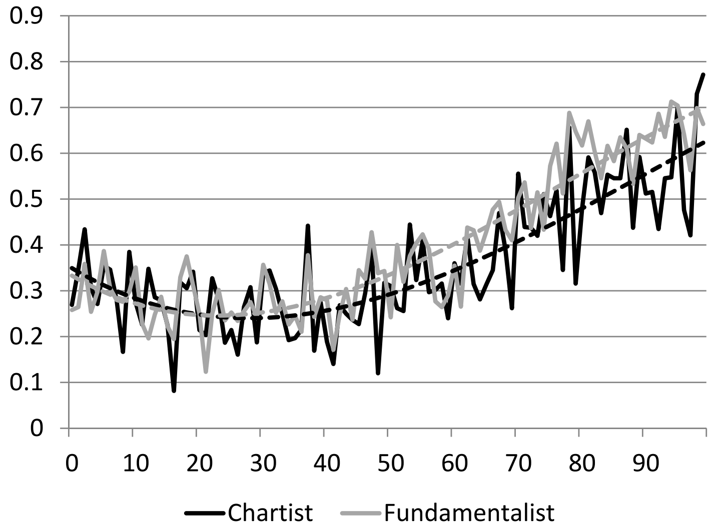
Panel A: average returns	1 mo	2 mo	3 mo	6 mo	12 mo	24 mo	36 mo
fundamentalists	0.06%	0.07%	0.10%	0.13%	0.08%	0.09%	0.07%
intermediates	0.17%	0.15%	0.12%	0.13%	0.09%	0.11%	0.10%
chartists	0.21%	0.18%	0.15%	0.13%	0.09%	0.10%	0.09%
t-values fund. vs. chart.	**2.34	*1.81	0.94	0.16	0.56	0.45	0.56
Panel B: Sharpe Ratios	1 mo	2 mo	3 mo	6 mo	12 mo	24 mo	36 mo
fundamentalists	0.06	0.11	0.14	0.20	0.10	0.16	0.17
intermediates	0.23	0.21	0.17	0.18	0.13	0.16	0.17
chartists	0.25	0.23	0.19	0.19	0.12	0.15	0.16
t-values fund. vs. chart.	**2.31	1.56	0.76	0.13	0.37	0.11	0.27

Figure 1: Observed momentum-following, depending on size of previous trends



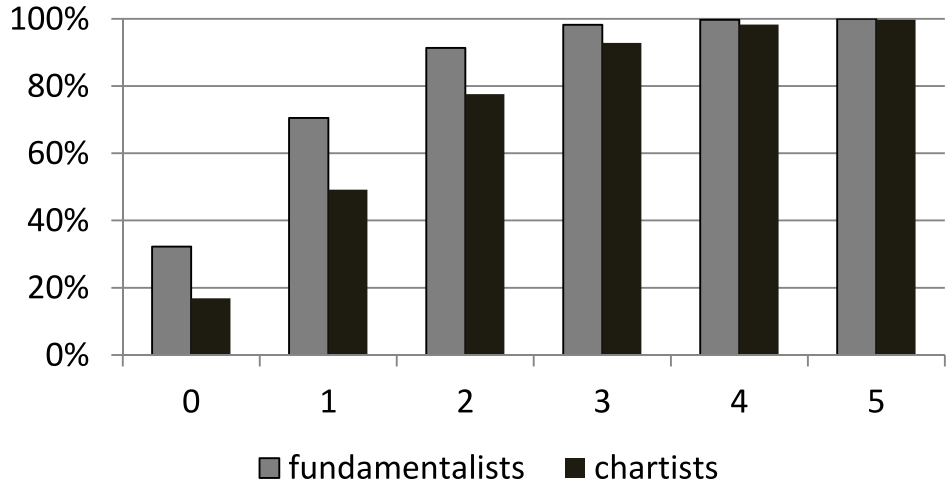
We sort the previous 30 days trends according to their absolute magnitude, and attach percentiles to them (x-axis). This plot represents the average SHARE^{30} over all forecasts given at a specific percentile, for chartists (black) and fundamentalists (grey) separately. For both chartists and fundamentalists, we fit a separate 3rd order polynomial, represented by the dashed line.

Figure 2: Observed PPP-orientation, depending on size of fundamental misalignment



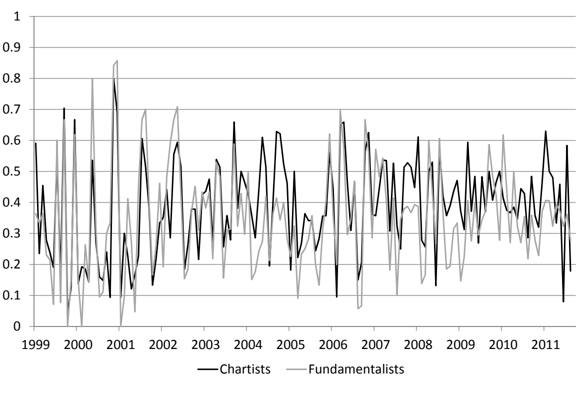
We sort the current absolute fundamental deviation (based on the deviation of the real exchange rate from its 10-year moving average), and attach percentiles to them (x-axis). This plot represents the average SHARE^{PPP} over all forecasts given at a specific percentile, for chartists (black) and fundamentalists (grey) separately. For both chartists and fundamentalists, we fit a separate 3rd order polynomial, represented by the dashed line.

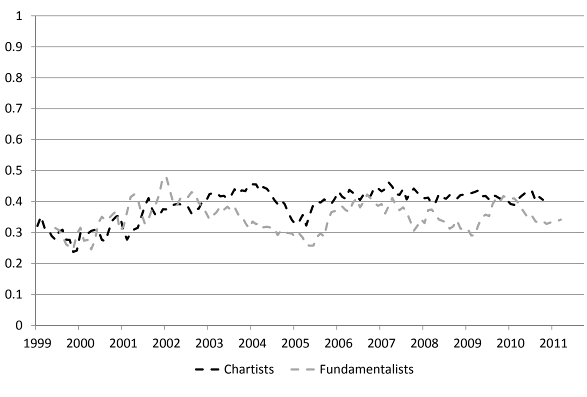
Figure 3: Switching probability, illustration



This plot represents the estimated average probability (on the y-axis) that fundamentalists and chartists switch the direction of their forecast x times or less over the time span of one year, where x is represented by the x-axis.

Figure 4: Proportion of forecasters in line with trend-following behavior





These plots represent the proportion of forecasters whose forecasts are in line with a momentum-following strategy which follows the trend of the previous 30 days. The graphs plot separate lines for fundamentalists and chartists, respectively. The graph on the left hand side shows SHARE_t^{30} directly, whereas the dashed lines in the graph on the right hand side represent the corresponding moving averages (average over the five preceding, the current, and six subsequent months).

Appendix

The Appendix reports our robustness test in more detail and thus complements the very short robustness section in the main text. Overall, we address seven possible concerns: (i) We document that the considered set of forecasters is representative. (ii) We define different classifications of chartists and fundamentalists and provide main results with these alternative classifications. (iii) We test for possible interference between chartists and fundamentalist behavior by considering two-dimensional market phases. (iv) We test whether our result on the importance of trends and deviation from PPP for expectation formation is robust to the possibility that forecasters follow a PPP strategy or a carry trade strategy. Furthermore, we test whether the results hold when (v) controlling for volatility and (vi) without including the autoregressive term in Eq. (7). (vii) Finally, we test the robustness of our approach by substituting the trading strategy as a measure of performance by a measure of forecast accuracy.

Representativeness. The considered set of forecasters (those who have provided us with a self-assessment of preferred forecasting tools at the surveys of methods) is representative of the entire set of forecasters in terms of their predictions: as Table 11 demonstrates, the average percentage shares of the considered forecasters predicting an appreciation, no-change, or a depreciation is very similar to the respective percentage shares of all forecasters, with deviations amounting to only 1 to 1.5 percentage points. In addition, the proportions measured for our panelists on the one hand, and for the entire set of forecasters on the other, are also highly correlated ($\rho > 0.95$) when compared over time.

[Table 11 about here]

Controlling for different classifications of chartists and fundamentalists. In the following, we demonstrate that the results of this paper are not driven by the chosen group size of chartists and fundamentalists in the baseline definition of this paper (i.e., "chartists" need to attach a higher weight on technical than fundamental analysis, and "fundamentalists" attach a weight of at least 90 percent to fundamental information.) We consider several alternatives: firstly, we define chartists, intermediates and fundamentalists according to the 33% and 66% percentile of the weight attached to fundamental information (Alternative I). This approach leads to broader groups of chartists and fundamentalists and reduces substantially the size of the intermediate group, which is the largest in the baseline specification. Similarly, we classify fundamentalists and chartists according to the 33% and 66% percentile of the weight attached to technical information (Alternative II). While these two approaches lead to a wider definition of chartists and fundamentalists compared to the baseline definition, the third approach suggests a sharper distinction between chartists and fundamentalists with group sizes of 30-35 forecasters in each group (in contrast to 60-65 forecasters in the baseline regression): we classify forecasters as chartists if they attach a weight of at least 50 percent to technical analysis, and as fundamentalists if they attach a weight of at least 90 percent to fundamental information (Alternative III). Figure 5 illustrates the different definitions.

[Figure 5 about here]

Table 12 shows the characteristics of the defined groups in more detail.

[Table 12 about here]

Table 13 shows the revealed behavior for different groups.

[Table 13 about here]

Table 14 displays the switching probability for the different groups.

[Table 14 about here]

Table 15 displays the profitability for the different groups.

[Table 15 about here]

Controlling for two-dimensional market phases. The approach chosen in the main body of the paper considers the share of forecasts made in line with a particular forecasting model, e.g., trend-following behavior or PPP orientation. The drawback of this approach is obviously that we cannot distinguish with certainty whether a forecast has been made *because* of the trend or the PPP orientation when both models point into the same direction. We would expect that chartists and fundamentalists are more alike when both the deviation of the exchange rate from its fundamental value and the past trend are more pronounced at the same time. The following exercises demonstrate that this is indeed the case.

To analyze this, we distinguish between four market phases according to a 2×2 dimensional space: in particular, we consider each combination out of high/low trend and high/low fundamental misalignment states. We define high (low) fundamental deviation states as in Table 8, and likewise, high (low) trend state when the past absolute trend (30 days) is above (below) its median. Table 16 shows the average SHARE^{30}, SHARE^{90}, and SHARE^{PPP} for each of the double-sorted states.

[Table 16 about here]

Table 16 demonstrates that, indeed, chartists and fundamentalist behave most similarly when both PPP misalignment is large and a larger trend has occurred. In this particular market phase, it is unclear whether forecasters follow the trend of the past 30 days because they use technical analysis, or because they anticipate a continuation of the fundamental realignment. In contrast, the differences between chartists and fundamentalists are most pronounced when trends are high (because chartists make use of them excessively) and PPP deviation is low (because trends are unrelated to fundamental realignment).

Controlling for alternative trading rules. So far and throughout this study, our LHS variable in Eq. (7) corresponds to the change in the share of forecasters which are *in line* with a forecast based on a momentum-following forecasting rule. However, it has to be noted that a forecast, while being *in line* with a particular rule, is nevertheless not *based* with certainty on that particular rule. In this paragraph we address the possibility that forecasters have made their forecasts on a different, PPP-oriented, trading rule or carry trade rule.

To ensure that our results in the main part are not affected by such coincidence, we consider both a forecasting rule based on fundamental analysis, i.e. a rule presented expecting mean-reversion to PPP, and a carry-trade-based forecasting rule.[10] We compute the proportion of forecasters whose forecasts are in line with those strategies, in particular SHARE_t^{PPP} and SHARE_t^{CT}. We then include $\Delta\text{SHARE}_t^{PPP}$ and $\Delta\text{SHARE}_t^{CT}$ as control variables into the regression in Eq. (7).

Table 7, (vi), displays the results of this specification, and reveals that, in fact, the coefficient for $\Delta\text{SHARE}_t^{PPP}$ is positive and significant at the five-percent level. Thus, in our sample, there appears to be a slight tendency for momentum rules and fundamental rules to point into the same direction. Importantly, however, the inclusion of these control variables does not substantially alter any of the other coefficients. Overall, the main results for *Hypotheses 4* and *5* are also confirmed in this setting.

Controlling for volatility. We also test whether our results in Section 4.2 hold when we control for volatility. A positive association between turbulence in markets and the use of chartist rules has been postulated by De Grauwe and Grimaldi (2006). More specifically, we compute the standard deviation of daily returns over the 30 days before an individual forecast has been made, and take

[10] The PPP rule follows the concept from Eq. (4), whereas the carry trade rule is given by

$$E[\Delta s_{t,t+k}] = \phi^{(k,CT)}(i_t^{EUR} - i_t^{US}) \text{ with } \phi^{(k,CT)} > 0$$

with i_t^{EUR} and i_t^{US} representing the 3-month-interbank rates in the Eurozone and the United States, respectively.

the cross-sectional mean of these values for each survey period t, henceforth $\sigma_t^{(30)}$. We interpret a survey period characterized by high average volatility measures as particularly turbulent, and we consider changes in volatility $\Delta\sigma_t^{(30)}$ as a variable of interest in our regression Eq. (7).

As Table 7, (vii), shows, the coefficient for $\Delta\sigma_t^{(30)}$ is not significantly different from zero; in addition, the results from the main part remain virtually unchanged. This result also holds when we compute volatility over different horizons (10 days or 90 days), or when we include the variance instead of the standard deviation as a measure of volatility (unreported).

Ignoring the autoregressive term. So far, we have studied the dynamics of joining or abandoning trend-following forecasting by considering Eq. (7), which captures a lagged dependent variable. As a robustness check, we also reconsider the dynamics with a specification without an AR(1) term, such that

$$\Delta\text{SHARE}_t^{30} = a_0 + a_2 \Delta X_t + e_t \tag{A.1}$$

Table 17 presents the results and reconfirms that increases in trend size lead to an increased fraction of professionals with forecasts in line with momentum strategies. It also underlines that this fraction decreases when the squared distance from the fundamental value increases. Our conclusions from the main part with respect to *Hypotheses 4* and *5* thus do not depend on the inclusion of a lagged dependent variable into the time series regressions.

[Table 17 about here]

Forecast errors. To illustrate that the results of our discussion of *Hypothesis 6* are not driven by the way we formulate trading strategies, we also apply an entirely different concept and compute the individual forecasters' average absolute forecast errors.

To do so, the directional forecasts (i.e., the USD appreciates, stagnates, depreciates) are coded for simplicity in $X_{i,t+k}^e = \{-1, 0, 1\}$. Likewise, the realizations (ex post changes of exchange rates) are also categorized into three corresponding groups. For the neutral (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 as large as the share of forecasts in this category. Thus, the thresholds differ according to the forecasting horizon.[11] It should be noted that forecasters can

[11] The neutral category is chosen for one-month changes within the range of -1.19 percent and +1.19 percent, two-month changes between +/- 1.7 percent, three-month changes between +/-2 percent, six-month changes between +/- 4 percent, twelve-month changes between +/- 6.455 percent, 24-month-changes between +/- 5.7 percent, and 36-month-changes between +/- 8.85 percent.

be mistaken to a small and a large extent: they make a small error when they predict an unchanged variable, whereas the actual outcome is an increase, but a large error if they predict a decline. We take this into account by computing absolute forecast errors by $|\epsilon|^e_{i,t+k} = |X^e_{i,t,t+k} - X_{t,t+k}|$, which takes on the value of 2 for a severe error, 1 for a small error and 0 for a correct prediction. Table 18 presents the average absolute forecast errors for the groups of chartists and fundamentalists.

[Table 18 about here]

Table 18 shows very similar results to our findings in the main part, which confirms that our support for *Hypothesis 6* is not driven by the choice of the trading strategy discussed above: chartists commit less (and less severe) forecasting errors on one-month horizons. In contrast, there are no significant differences between chartists and fundamentalists when the forecasts are interpreted with respect to their predictability on longer horizons.

Table 11: Comparing panelists with all forecasters

This table compares the forecasts issued by the analysts considered in this study (*panelists*: the 396 forecasters who have also responded to special questions about their preferred forecasting tools) with all 744 forecasters in the dataset (*all forecasters*). (Both groups only include the forecasters with at least 10 survey responses.) For each point in time, we compute the proportion of forecasters (for both groups separately) who predict an appreciation, no-change, and a depreciation of the USD against the Euro. The means and standard deviations (over time) of these proportions are compared in this table. The table also reports the mean of the absolute difference as well as the Pearson correlation coefficient of the time series of proportions for both panelists and all forecasters.

		Apprec. of USD		**No-change**		**Deprec. of USD**	
	N	Mean	Std.	Mean	Std.	Mean	Std.
Panelists	396	0.219	0.116	0.290	0.059	0.490	0.137
All forecasters	744	0.220	0.116	0.295	0.062	0.485	0.138
Mean of absolute differences		0.011		0.013		0.014	
Correlation		0.993		0.958		0.991	

Table 12: Groups

This table reports characteristics of the defined groups of fundamentalists, chartists, and intermediates according to different classification schemes. These include the baseline definition (see also Table 2), as well as the alternative specifications introduces above. The table displays the mean, standard deviation, minimum and maximum weight (in percent) for fundamental and technical analysis, respectively, for all groups separately.

			Fundamental analysis				Technical analysis			
		N	Mean	SD	Min	Max	Mean	SD	Min	Max
Baseline	fundamentalists	66	88.6	8.4	80.0	100.0	7.2	7.7	0.0	20.0
	intermediates	269	58.2	12.1	20.0	78.3	27.3	10.3	0.0	50.0
	chartists	61	30.2	10.3	0.0	45.0	56.0	11.7	40.0	92.5
Alternative I	fundamentalists	94	84.7	9.4	71.7	100.0	9.9	8.0	0.0	25.0
	intermediates	151	63.5	5.4	51.7	67.5	25.5	8.7	0.0	43.3
	chartists	151	38.4	10.6	0.0	50.0	42.8	15.2	0.0	92.5
Alternative II	fundamentalists	159	75.3	14.8	30.0	100.0	12.3	7.6	0.0	20.0
	intermediates	122	56.7	11.7	20.0	76.7	29.6	3.6	20.5	35.0
	chartists	115	38.8	12.5	0.0	60.0	49.2	11.5	36.7	92.5
Alternative III	fundamentalists	31	96.8	4.3	90.0	100.0	0.89	2.3	0.0	10.0
	intermediates	333	58.5	15.3	10.0	87.5	27.4	12.1	0.0	50.0
	chartists	32	27.0	10.2	0.0	42.5	64.5	9.7	51.7	92.5

Table 13: Revealed behavior for different groups, averages

Panel A reports the average individual percentage share of forecasts made in line with the momentum strategy SHARE^{DD} (where DD denotes the days of the considered trend, i.e. 10, 30, 60, 90, and 180 days) for the groups of chartists, fundamentalists and intermediates. Panel B reports the average individual percentage share of forecasts made in line with PPP. The last row displays the results of t-statistic, where the H_0 corresponds to equal means between chartists and fundamentalists. (***: 1%, **: 5%, *: 10% significance level).

		Panel A					**Panel B**
		SHARE^{10}	SHARE^{30}	SHARE^{60}	SHARE^{90}	SHARE^{180}	SHARE^{PPP}
Baseline	fundamentalists	0.34	0.34	0.35	0.37	0.37	0.33
	intermediates	0.38	0.38	0.39	0.39	0.39	0.36
	chartists	0.39	0.40	0.40	0.40	0.41	0.33
	t-test fund. vs. chart.	**2.46	**2.72	**2.48	1.41	1.23	0.02
Alt. I	fundamentalists	0.35	0.34	0.35	0.38	0.38	0.31
	intermediates	0.39	0.38	0.39	0.39	0.39	0.34
	chartists	0.39	0.39	0.40	0.40	0.40	0.37
	t-test fund. vs. chart.	***3.13	***3.45	***2.94	*1.90	1.26	**2.55
Alt. II	fundamentalists	0.36	0.36	0.37	0.38	0.39	0.33
	intermediates	0.39	0.38	0.39	0.40	0.39	0.35
	chartists	0.39	0.39	0.40	0.40	0.39	0.37
	t-test fund. vs. chart.	**2.13	**2.58	**2.10	1.25	0.26	*1.74
Alt. III	fundamentalists	0.33	0.32	0.34	0.37	0.36	0.35
	intermediates	0.38	0.38	0.39	0.39	0.39	0.34
	chartists	0.39	0.39	0.40	0.40	0.40	0.36
	t-test fund. vs. chart.	*1.80	**2.13	*1.72	0.47	1.09	0.07

Table 14: Switching probability

Panel A reports Pearson correlation coefficients for the correlation of the individual probability of switching the direction of an USD/EUR forecast from one month to the next with with the individual survey response about the weights (in percent) attributed to fundamental and technical analysis, respectively. Panel B reports the average individual probability of switching the direction of an USD/EUR forecast from one month to the next for the groups of chartists, fundamentalists and intermediates. The last row displays the results of t-statistic, where the H_0 corresponds to equal means between chartists and fundamentalists. (***: 1%, **: 5%, *: 10% significance level).

	Mean switching probability, by group			
	Baseline	Alternative I	Alternative II	Alternative III
fundamentalists	0.09	0.09	0.09	0.10
intermediates	0.11	0.10	0.12	0.11
chartists	0.14	0.13	0.13	0.12
t-test fund. vs. chartists	**2.24	***2.70	***3.56	0.59

Table 15: Performance of trading rules, averages by groups

This table reports the cross-sectional averages (separately for fundamentalists, chartists and intermediates) of the average monthly return (Panel A) and the annualized Sharpe Ratio (Panel B) from trading strategies based on individual forecasts. These trading strategies translate a appreciation (depreciation) expectation into a long (short) position, taken in the forward market; the positions will be closed k months later in the spot market. We consider investments on different horizons, i.e. 1, 2, 3, 6, 12, 24 and 36 months. The last row displays the results of t-statistic, where the H_0 corresponds to equal means between chartists and fundamentalists. (***: 1%, **: 5%, *: 10% significance level).

	Average returns	1 mo	2 mo	3 mo	6 mo	12 mo	24 mo	36 mo
	fundamentalists	0.06%	0.07%	0.10%	0.13%	0.08%	0.09%	0.07%
Baseline	intermediates	0.17%	0.15%	0.12%	0.13%	0.09%	0.11%	0.10%
	chartists	0.21%	0.18%	0.15%	0.13%	0.09%	0.10%	0.09%
	t-values fund. vs. chart.	**2.34	*1.81	0.94	0.16	0.56	0.45	0.56
	fundamentalists	0.09%	0.09%	0.10%	0.13%	0.08%	0.09%	0.08%
Alt. I	intermediates	0.16%	0.15%	0.12%	0.12%	0.10%	0.11%	0.11%
	chartists	0.20%	0.16%	0.14%	0.13%	0.09%	0.10%	0.09%
	t-values fund. vs. chart.	**2.34	*1.72	0.89	0.08	0.45	0.76	0.56
	fundamentalists	0.11%	0.12%	0.10%	0.12%	0.09%	0.10%	0.10%
Alt. II	intermediates	0.18%	0.16%	0.13%	0.13%	0.10%	0.10%	0.09%
	chartists	0.20%	0.16%	0.14%	0.13%	0.08%	0.10%	0.09%
	t-values fund. vs. chart.	*1.94	1.13	1.26	0.36	0.26	0.07	0.59
	fundamentalists	0.04%	0.08%	0.07%	0.12%	0.06%	0.07%	0.06%
Alt. III	intermediates	0.17%	0.15%	0.13%	0.13%	0.09%	0.10%	0.09%
	chartists	0.14%	0.13%	0.09%	0.11%	0.09%	0.11%	0.12%
	t-values fund. vs. chart.	1.01	0.55	0.25	0.13	0.49	0.98	*1.69

Table 16: Revealed behavior for different groups, averages

This table reports the average individual percentage share of forecasts made in line with the momentum strategy SHARE^{DD} (where DD denotes the days of the considered trend, here 30,180 days) for the groups of chartists, fundamentalists and intermediates, as well as the average individual percentage share of forecasts made in line with PPP. The averages are computed conditional on the double-sorted states higher/lower trend and higher/lower fundamental (PPP) deviation. The last row displays the results of t-statistic, where the H_0 corresponds to equal means between chartists and fundamentalists. (***: 1%, **: 5%, *: 10% significance level).

		Weaker Trend			**Stronger Trend**		
		SHARE^{30}	SHARE^{180}	SHARE^{PPP}	SHARE^{30}	SHARE^{180}	SHARE^{PPP}
Lower	fundamentalists	0.30	0.35	0.23	0.35	0.37	0.26
PPP	intermediates	0.35	0.39	0.27	0.41	0.42	0.29
Deviation	chartists	0.36	0.41	0.24	0.44	0.44	0.27
	t-test fund. vs. chart.	**2.15	1.65	0.14	***2.94	**2.05	0.36
Higher	fundamentalists	0.33	0.41	0.39	0.39	0.39	0.43
PPP	intermediates	0.35	0.35	0.43	0.42	0.38	0.45
Deviation	chartists	0.37	0.38	0.41	0.40	0.36	0.43
	t-test fund. vs. chart.	1.08	0.82	0.54	0.26	0.52	0.14

Table 17: Explaining switching into momentum strategies, time series regressions, without autoregressive term

This table reports the results of a regression of the type

$$\Delta\text{SHARE}_t^{30} = a_0 + +a_1\Delta X_t + e_t$$

where $\Delta\text{SHARE}_t^{30}$ denotes the change in the proportion of forecasts made in t which point in the same direction as a trading rule following the trend over the previous 30 days, and ΔX_t represents the changes in several control variables. These control variables include the ex-post return of a strategy which has followed the trend of the previous 30 days, $r_t^{expost(30)}$, the previous month's return of a momentum-strategy chosen on the basis of the trend the month before, $r_t^{TR(30)}$, the deviation of the real exchange rate from its moving average of the preceding 10 years, $|q_t - \bar{q}_t|$, and the square of this distance, $(q_t - \bar{q}_t)^2$. In addition, we include $\Delta\text{SHARE}_t^{PPP}$ and $\Delta\text{SHARE}_t^{CT}$, which denote the change in the proportion of forecasts made in t which point in the same direction as a PPP-oriented (carry-trade oriented) forecast as further control variables. Due to potential time overlaps (the forecasts are made on a six-month horizon, whereas we sample on a monthly basis), we use Newey-West standard errors with a lag length of five months. Standard errors are provided in parentheses. (***: 1%, **: 5%, *: 10% significance level).

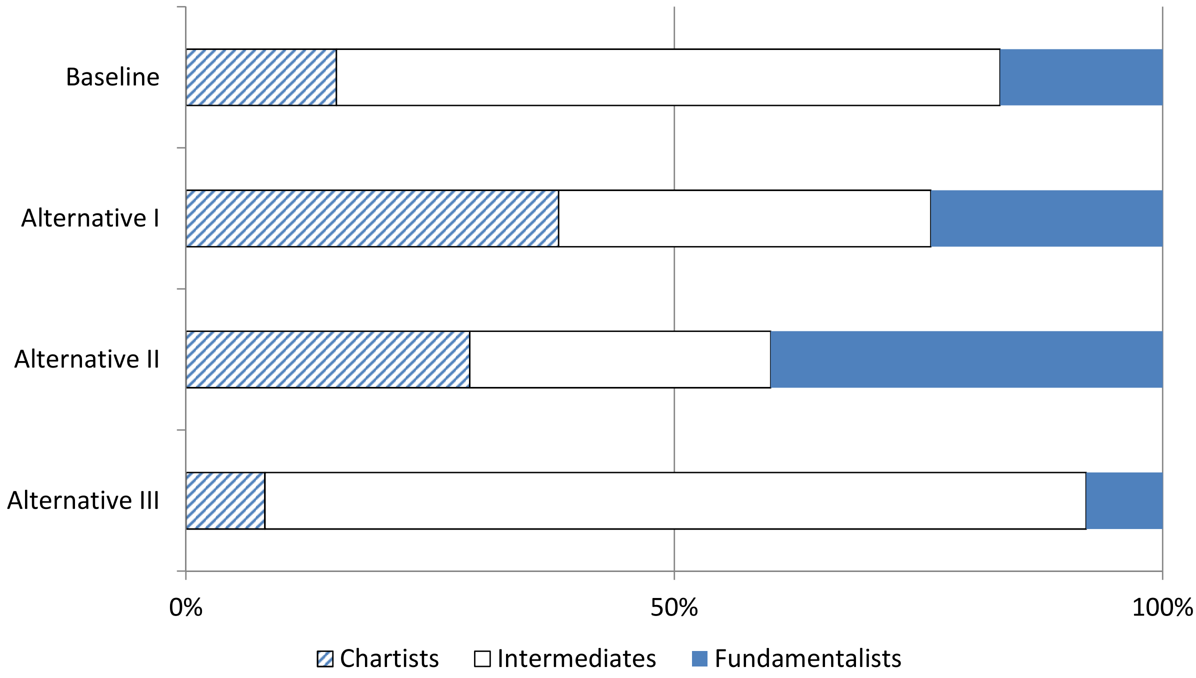
	(i)	(ii)	(iii)	(iv)	(v)
$\Delta r_t^{expost(30)}$	2.603				2.637
	***(0.839)				***(0.719)
$\Delta r_t^{TR(30)}$		-0.583			
		(0.734)			
$\Delta\|q_t - \bar{q}_t\|$			-0.685		
			(0.894)		
$\Delta(q_t - \bar{q}_t)^2$				-4.895	-4.835
				***(-1.824)	**(-1.948)
const.	-0.001	-0.001	0.001	0.001	0.001
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
T	151	151	151	151	150
R^2	0.07	0.01	0.01	0.06	0.13
adj. R^2	0.06	0.00	0.00	0.06	0.12

Table 18: Performance of trading rules, average absolute forecast errors by groups

This table reports the cross sectional average (for fundamentalists, chartists, and intermediates) of the average absolute forecast errors made by individual forecasters. We compare the forecasts with realized changes on different horizons, i.e., 1, 2, 3, 6, 12, 24, and 36 months. The last row displays the results of t-statistic, where the H_0 corresponds to equal means between chartists and fundamentalists. (***: 1%, **: 5%, *: 10% significance level).

Average absolute forecast error	1 mo	2 mo	3 mo	6 mo	12 mo	24 mo	36 mo
fundamentalists	0.92	0.90	0.88	0.81	0.83	0.70	0.67
intermediates	0.88	0.87	0.86	0.84	0.83	0.74	0.71
chartists	0.87	0.86	0.86	0.82	0.81	0.75	0.71
t-values fund. vs. chart.	**2.10	1.46	0.60	0.10	0.55	1.12	1.00

Figure 5: Robustness: different definitions of chartists and fundamentalists



This plot represents the alternative definitions of the groups of “chartists“, “intermediates“ and “fundamentalists“ considered in these robustness exercises in comparison to the baseline definition which is chosen throughout the main part of this paper.