ESSAYS ON EXPECTATIONS IN FINANCIAL MARKETS

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Kurzfassung

Diese Dissertation besteht aus vier Essays und behandelt unterschiedliche Fragestellungen aus der Finanzmarktforschung. Ihr liegt dabei die Überzeugung zugrunde, dass eine sorgfältige Analyse *individueller Erwartungen* dazu beitragen kann, vieldiskutierte offene Fragen zu beantworten und ökonomische Mechanismen besser zu verstehen. In jedem einzelnen Essay wird daher auf umfragebasierte Erwartungsdaten zurückgegriffen, um Themen aus verschiedenen Literaturbereichen zu erörtern: die Zinserwartungshypothese, das Wechselkurs-Prognose-Problem, Heterogene Agenten in Währungsmärkten und die Beziehung zwischen Aktien- und Währungsmärkten. Das erste Essay untersucht, wodurch Erwartungen bezüglich Veränderungen der Risikoprämien bei langfristigen Anleihen bestimmt werden. Auch wird herausgearbeitet, dass diese Erwartungen nachfolgende Renditen an Anleihemärkten prognostizieren können. Im zweiten Essay werden die beobachteten Erwartungen als Prognosen interpretiert. Die Hauptidee ist es hierbei, die Vorhersagegenauigkeit bezüglich unterschiedlicher Variablen miteinander zu verbinden, um Zusammenhänge zwischen den Realisationen dieser Variablen aufzudecken. Im dritten Essay werden die Erwartungen auf die zugrunde liegenden Strategien heterogener Agenten zurückgeführt, wodurch die Merkmale der sich gegenüberstehenden Konzepte Chartanalyse und Fundamentalanalyse dokumentiert werden können. Schließlich werden im vierten Essay Erwartungen dazu benutzt, die Phasen zu bestimmen, in denen Finanzmärkte durch jene Mechanismen angetrieben werden, die ein spezifisches Modell unterstellt.

Schlagworte: Individuelle Erwartungen, Finanzmärkte, Umfragedaten.

Abstract

This doctoral thesis collects four essays on several phenomena in financial markets which are motivated by the conviction that a thorough analysis of *individual expectations* can shed light on economic puzzles and mechanisms that are intensively investigated in literature yet poorly understood. Hence, in each of these essays, we use survey data to address issues from different strands of literature: the expectations hypothesis of interest rates, the exchange rate forecasting puzzle, heterogeneous agents in the market for foreign exchange and the relation between equity markets and exchange rates. In the first essay, we analyze the determinants of expectations about changes in term premia, and we illustrate that these expectations predict subsequent returns in bond markets. In the second essay, we take the observed expectations as forecasts of future financial variables. The core idea of this essay is to connect forecast performance for different macroeconomic variables, which helps to uncover links between the realizations of these variables. In the third essay, we employ expectations in a way that they reflect individual strategies of heterogeneous agents, which allows us to document the features of chartism and fundamentalism as two opposing concepts. Finally, in the fourth essay, we use expectations to determine regimes in which financial markets are driven by the mechanisms implied in one specific model.

Key words: Individual Expectations, Financial Markets, Survey Data.

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This thesis contains four scientific papers, which I have written as both a doctoral student at Leibniz University Hanover and -at the same time- an economist at the Centre for European Economic Research (ZEW) in Mannheim. The fact of being affiliated with two distinct academic institutions has substantially broadened my horizon. In both places, I have had the opportunity to work with great researchers and personalities, who have considerably influenced my academic progress and whom I would like to thank on this occasion.

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Mannheim, November 2012 *Christian David Dick*

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Introduction

This thesis collects four essays on several phenomena in financial markets. These essays are all motivated by the conviction that a thorough analysis of *individual expectations* can shed light on economic puzzles and mechanisms that are intensively investigated in literature yet poorly understood. Accordingly, the conceptual framework chosen for all topics in this thesis is the empirical analysis of economic expectations taken from *survey data*. Based on this approach, we study problems from different strands of literature, such as the expectations hypothesis of interest rates, the exchange rate forecasting puzzle, heterogeneous agents in the market for foreign exchange and the relation between equity markets and exchange rates.

There are different approaches to uncovering economic relations by looking at survey data. In particular, the nature of survey-expectations allows the extraction of information according to several interpretation schemes: expectations contain *additional information* about the state of the economy (beyond observable fundamentals), they can be interpreted and evaluated as *forecasts*, they reflect *strategies by individual agents* to conceptualize reality and can thus be used to trace back these strategies, and they may inform about the *current regime* when several economic mechanisms alternate. In the following, we assume that all of these interpretations are valid, and make use of the various facets of expectations in different manners throughout the four chapters.

In the first chapter, the expectations from survey data are considered representing additional insights about the fundamental state of economy which go beyond observable macroeconomic information; consequently, we analyze what determines these expectations, and we illustrate that they affect (subsequent returns in) financial markets. In the second chapter, we take the observed expectations as forecasts of future financial variables. The core idea of that chapter is to connect forecast performance for different macroeconomic variables, which helps to uncover links between the realizations of these variables. In the third chapter, we employ expectations in a way that they reflect individual strategies of heterogeneous agents, which allows us to document the features of chartism and fundamentalism as two opposing concepts. Finally, in the fourth chapter, we use expectations for determining regimes in which financial markets are driven by the mechanisms implied in one specific model, and others that are dominated by further mechanisms.

The first chapter of this thesis is motivated by the failure of the expectations hypothesis of interest rates, which has been documented by, e.g., Fama and Bliss (1987), Campbell and Shiller (1991) or, more recently, Cochrane and Piazzesi (2005).[1] It has been shown by these authors, among others, that term premia in bond markets (and correspondingly, excess returns of holding bonds) are time-varying and predictable. We contribute to this literature by highlighting that expectations contain information which can be used for predicting time-varying risk premia. More specifically, we suggest a measure of expected changes in term premia on long-term bonds which can be obtained in real-time from survey data. Based on the individual forecasts collected in the Survey of Professional Forecasters, we analyze how this proxy for expected term premium changes relates to further macroeconomic expectations. We also investigate whether measures of aggregate macroeconomic uncertainty influence our proxy. We demonstrate that expected changes in term premia are not only time-varying, but also determined by other macroeconomic forecasts. Moreover, the expectations contain information about excess returns in bond markets. To sum up the key results, the expected term premia are determined by expectations about real GDP growth, and they are affected by both output growth uncertainty and inflation uncertainty. Interestingly, it transpires that expectations about real macroeconomic variables have a stronger influence than inflation expectations. We also relate our proxy to the conventional term structure factors level,

[1] A revised version of this chapter with the title *Macro Expectations, Aggregate Uncertainty, and Expected Term Premia* (which is joint work with Maik Schmeling and Andreas Schrimpf) is accepted for publication in the *European Economic Review* (see Dick, Schmeling, and Schrimpf (2012)).

slope, and curvature. It appears that the level and the slope factor reflect information which is also contained in the considered uncertainty measures; in contrast, curvature captures similar information as our proxy for expected changes in term premia. When aggregating the individual expectations about term premium changes, this measure is able to predict excess returns in bond markets over the subsequent twelve months.

In the second chapter of this thesis, we use expectations for deepening our understanding of actual (realized, not expected) movements in financial markets, more precisely, the market for foreign exchange.[2] Our choice of this market is motivated by the well-documented *exchange rate forecasting puzzle*, i.e., the empirical failure of theoretical exchange rate models to outperform random walk forecast at intermediate horizons (e.g., Meese and Rogoff, 1983; Cheung, Chinn, and Garcia-Pascual, 2005, among others.) This result presents a puzzle, as it does not only put into question the usefulness of exchange rate models, but even the connection between exchange rates and fundamentals as such. Thus, we reconsider the link between exchange rates and their theoretical macroeconomic fundamentals in the medium-term by the means of an indirect approach, which centers around observed expectations and hence avoids shortcomings of conventional strategies. Our analysis gives reason to believe that exchange rates are indeed related to economic fundamentals over medium-term horizons, such as a month or longer. In particular, by using a large panel of individual professionals' forecasts, we are able to document that the quality of exchange rate forecasts and a sound understanding of macroeconomic fundamental variables (i.e., interest rate forecasts) are closely related. This result is also confirmed when we apply regression techniques with individual fixed effects and when we take further control variables into consideration. The relationship between exchange rates and fundamentals is variably important over time, and we demonstrate that it is more pronounced in market phases when fundamental

[2]This chapter is an earlier version of joint work with Lukas Menkhoff and Ronald MacDonald. An even earlier version has appeared as a discussion paper entitled *Individual Exchange Rate Forecasts and Expected Fundamentals* (henceforth Dick, MacDonald, and Menkhoff, 2011).

misalignments are obvious. This is the case when the price of a currency strongly deviates from a fundamental price, when the interest rates in the two countries are substantially different, and when exchange rates are exposed to little momentum trading. We also document that exchange rate forecasters share a common exchange rate model, but that they are only able to use it for accurate exchange rate forecasts when they rely on good interest rates forecasts.

The third chapter of this thesis is devoted to an investigation of the expectations of different types of forecasters.[3] For more than two decades, there are serious attempts in financial economics to abandon the representative agent framework and to model expectations for different agents heterogeneously instead. Early papers introducing this idea include De Long, Shleifer, Summers, and Waldmann (1990), who demonstrate how irrational (either bullish or bearish) agents introduce additional risk, or Day and Huang (1990), who distinguish between sophisticated investors and naive (and thus purely trend-following) investors in stock markets, or Brock and Hommes (1997), who simulate the dynamics of heterogeneous traders switching between trend-following or a fundamental-based decision rules. Our particular analysis follows this line of thought, focusing on the expectations of chartists and fundamentalists in foreign exchange markets. We document that these two groups differ from each other with respect to their expectation formation. It can be seen that chartists switch more often between forecast directions than fundamentalists. As a matter of fact, the expectations of chartists and fundamentalists vary to a substantial extent, as they tend to react to pronounced exchange rate trends. Our results also correspond to non-linear exchange rate models as we show that forecasters make mean-reverting forecasts only in phases in which exchange rates differ substantially from their fundamental values. We also investigate the forecast performance of chartists and fundamentalists. We learn that both groups predict equally accurately. This finding explains why chartists are not systematically less prof-

[3]The chapter is an earlier version of a joint work with Lukas Menkhoff with the title *Exchange Rate Expectations of Chartists and Fundamentalists*. It has also appeared as a discussion paper, see Dick and Menkhoff (2012).

itable than fundamentalists, and hence, are also able to remain active in financial markets. The details of our findings could potentially inform exchange rate models with heterogeneous agents, such as Frankel and Froot (1990), De Grauwe and Grimaldi (2006) or Bauer, De Grauwe, and Reitz (2009).

The fourth chapter of this thesis investigates the connection between exchange rate movements, capital flows, and stock market returns. This research follows a line of studies focusing on the role of financial investors (rather than agents in real markets) in exchange rate determination. Hau and Rey (2006) illustrate a concept called *uncovered equity parity*, according to which exchange rates, capital flows, and stock market returns are determined endogenously; specifically, differential stock market returns cause portfolio rebalancing, which is ultimately responsible for the appreciation or depreciation of currencies. Our research follows this line of reasoning and puts into focus investor's expectations, in particular with respect to the implicitly expected correlation between exchange rate movements and relative stock market returns. These expectations are found to be time-varying, which should have implications for portfolio allocation decisions. Based on the time variation in expectations, we are able to identify different regimes. Furthermore, we illustrate that the magnitude of *realized* correlation between exchange rate movements and relative stock returns depends on such regimes. This finding is consistent with the view that exchange rates are partly determined by portfolio rebalancing, as suggested by Hau and Rey (2006), but that there are also additional mechanisms outside of that model. Hence, our expectation measure can be used for distinguishing different regimes in the market for foreign exchange with different dominating mechanisms.

1. Using expectations to study risk premia in bond markets*

1.1 Introduction

Using panel data from the Survey of Professional Forecasters (SPF), we construct a simple proxy of forecaster-specific expectations about changes in future term premia which are basically equivalent to expected bond excess returns.[4] These term premium expectations are not estimated, are available in real-time, clearly time-varying, and reasonably persistent. We then employ a dynamic panel regression framework to investigate macro determinants of these term premium expectations at the level of individual forecasters. Our results indicate that individual term premium expectations are most strongly influenced by *expectations* about real GDP growth and a measure of aggregate uncertainty about future real macro conditions. Inflation expectations and aggregate inflation uncertainty are also important, but are dominated by real factors. Finally, an aggregate measure of term premium expectations across forecasters has predictive power for future bond excess returns over forecast horizons of up to one year.

There is ample evidence that the expectations hypothesis of the term structure of interest rates

*A revised version of this chapter with the title *Macro Expectations, Aggregate Uncertainty, and Expected Term Premia* (which is joint work with Maik Schmeling and Andreas Schrimpf) is accepted for publication in the *European Economic Review* (see Dick, Schmeling, and Schrimpf (2012)).

[4]To be precise at this initial stage already, the relation between our proxy of expected term premium changes and expected future bond excess returns is almost a 1:1 negative relationship. Rising investors' expectations about term premia in the future are associated with lower expected bond prices in the future, i.e. lower expected bond returns from today's perspective.

does not hold empirically and that investors tend to demand a compensation for holding long-term bonds. These term premia – or bond risk premia – compensate investors for higher risk and drive a wedge between short rates controlled by the central bank and longer-maturity rates. Since the latter are crucial for spending and investment decisions in the economy, term premia are relevant in many branches of macroeconomics and finance and the literature has convincingly demonstrated that term premia are time-varying (see e.g. Cochrane and Piazzesi, 2005; Ludvigson and Ng, 2009) and at least partly driven by the state of the business cycle. As this adds complexity to the conduct of monetary policy as well as investment and borrowing decisions of the private and public sector, an active field of research is devoted to a better understanding of time-varying risk premia in bond markets (see e.g. Ang and Piazzesi, 2003; Rudebusch, 2010; Wright, 2011).

This essay contributes to the strand of literature linking macroeconomic information to bond yields and bond risk premia. While existing studies in this literature typically investigate aggregate term premium estimates, we focus on survey-based term premium expectations at the level of *individual* forecasters. This approach has two advantages: First, relying on survey information allows us to focus on the role of forward-looking macro *expectations* to understand term premia, whereas most earlier papers focus on the impact of *current* macro conditions.[5] Second, the forecasters in our panel naturally differ in their expectations about future macro conditions and term premia. We can exploit this cross-sectional variation to obtain more powerful tests when analyzing determinants of bond risk premia. Unlike in aggregate data where cross-sectional differences in expectations are washed out,[6] individual data allow us to identify stable relationships between macro expectations and term premia in the cross-section of forecasters. The explicit focus on

[5]One exception is Chun (2011) who also studies the impact of macro expectations on term premia. However, Chun works at the aggregate level and does not study a panel of forecasters.

[6]For instance, consider the extreme case of only two investors where one forecaster expects a rise in the inflation rate of +2% and rising term premium of 1% and the other expects a decline in the inflation rate of -2% and a declining term premium of -1%. A panel regression will easily identify a positive relation between inflation expectations and term premia, whereas an aggregate analysis, relying on cross-sectional averages, will have little power to detect a significant relation since average inflation and term premium expectations will be equal to zero.

forward-looking macro variables and the use of individual real-time expectations is a novel aspect of our analysis compared to earlier literature.

Relative to pure time-series analyses of bond risk premia where future bond returns are regressed on current macro variables (e.g. Ludvigson and Ng, 2009) or other bond predictors (e.g. Cochrane and Piazzesi, 2005), our survey approach has the advantage that it delivers an *observable* proxy for changes in term premium expectations and, equivalently, expected excess returns (available in real-time). Hence, we do not have to estimate expected returns, i.e. term premia, from noisy actual return data, which facilitates the detection of potential links between macro variables and bond risk premia.

Our main interest lies in the relation of term premia with expected future key macro business cycle variables - output growth and inflation - and aggregate uncertainty about these macro factors. Thus, in our benchmark specification, we regress individual term premium expectations on individual expectations about future real GDP growth and inflation (and instrument for these contemporaneous macro expectations) and measures of aggregate GDP and inflation uncertainty while controlling for lagged individual term premium expectations and further variables. As noted above, we find that nominal factors (expected inflation and inflation uncertainty) do matter for term premia to some extent, but that real factors (expected output growth and uncertainty about future output growth) clearly dominate the nominal factors. The main relations are such that higher expectations about output growth imply rising term premium expectations in the future, which is equivalent to lower expected bond returns. This result makes sense from a standard asset pricing perspective where good states of nature are associated with low risk premia. Likewise, higher aggregate uncertainty also leads forecasters to expect lower excess returns, which seems well in line with a flight-to-quality effect for U.S. treasury bonds in times of high macro uncertainty.

Our results confirm findings from earlier papers which show that output growth and/or inflation matter for risk premia (Ang and Piazzesi, 2003; Bikbov and Chernov, 2010; Diebold, Rudebusch, and Aruoba, 2006; Chun, 2011; Ludvigson and Ng, 2009; Wright, 2011), and that macro uncertainty is important (Söderlind, 2009; Wright, 2011) but it does so by focusing on the relation between expected macro conditions and expected term premia whereas earlier papers usually examine the effect of current macro fundamentals. Furthermore, we investigate the relation of our term premium expectations with classic yield curve factors (level, slope, and curvature) as well as the Cochrane and Piazzesi (2005) return forecasting factor. We find that the level and slope of the yield curve seem to capture effects similar to our measures of aggregate uncertainty, which sheds some light on the economic forces underlying these two yield factors. Curvature, in turn, seems to be related to forecasters' term premium expectations themselves, which lines up with findings in Cochrane and Piazzesi (2008).

Finally, we test whether our proxy for term premium expectations is related to future bond excess returns. To this end, we run predictive regressions of bond returns on aggregate term premium expectations in the spirit of Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009). We find that our real-time proxy for term premium expectations forecasts future bond excess returns with predictive R^2s of up to 23% at an annual forecast horizon. This is quite remarkable in our view, given that our term premium proxy is a non-estimated variable (i.e. it is free of potential look-ahead or errors-in-variables problems) and is readily available in real-time. Furthermore, results from our forecasting exercise are in line with the view that our factor proxies for *future changes in risk premia* and not the current level of risk premia as in, e.g., Cochrane and Piazzesi (2005) or Ludvigson and Ng (2009), so that our factor differs from earlier proxies in the bond literature.

The remainder of this chapter proceeds as follows. The next section selectively reviews related literature, Section 1.3 describes the construction of our proxy for term premium expectations, Section 1.4 details the data and our panel regression framework, Section 1.5 presents empirical results, 1.6 describes several robustness checks and Section 1.7 concludes. Note that there are also additional robustness checks reported in the appendix.

1.2 Related literature

The expectations hypothesis (EH) of interest rates has been serving as a classical point of reference in economics and finance for decades. In its most basic form, it implies that bond risk premia (term premia) are constant over time.[7] However, failures of this concept have been documented for more than 20 years. Early references include Fama and Bliss (1987) and Campbell and Shiller (1991) who show that the difference between forward rates and spot rates or the term spread, respectively, forecast bond (excess) returns. Taking account of this predictability, modern economic models understand risk premia in bond markets to be, in fact, time-varying. Due to the importance of term premia for economics and finance, there is now a vast literature on this topic. Hence, we do not attempt to survey the whole field but rather focus on a few selected studies which investigate the link between macro factors and bond yields. We also pay special attention to the use of survey data for term premium modeling. For a more comprehensive literature overview, see e.g. Diebold, Piazzesi, and Rudebusch (2005) or Kim (2009).

One approach of linking bond risk premia to macro factors is to run predictive regressions of future bond (excess) returns on current macro factors.[8] This is done, e.g., by Ludvigson and Ng (2009) who extract macroeconomic factors from a large data set and find that bond returns are highly predictable with predictive R^2s of up to 26% for U.S. bonds, indicating that term premia

[7]There are different ways of stating the EH as well as its implications (cf. Cochrane, 2005). Here, we refer to the EH as the proposition that there are no time-varying term premia and that holding period excess returns on long-term bonds are not predictable. For a more precise statement see Eq. (1.1) in Sec. 1.3.

[8]Throughout this chapter, we use the terms "term premium" and "bond risk premium" synonymously.

are clearly time-varying. They find that a real output factor is an important driver of bond excess returns. A related approach is to run predictive regressions on bond-related variables to compute forecasting factors, and relate these to the business cycle in a second step. For example, Cochrane and Piazzesi (2005) construct a factor based on a linear combination of forward rates for bonds with different maturities to forecast bond excess returns. These authors also show that their factor is related to the business cycle (see also Koijen, Lustig, and Van Nieuwerburgh, 2010, for a related analysis).

The link between yield curve and macro variables is also studied within macro-finance models that directly model macro factors together with yield curve models. For example, Ang and Piazzesi (2003) find that output shocks are an important driver of curvature, whereas inflation shocks matter most for the level of the yield curve. They also find that the forecast performance of an affine model with macro factors is better than that of a model with only latent factors. Piazzesi (2005) shows that the slope of the yield curve is driven by shocks to monetary policy.[9] Outside the class of affine no-arbitrage models, Diebold and Li (2006) build on Nelson and Siegel (1987) to develop a method to estimate dynamic yield curve factors precisely for each period from yield data. Several recent papers apply this methodology to study the impact of macro factors on the yield curve and on bond risk premia. Diebold, Rudebusch, and Aruoba (2006) examine the dynamic interaction between macro factors and the yield curve, finding strong evidence for effects of macro on yields but also for effects running from yields to macro variables. Diebold, Li, and Yue (2008) study global yield curve factors which are related to the global business cycle and have resemblance to worldwide inflation and real activity. We contribute to this active literature

[9]There are, of course, other approaches relying on macro-finance linkages based on more standard equilibrium models which also serve to capture the failure of the Expectations Hypothesis and the existence of time-varying risk premia. For example, Wachter (2006) and Buraschi and Jiltsov (2007) study equilibrium models with habit-formation as in Campbell and Cochrane (1999). Bansal and Shaliastovich (2008) and Rudebusch and Swanson (2008) build models with long-run risks based on Bansal and Yaron (2004) to capture failures of the EH and the existence of time-varying bond risk premia. Buraschi and Jiltsov (2005) study risk premia in a money-augmented real business cycle model with taxes and endogenous monetary policy.

by directly investigating the relationship between these yield curve factors and the expectations of individual forecasters about future term premia movements.

Our approach of relying on survey information is not at all uncommon in the bond literature. Chun (2011) also uses analyst forecasts on GDP, inflation, and the Federal Funds rate to link fluctuations in bond yields to expectations about monetary policy and macro conditions. Thus, he studies the impact of forward-looking macro expectations on the bond yields, an approach we also follow in this essay.[10] Piazzesi and Schneider (2009) use median forecasts along with predictive regressions to disentangle (aggregate) subjective risk premia and prediction errors of professional forecasters. Wright (2011) uses survey information on long-term inflation, GDP, and interest rates to construct term premium estimates. He also studies the effect of inflation and output uncertainty on risk premia in a panel of countries. Wright ascribes a large amount of the variation in term premia to the role of inflation uncertainty. This result seems to make sense, since Piazzesi and Schneider (2006), Campbell, Sunderam, and Viceira (2009), or Rudebusch and Swanson (2008) all argue that inflation uncertainty matters for term premia, a point we pay special attention to in this chapter. Söderlind (2009) uses survey information to construct proxies for inflation and output growth uncertainty and finds that uncertainty (as well as liquidity factors) is a significant driver of bond risk premia over the period from 1997 to 2008. Söderlind also finds that output growth uncertainty lowers the term premium whereas inflation uncertainty increases it.

While our study is related to all these papers, we go beyond the existing contributions in the following way: We propose a proxy for term premium expectations which is basically model-free, real-time and easily implementable, and explore a panel of individual forecasters to relate these proxies to macroeconomic *expectations*, measures of aggregate macro uncertainty, and measures of real-time macro activity. To the best of our knowledge, we are the first to analyze these issues

[10]However, Chun does not investigate individual forecasters or the impact of inflation and output growth uncertainty.

in a comprehensive and coherent approach.

1.3 Measuring term premium expectations

There are a number of ways to derive term premia from surveys which differ with respect to their data requirements and/or their reliance on expected bond returns versus bond yields (see e.g. Piazzesi and Schneider, 2006, 2009; Wright, 2011, for different approaches). We propose a simple way to calculate term premium expectations of individual forecasters that can be readily implemented with minimal data requirements and mild assumptions and approximations. Afterwards, we describe the construction of our term premium expectation proxy and then discuss how to interpret the proxy and how it relates to the related concept of expected bond excess returns.

Construction of our proxy. The expectations hypothesis (EH) implies that long-term yields on zero-coupon bonds are equal to the average of the expected future short-term interest rates and a constant term premium (Campbell and Shiller, 1991),

$$y_t^n = \pi + \frac{1}{k} \sum_{i=0}^{k-1} E_t[y_{t+mi}^m], \tag{1.1}$$

where y_t denotes a log yield measured in quarter t, n (m) denotes the quarters to maturity of the long-term bond (of a T-bill), $k = n/m$, and π equals the non-varying term premium of holding the long-term bond. Since numerous studies have documented that the EH does not hold due to time-varying term (or risk) premia (e.g. Fama and Bliss, 1987; Campbell and Shiller, 1991), we follow Cochrane and Piazzesi (2008), introducing a time subscript t to π in Equation (1.1). Considering T-bills with a time to maturity of exactly $m = 1$ quarter as the short rate, we formulate the relationship between long-term and short-term interest rates as

$$y_t^n = \pi_t + \frac{1}{n}\sum_{i=0}^{n-1} E_t[y_{t+i}^1], \tag{1.2}$$

and in terms of expectations for the interest rate h quarters ahead, we have

$$E_t[y_{t+h}^n] = E_t[\pi_{t+h}] + \frac{1}{n}\sum_{i=0}^{n-1} E_t[E_{t+h}[y_{t+h+i}^1]]. \tag{1.3}$$

Using the law of iterated expectations and taking differences of Eqs. (1.3) and (1.2), we obtain the expected changes in long-term yields

$$E_t[y_{t+h}^n] - y_t^n = E_t[\pi_{t+h}] - \pi_t + \frac{1}{n}\sum_{i=0}^{n-1} E_t[y_{t+h+i}^1] - \frac{1}{n}\sum_{i=0}^{n-1} E_t[y_{t+i}^1]. \tag{1.4}$$

Rearranging terms yields the expected change in term premia $E_t[\Delta\pi_{t+h}]$, which is given by

$$E_t[\Delta\pi_{t+h}] = E_t[\pi_{t+h}] - \pi_t = E_t[y_{t+h}^n] - y_t^n - \left(\frac{1}{n}\sum_{i=0}^{n-1} E_t[y_{t+h+i}^1] - \frac{1}{n}\sum_{i=0}^{n-1} E_t[y_{t+i}^1]\right). \tag{1.5}$$

As there are overlapping time periods in the two sum operators (in parentheses on the RHS), some of the expected future short rates cancel out. Choosing $h = 1$ for simplicity, Eq. (1.5) can be written as

$$E_t[\Delta\pi_{t+1}] = E_t[\pi_{t+1}] - \pi_t = E_t[y_{t+1}^n] - y_t^n - \frac{1}{n}\left(E_t[y_{t+n}^1] - y_t^1\right), \tag{1.6}$$

which is the expected change in long-term yields minus the difference of the "corner" short-term interest rates (the one which is expected today for the period following the maturity of the long-term bond ($E_t[y_{t+n+1}^1]$) as well as the current one (y_t^1)).

Note that the number of overlapping time periods which cancel out in the two sum operators decreases when a larger forecast horizon h is considered. As a consequence, the expected change in the risk premium includes the difference between the sum of the h "corner" interest rates on each side. For example, for a horizon of $h = 2$, (1.5) reads

$$E_t[\Delta\pi_{t+2}] = E_t[y^n_{t+2}] - y^n_t - \frac{1}{n}\left(E_t\left[y^1_{t+n+1} + y^1_{t+n}\right] - E_t[y^1_{t+1}] - y^1_t\right) \tag{1.7}$$

and similarly for longer horizons. Hence, our measure relates to *expectations about future changes in term premia* and is just the expected yield change of a long-term bond plus a minor adjustment for (expected and current) short rates. However, the latter minor adjustment part does not, in fact, matter for our results presented below as we will show in the robustness section of this chapter.

Empirical construction of the proxy. Based on Eqs. (1.6) and (1.7), we calculate the expected change in term premia from forecasters' expectations about long-maturity and short-maturity yields. We consider T-bond yields (10 years to maturity) from the SPF to obtain the expectation value in the first component on the RHS in Eqs. (1.6) and (1.7), $E_t[y^n_{t+h}] - y^n_t$. Of course, yield expectations in the SPF do not apply to zero-coupon bonds, but we stress that we are examining expectations about *yield changes* and not the level of yields. The yield change of a zero-coupon bond is likely to be much better approximated by the yield change of a coupon bond compared to approximating yield levels of zero-coupon bonds by coupon bonds. In fact, the correlation of zero-coupon bond yield changes in the Gürkaynak, Sack, and Wright (2007) data and changes of T-bond yields (from the FED St. Louis) is approximately 93%. Thus, working with expected yield changes for T-bonds from the SPF does not seem to be an overly strong approximation.[11]

To complete the computation of $E_t[\Delta\pi_{t+h}]$ in Eqs. (1.6) and (1.7), we further need to identify

[11] We provide further robustness on this later in this chapter.

the expected short-term interest rates in the second component on the RHS. The expected short rates for subsequent quarters ($E_t[y^1_{t+h}]$) are directly available in the SPF data. However, the dataset does not contain subjective information about the expected short-term interest rates in the distant future $E_t[y^1_{t+n}]$. Therefore, we assume that forecasters expect short-term interest rates in the distant future to equal the unconditional mean of the short-term interest rates for the time period 1981 to the current point in time t, which implies that forecasters rely on past long-run averages when it comes to long-run forecasting.[12] We find this a reasonable assumption.[13] Furthermore, we also note that the expression with the short-term interest rate differences is multiplied by $1/n$ (which equals $1/40$ in our case, since we are working on a quarterly frequency and consider ten year maturities). Hence, the expected change in bond yields dominates the expression on the RHS of Equations (1.6) and (1.7), such that we do not expect the results to be driven by the identifying assumption about long-run forecasts for the short rate as noted above.

In short, we are relying on a combination of expected changes in yields of long and short maturities to obtain an observable proxy for expected changes in term premia. While we have to make some simplifying assumptions, these do not appear to be overly strong and they certainly do not drive our results. Advantages of our proxy are that it can be easily computed in real-time and has no hindsight bias, that it can be constructed for average survey expectations or individual forecaster expectations, and that it is directly observable and does not have to be estimated.

Interpretation of the proxy. Now, what does "expected change in term premia" mean in economic terms? Our term premium expectation factor captures information about *future changes*

[12]For robustness, we also consider the unconditional mean of the short-term interest rates for the time period 1981 to 2009 and do not find important changes.

[13]In our setup, the long-term bond has a maturity of 10 years. Therefore, it is plausible that forecasters have only vague ideas about short-term interest rates 40 quarters ahead, and hence forecast the recursive unconditional mean. As long as the short-rate is stationary, standard time-series models will also deliver a forecast close to the unconditional mean when iterated 40 periods into the future. Similarly, standard affine term structure models with no-arbitrage restrictions generally also have an inherent tendency to produce forecasts equal to the recursive unconditional mean (see also the discussion in Cochrane and Piazzesi, 2008).

in term premia, so that our results below cannot be interpreted in the same way as in many other papers where macro factors (or other proxies for business cycle risk) ought to capture the *current levels* of risk premia. For instance, the point in Ludvigson and Ng (2009) is to find business cycle state variables which measure contemporaneous levels of risk premia. Hence, a higher risk premium today signals high required returns and should thus translate into high returns going forward.

How, then, can our proxy be interpreted? In our case, we investigate a proxy for future changes in risk premia which is a different concept: expectations about positive risk premium changes imply that required returns, i.e. discount rates, will rise in the future (without making statements about current levels of risk premia) and should thus translate into lower excess returns in future periods (as future bond prices will fall due to increases in future required risk premia).

To underline the relationship between our proxy and expected excess returns, consider the definition of expected excess returns as

$$E_t[rx_{t,t+h}^{n+h}] = E_t[p_{t+h}^{(n)}] - p_t^{n+h} - y_t^h, \tag{1.8}$$

where $p_t^{(n)}$ denotes the log price in t of a zero bond with a time to maturity of n. As the bond yield is defined as $y_t^n = -p_t^{(n)}/n$, one can solve for $p_t^{(n)} = -ny_t^{(n)}$ and rewrite Eq 1.8 as

$$E_t[rx_{t,t+h}^{n+h}] = -nE_t[y_{t+h}^{(n)}] + (n+h)y_t^{n+h} - y_t^h \tag{1.9}$$

To empirically illustrate how tight the relationship between expected excess returns and our proxy for expected in term premium changes actually is, we take $E_t[y_{t+4}^{(n)}]$ from individual survey expectations and compute both the expected excess returns as well as the proxy for the one-year ahead expectations ($h = 4$). (For $y^{(n)}$ and $y^{(n+4)}$ in Eq. (1.9), we take coupon bond yields of a maturity of 10 and 11 years (40 and 44 quarters), respectively.) The correlation coefficient of $E_t[rx^{n+4}_{t,t+4}]$ and $E_t[\Delta\pi_{t+4}]$ (quarterly mean across sample) is -0.95, which establishes that a *positive value of our proxy* is basically equivalent to a *negative expected excess return*. This, in turn, offers a straightforward economic intuition for our results reported below and we will interpret our results both in terms of expected term premium changes and in terms of expected excess returns, where the latter is just the flip side of the former concept.

However, note that while expected excess returns may be easier in terms of their interpretation, our proxy of expected term premium changes is more suitable for empirical work since it can be computed for quarterly instead of yearly horizons. This point is an important feature of our approach which facilitates the analysis of a relatively short sample.

1.4 Data and empirical approach

1.4.1 Data sources and variable construction

Data description. Our analysis of the determinants of individual investors' term premium expectations requires expectations about future bond yields and macro variables. We rely on the *Survey of Professional Forecasters* (SPF) to obtain these micro-level expectations. The SPF covers participants from financial firms, banks, consulting firms, or research centers. The average participation is about 38 forecasters per quarter. We choose the SPF because it contains our variables of interest, because it allows us to calculate sensible measures of forecaster uncertainty (see below), and because its use as a data source is widely established in academic studies (e.g. Ang, Bekaert, and Wei, 2007). Our sample covers 70 quarters from 1992Q1 to 2009Q2 and a total of 153 different forecasters.[14]

[14]The SPF did not include questions about Treasury yield expectations before 1992.

We obtain the expected change in the term premium for each forecaster from his or her predictions of 10-year Treasury Bond Yields and 3-months T-bill rates for the subsequent quarters, see Eq. (1.6) or (1.7) above. We also include the expectations about real GDP and inflation as explanatory variables in our analysis. For real GDP, we calculate the expected (log) growth rate, i.e. the forecast relative to the nowcast for the current quarter, so that we look at expected output growth. The expected inflation rate is included in levels.

Timing of survey expectations. The SPF questionnaires are sent to the participants at the end of the first month of each quarter. As the deadline for returning the questionnaires is the middle of the second month of the respective quarter, the professional forecasters respond within a two-week time-frame. Based on this response procedure, we refer to the period from the last survey deadline to the current one as a *survey quarter*. Note that unlike the *target quarter*, which corresponds to the conventional calendar quarters, *survey quarters* are spaced from Nov/16-Feb/15, Feb/16-May/15, May/16-Aug/15 and Aug/16 to Nov/15 in each year.

Interest rates and yields. We collect three months U.S. T-bill rates and U.S. Corporate Bond Yields (by the Federal Reserve) from *Datastream*. Bond yields for longer maturities are taken from the smoothed U.S. Treasury yield curve data provided by Gürkaynak, Sack, and Wright (2007), which are also used to construct yield curve factors as in Diebold and Li (2006) and the bond factor of Cochrane and Piazzesi (2005), denoted CP.

These daily time series can be transformed into several variables required by our analysis: We consider the *last* realization in January, April, July and October of T-bill rates and ten-year-to-maturity bond yields in the respective information sets (including for the computation of risk premia as indicated in Equations (1.6) and (1.7). In contrast, we take the *mean* of the daily short rates and 10 years bond yields to construct series of *realized* changes in term premia. We also compute the log change of interest rates between the first and the last day in a survey quarter ($\Delta TBOND$, $\Delta TBILL$) as well as the standard deviation of daily interest rates within a survey quarter ($\sigma(TBOND)$, $\sigma(TBILL)$), respectively.

Finally, we also make use of CRSP data to compute excess returns in bond markets.

Macroeconomic variables. To operate with macroeconomic figures which have actually been available to the forecasters, we exploit the real time data collected by the *Federal Reserve Bank of Philadelphia*. In particular, we consider the U.S. total industrial production index (IP), the consumer price index (CPI), the real gross domestic product (RGDP) as well as the nominal money stock (M2). The real time data set ignores future data revisions or redefinitions and facilitates a relatively accurate timing of the information inflow. As the SPF does not include the exact individual response date, we assume that economic figures are included in the forecasters' information set if they are released by the end of the first month in a quarter (January, April, July, October). We transform all variables to (log) year-over-year growth rates (except for inflation). As the CPI has only been available in the real time data since Q1 1994, we compute inflation rates from ex-post data for the previous period. We compute the yoy (log) real money growth by subtracting the (log) yoy inflation rate from the (log) nominal money growth. The IP, CPI, and M2 are published by the releasing institutions on a monthly basis in the middle of the subsequent month. As a consequence, we consider the values for December, March, June, and September, respectively. As only the releases in February, May, August and November for the CPI and the money stock are available in the real time data set of the Federal Reserve Bank of Philadelphia, we rely on revised data for the first month of a quarter for these two variables. GDP is released in the second month of a quarter for the preceding quarter. Accordingly, the information set includes the GDP figure of the third quarter at the end of January, of the fourth quarter at the end of April, of the first quarter at the end of July, and of the second quarter at the end of October.

Uncertainty measures. We also derive measures of uncertainty from the density forecasts about real GDP (PRGDP) and inflation (PRPGDP) of the survey. These survey questions ask the forecasters to indicate what probabilities they ascribe to each of ten possible ranges of percentage changes of the GDP levels as well as the price level in the current year and the next year, respectively. The lower and upper category are open-ended. We compute empirical moments of the individual distributions as follows: we consider the outer ranges as closed categories with a midpoint which is equally spaced to the other midpoints in the scale. Based on the midpoints of all categories, we compute the individual means $\theta_{t,i}$ and variances $\sigma^2_{t,i}$ for the probability distributions at each point in time.[15] We adjust the cross-sectional average variance $\sigma^2_t = \frac{1}{N}\sum_{i=1}^{N}\sigma^2_{t,i}$ for seasonality by subtracting a season-specific average of σ^2_t from the original values. The adjusted series serve as time-varying measures of aggregate uncertainty about GDP ($\Psi(RGDP_{TY})$,$\Psi(RGDP_{NY})$) and the inflation rate ($\Psi(\text{INF}_{TY})$,$\Psi(\text{INF}_{NY})$) in the current (TY) and the next year (NY), respectively.

Figure 1.1, Panel (a), shows a time-series plot of our proxies for inflation and GDP uncertainty. Note that our procedure of measuring uncertainty yields somewhat different results than earlier papers. For example, Wright (2011) finds that uncertainty (measured as forecast dispersion) increases heavily during the financial crisis in 2007 to 2009. We also find increased uncertainty before the outbreak and at the beginning of the crisis, but uncertainty quickly decreases as forecasters become quite certain that GDP growth and inflation rates will fall. Thus, part of the large forecast dispersion in Wright (2011) seems to stem from forecasters' disagreement, but not necessarily from their uncertainty.

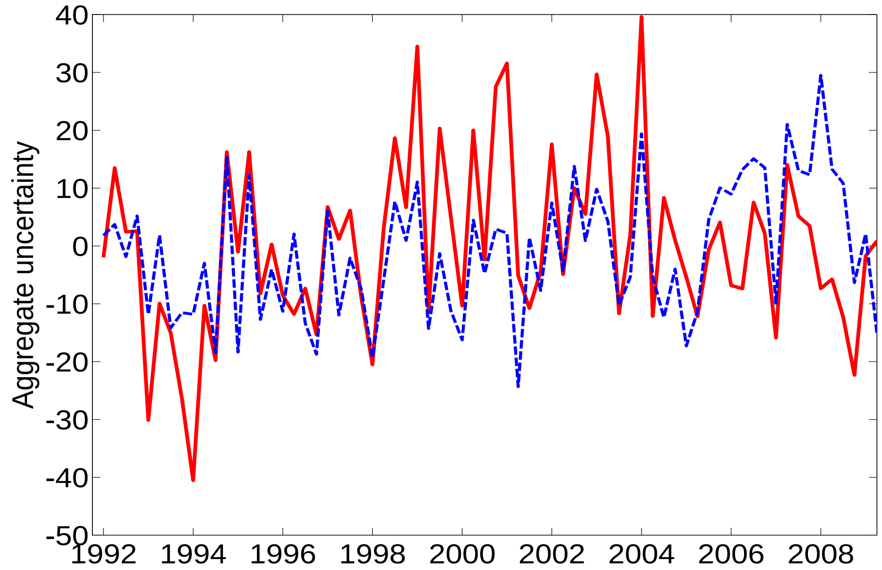
Panel (b) of Figure 1.1 shows a scatter plot of inflation and output growth uncertainty. As may

[15] Our choice of inferring uncertainty from density forecasts and not from cross-sectional point forecast dispersion (as e.g. in Wright, 2011) is based on findings in the literature which suggest that forecast dispersion may be a somewhat crude proxy for uncertainty (although the two measures are correlated, of course). For the sake of brevity, we refer to Giordani and Söderlind (2003), Lahiri and Sheng (2010), Liu and Lahiri (2006), and Pesaran and Weale (2006) for details on these issues.

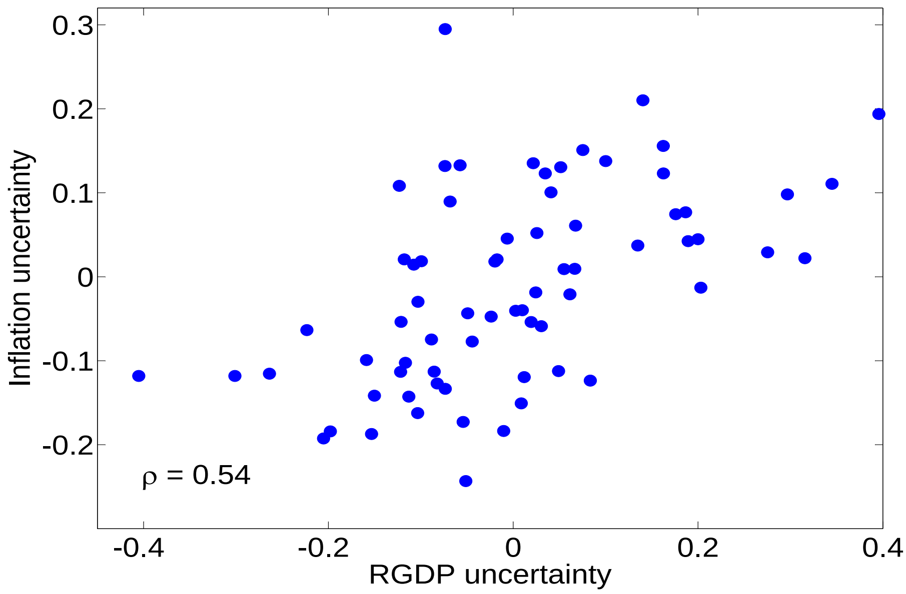
be expected, the two series are positively correlated (e.g., $Corr(\Psi(\text{RGDP}_{NY}), \Psi(\text{INF}_{NY})) = 0.5$). Thus, we compute an orthogonalized measure of inflation uncertainty, namely the residuals of the regression of $\Psi(\text{INF}_{NY})$ on $\Psi(\text{RGDP}_{NY})$ and a constant. The resulting time series (denoted $\Psi(\text{INF}_{NY})^{\perp}$) has a high correlation of 0.86 with the unadjusted inflation uncertainty measure $\Psi(\text{INF}_{NY})$ but is uncorrelated with real GDP uncertainty by construction.

1.4.2 Construction of bond factors and excess returns

Level, slope, and curvature. Diebold and Li (2006) demonstrate that the three time-varying parameters of an exponential components framework are suitable to represent the yield curve factors “level”, “slope”, and “curvature”. This method allows us to estimate precise yield factors for each period without making use of data beyond the forecasters’ information set. We compute these factors based on a monthly series of bond yields for different maturities (last trading days in the months). Note that unlike Diebold and Li (2006), who model unsmoothed Fama-Bliss bond yields, we estimate the loading factors for the maturities of 1,2,3...10 years based on the smoothed data from Gürkaynak, Sack, and Wright (2007). A comparison of our measures for level, slope, curvature, and those of Diebold and Li (2006) for the period 1971/01 to 2000/12 yields a correlation coefficient of 0.99 (level), 0.99 (slope) and 0.73 (curvature). Note that the “slope factor” from this procedure has been shown to be almost perfectly negatively correlated with an empirical slope factor (defined as the ten-year yield minus the three-month yield), such that it is high when short rates exceed long rates. To make our results more easily interpretable on conventional grounds, we multiply the slope factor with minus one so that high values indicate a steep yield curve and vice versa.



(a) Time-series of RGDP and inflation uncertainty



(b) Correlation of RGDP and inflation uncertainty

Figure 1.1: Macro uncertainty

This figure shows plots of aggregate uncertainty about the following year's real gdp growth (blue, dashed line) and next year's inflation (red, solid line) in Panel (a) and cross-plots of the two series in Panel (b). ρ denotes the simple linear correlation coefficient between the two series.

Cochrane-Piazzesi factor. We compute a monthly series of the excess return forecasting factors put forth by Cochrane and Piazzesi (2005) (the "CP-Factors") by a recursive strategy as follows: First, we transform the monthly series of bond yields into prices, forward rates and excess returns. To avoid multicollinearity in our regression of average excess returns on forward rates, we only keep the one, three and five-year forward rates on the RHS (following an approach proposed in Cochrane and Piazzesi (2008) to work with the smoothed bond yields in the data of Gürkaynak, Sack, and Wright (2007)). We ensure a real-time computation (avoiding potential "look-ahead bias") of the CP-Factors by rolling a 10-year estimation window forward. The period 01/1965 to 12/1974 serves as our initialization period. Afterwards, the CP-factor is estimated recursively; consequently, e.g., the forward curve information from 01/1974 is only included in the estimation of the CP-Factor from 01/1974 to 01/1984.

Excess returns. We obtain monthly series of excess returns of holding a bond with 12, 24, 36, 48, 60 and (smaller than) 120 months to maturity by taking the difference between the monthly return series from CRSP data and the return of a risk free asset (1 month T-bill) from Kenneth French's database. Quarterly return series and series at lower frequencies are constructed from these monthly time series.

1.4.3 Empirical approach

Overview econometric panel approach. We are interested in the determinants of expected term premium changes of individual investors. These determinants include other forward-looking variables (individual macro expectations) which have to be treated as being endogenous, as well as variables that can be considered exogenous. We thus specify our general (dynamic) panel regression model as

$$e_{i,t} = a_1 e_{i,t-1} + \Xi_{i,t}\gamma + \Psi_t\delta + Z_t\beta + \epsilon_{i,t} \tag{1.10}$$

where $e_{i,t}$ is a shortcut for the expected change in term premia, i.e. $e_{i,t} \equiv E_{i,t}[\Delta\pi_{t+h}]$. $\Xi_{i,t} \equiv E_{i,t}[X_{i,t+h}]$ denotes a vector of subjective expectations of forecaster i about macroeconomic variables such as expected output growth and expected inflation, vector Ψ_t collects measures of aggregate uncertainty about future output growth and inflation rates, and Z_t denotes a vector of additional exogenous control variables. Our interest centers on the effect of expected macro movements $\Xi_{i,t}$ and uncertainty about macro movements Ψ_t on individual expectations about future bond risk premia $e_{i,t}$. Lagged (expected) risk premium changes and other observed macro factors in Z merely serve as control variables or are included to highlight additional aspects regarding the relation of our term premium expectations with other well-known factors. The specification of the error term $\epsilon_{i,t} = \alpha_i + \mu_{i,t}$ takes into account that forecasters' expectations may exhibit unobserved heterogeneity. Hence, we work with a fixed effects setting and investigate time variation in term premia.

In Eq. (1.10), we regress current expectations about future risk premium changes $e_{i,t}$ on expectations about other macroeconomic variables $E_{i,t}[X_{i,t+h}]$ to single out the effect of expected macro movements on bond risk premia. While this approach is natural for our analysis, it generates a potential endogeneity problem since there is no reason to assume that causality strictly runs from $E_{i,t}[X_{i,t+h}]$ to $e_{i,t}$ and not vice versa. To tackle this challenge we rely on instrumental variable estimators for all our main results and instrument for current macro expectations with lagged macro expectations. We do this within the Generalized Method of Moments (GMM) framework of Arellano and Bond (1991). Furthermore, we take care of potential problems arising from the inclusion of too many instruments in panel regressions with a large time dimension relative to the cross-sectional dimension of the panel, and we account for autocorrelation and heteroskedasticity in our inference. As our dataset is an unbalanced panel, we rely on jackknifed standard errors, which are based on repeated estimations while omitting randomly one observation in each iteration step. We have also checked that our results are not driven by the specific estimation method of Arellano and Bond (1991) and obtained findings very similar to those reported below in other estimation setups (e.g. 2SLS) or in a pooled regression framework.

Details econometric panel approach. While the above remarks have briefly summarized our empirical approach, this paragraph is more explicit with respect to the technical details of it. As mentioned above, we estimate panel regressions with both endogenous and exogenous variables on the right-hand side of the equation. We specify the error term as $\epsilon_{i,t} = \alpha_i + \mu_{i,t}$, which takes into account that forecasters' expectations may exhibit unobserved heterogeneity (in a fixed-effects panel regression setting).

As the unobserved component α_i is correlated with the lagged dependent variable, OLS would deliver inconsistent estimates. In the dynamic panel structure with a lagged dependent variable on the RHS, a fixed effects estimator is not appropriate either, as the differenced equation includes $\Delta e_{i,t-1} = e_{i,t-1} - e_{i,t-2}$ as a regressor, which is by construction correlated with the error term $\Delta\mu_t = \mu_{i,t} - \mu_{i,t-1}$. To circumvent these problems, Arellano and Bond (1991) propose the moment conditions with respect to the differenced equation

$$E\left[e_{i,t-s}(\mu_{i,t} - \mu_{i,t-1})\right] = 0 \tag{1.11}$$

for $s \geq 2$ and $t = 3, ..., T$. To avoid potential problems caused by weak instruments and in order to improve efficiency, System GMM includes both the differenced as well as the additional orthogonality conditions for the errors in the level equation

$$E\left[\Delta e_{i,t-s}\epsilon_{i,t}\right] = 0 \tag{1.12}$$

for $s = 1$ and $t = 4, ..., T$ (e.g., Blundell and Bond (1998)). System GMM Dynamic Panel Approaches are frequently applied to datasets in which the time series dimension T is small. As our T is rather large (albeit smaller than the cross-sectional dimension N), the conventional System GMM approach generates too many instruments relative to N, which may cause Hansen's J statistics to underreject (Anatolyev and Gospodinov, 2011). To address this problem, we collapse the moment conditions shown in Equations (1.11) and (1.12) by addition into smaller subsets.[16] Intuitively, this treats each moment condition to apply to all available periods instead of to each particular point in time individually, such that the moment conditions in Equation (1.11) are generated for $s \geq 2$ (instead of for $s \geq 2$ and $t = 3, ..., T$). As described by Cameron and Trivedi (2005, p. 765), we also construct the instruments from the *exogenous* variables Z_t and Ψ_t to

$$\begin{aligned} E\left[\Delta Z_{i,t}(\mu_{i,t} - \mu_{i,t-1})\right] &= 0 \\ E\left[Z_{i,t}\epsilon_{i,t}\right] &= 0. \end{aligned} \tag{1.13}$$

For the *endogenous* variables, we limit the collapsed System GMM-style instruments

$$E\left[X_{i,t-s}(\mu_{i,t} - \mu_{i,t-1})\right] = 0 \tag{1.14}$$

to the second and third lags values ($s = 2, 3$) in the differenced equation, as well as

$$E\left[\Delta e_{i,t-1}\epsilon_{i,t}\right] = 0 \tag{1.15}$$

[16] For more details on this approach, see Roodman (2009).

for the equation in levels. To rely on efficient estimates when errors exhibit heteroskedasticity, we report the results from two-step GMM. As this methodology may deliver downward biased standard errors in small samples, we apply the correction suggested by Windmeijer (2005) to obtain accurate inference.

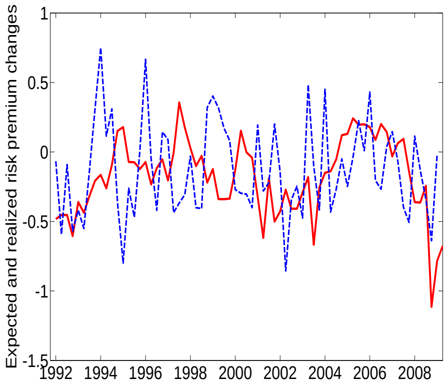
1.5 Results

1.5.1 Properties of term premium expectations

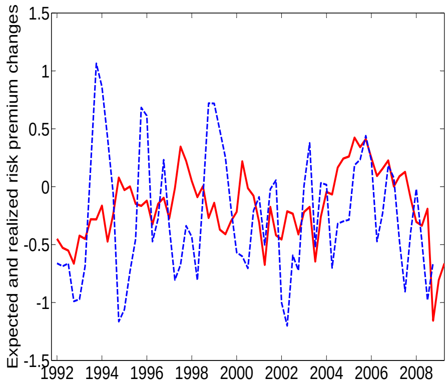
To set the stage, we plot time-series of aggregated expected term premium changes for horizons of one to four quarters in Figure 1.2 (red, solid line). We also show the "*realized term premium changes*" (blue, dashed line), which are computed by simply replacing expected log yield in Eq. (1.6) with actual future log yields. As one may expect, it can be seen that *expected* term premia are quite persistent and seem to be less volatile than *realized* changes in term premia. Compared to ex-post realizations of bond returns (or yield changes), the real time expectations about term premium changes appear to be a less noisy measure and should thus serve as a useful proxy to study the link between macro factors and term premia.

As a final note, there is a large decline in term premium expectations towards the end of our sample, starting with the onset of the financial crisis in 2007. This result is well in line with a 'flight-to-quality' effect and is also found in Wright (2011), lending some credence to the relevance of our proxy for term premium expectations.

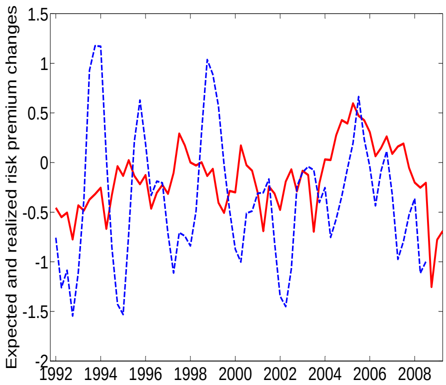
Table 1.1 shows descriptive statistics for *expected* term premium changes on the left side and for *realized* term premium changes on the right side for comparison. Both are negative on average. This confirms earlier analyses showing a decline of term premia in advanced countries over the time period of our sample (Wright, 2011). Furthermore, the standard deviations shown in Table 1.1



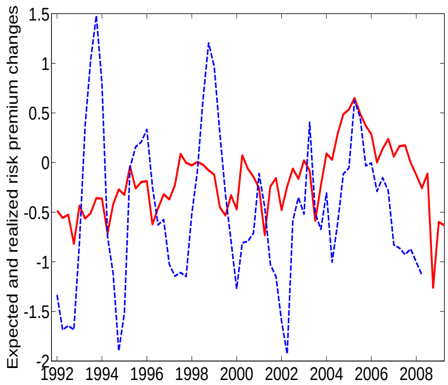
(a) $h = 1$ quarter



(b) $h = 2$ quarters



(c) $h = 3$ quarters



(d) $h = 4$ quarters

Figure 1.2: Expected and realized changes in term premia

This figure shows plots of expected (red, solid line) and realized changes (blue, dashed line) in term premia over different horizons of $h = 1, 2, 3,$ and 4 quarters.

validate the perception that *expected* term premium changes are less volatile than *actual* changes. This effect becomes more pronounced for longer forecast horizons h.

Table 1.1: Descriptive statistics: risk premia

This table reports descriptive statistics for expected and realized changes in bond risk premia (Panel A and Panel B, respectively). Numbers in brackets are t-statistics for the means and are based on Newey-West HAC standard errors. AC(1) denotes first-order autocorrelation and numbers in parentheses are p-values for the test of no autocorrelation (based on the Ljung-Box Q statistic). h denotes the horizon and ranges from one to four quarters ahead.

	Expected changes				Realized changes			
	$h=1$	$h=2$	$h=3$	$h=4$	$h=1$	$h=2$	$h=3$	$h=4$
Mean	-2.12	-2.03	-1.99	-2.28	-1.52	-3.07	-4.46	-5.83
t-stat.	[-3.27]	[-2.82]	[-2.48]	[-2.75]	[-2.79]	[-2.97]	[-3.13]	[-3.37]
Median	-1.75	-2.04	-1.96	-2.30	-1.72	-3.94	-4.49	-6.98
Stand. Dev.	0.95	1.05	1.17	1.20	1.17	1.84	2.28	2.66
Skewness	-0.64	-0.37	-0.26	-0.04	0.37	0.40	0.44	0.39
Kurtosis	3.75	3.48	3.53	3.48	2.77	2.48	2.83	2.78
AC(1)	0.69	0.69	0.69	0.69	0.21	0.57	0.73	0.73
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.21)	(0.00)	(0.00)	(0.00)

1.5.2 Macro expectations and aggregate uncertainty

As noted above, our main interest lies in the impact of macro expectations and uncertainty of individual term premium expectations as specified in Eq. (1.10). Thus, we now proceed to estimate dynamic panel regressions with fixed effects via GMM. We regress forecaster-specific term premium expectations on lagged term premium expectations, forecaster-specific expectations about output growth and inflation, as well as aggregate uncertainty about output growth and inflation and report our results in Table 1.2 for various combinations of explanatory variables.

We robustly find that individual term premium expectations, or expected bond excess returns, are positively autocorrelated: the lagged dependent variable has a coefficient of about 0.25-0.40 across specifications, which is highly significantly different from zero. This persistence makes sense since it is well known that expected excess returns on financial assets are persistent. We control for this persistence in all future regressions by including the lagged expected term premium change as a regressor.

Perhaps more interestingly, we find that expected real output growth ($E_{t,i}[\Delta\text{RGDP}]$) has a significantly positive impact as well, so that higher growth expectations induce forecasters to expect the term premium to rise or, equivalently, expected future excess returns to be low. This finding seems natural from a standard asset pricing perspective since good states of nature should lead to lower risk premia. Furthermore, this result supports findings in Ludvigson and Ng (2009) that real macro activity is a strong time-series predictor of bond excess returns. The strong evidence in our study reinforces the view that real factors are an important driver of bond risk premia. It should be noted, however, that Ludvigson and Ng (2009) find that return forecasts are high when *current* real activity is low and interpret this as a countercyclical bond risk premium. Our findings suggest that low *expected* output growth makes forecasters expect lower term premium changes going forward. As explained earlier, this is well in line with our findings: as declining risk premia in the future imply higher returns going forward, the two results are actually compatible in terms of their economic effects. The difference is thus one of interpretation and not of economic outcomes.[17]

We also find a positive coefficient for expected inflation ($E_{t,i}[\text{INF}]$). However, the impact of expected inflation on term premium changes is not significant in all specifications and becomes unimportant once we include uncertainty measures or include it jointly with real GDP expectations. At first sight, this result seems surprising since inflation is considered to be a prime candidate for driving term premia. Earlier papers usually see a stronger role of inflation in determining bond yields (see e.g. Ang and Piazzesi, 2003; Diebold, Rudebusch, and Aruoba, 2006; Rudebusch and Wu, 2008). However, we are investigating expected *changes* in term premia whereas most earlier papers show that inflation relates to the *level* of bond yields and risk premia. Furthermore,

[17] Also, this difference is not driven by using expectations (our study) instead of current output growth (as in Ludvigson and Ng (2009)). We show below that current output growth is positively related to expectations about changes in future term premia as well.

one has to bear in mind that our sample period (starting in 1992) is not one of particularly high inflation rates. In this specific macroeconomic setting, it may well be that inflation levels are relatively less important than real growth or uncertainty.[18]

Turning to our uncertainty measures, we find that uncertainty unambiguously leads forecasters to raise their expectations about future term premia, i.e. higher aggregate uncertainty in the current quarter leads forecasters to expect lower excess returns in the future. This finding seems to make sense from a ‘flight-to-safety’ perspective where higher macro uncertainty leads to a rush on safe assets such as U.S. government bonds which drives up their prices in the current period while lowering expected future returns on these assets.[19]

Interestingly, we find that both output growth uncertainty and inflation uncertainty are significant drivers of term premium expectations even when we include both uncertainty sources simultaneously (specification (ix)) by using the orthogonalized inflation uncertainty series. Strikingly, this finding indicates that both “*real uncertainty*” and “*nominal uncertainty*” (about real and nominal macro factors), by themselves, matter.[20]

Regarding the economic significance of our explanatory variables, we find (based on the joint specification (ix) in Table (1.2)) that the long-run impact after taking into account the autoregressive effects is about 20 basis points for a one-standard deviation shock to expected real GDP growth and about 3 basis points for the two uncertainty measures. While these effects may appear small at first sight, one has to put this into the perspective of an unconditional standard deviation

[18]This result is, again, in line with Ludvigson and Ng (2009) who find that inflation is far less important than real activity.

[19]Note that Anderson, Ghysels, and Juergens (2009) document a positive relationship between uncertainty and *stock* excess returns. However, due to flight-to-safety behavior, bond markets and stock markets tend to behave differently in times of high uncertainty (see, e.g., Connolly, Stivers, and Sun, 2005): investors tend to *sell* stocks in favor of bonds when uncertainty is high, which drives down stock prices in the current period while increasing expected future returns.

[20]Wright (2011) also finds that inflation uncertainty matters, but does not ascribe a large role to output uncertainty. Similarly, Söderlind (2009) finds that inflation uncertainty has a positive impact on term premia, but also that higher output uncertainty lowers risk premia. Our results – which are based on a different concept of measuring uncertainty as well as a different sample period – suggest otherwise.

Table 1.2: Determinants of expected bond risk premia

This table reports panel regression estimates where individual risk premium expectations are regressed on the lagged endogenous variable ($E_{t-1,i}[\Delta\pi_{t-1+h}]$), and macro expectations: expected NGDP growth ($E_{t,i}$[ΔNGDP]), expected RGDP growth ($E_{t,i}$[ΔRGDP]) and expected inflation ($E_{t,i}$[ΔINF]) over the next quarter. In addition, we present results for aggregate uncertainty about GDP growth ($\Psi(\text{RGDP}_{TY,NY})$) and inflation rates ($\Psi(\text{INF}_{TY,NY})$), where TY or NY denote uncertainty about this year or next year, respectively. $\Psi(\text{INF}_{NY})^{\perp}$ denotes inflation uncertainty orthogonalized with respect to GDP uncertainty. R^2_{COR} denotes a Pseudo-R^2, J denotes Hansen's J-statistic, "Test $\Delta\epsilon_t$ for AR(2)" shows the test for second-order residual autocorrelation, # Instr. denotes the total number of instruments used, N shows the total number of cross-sectional units, whereas NT denotes the total number of observations. Jackknifed standard errors are provided in parentheses. Asterisks denote the level of significance, ***: 0.01, **: 0.05, *: 0.10.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
$E_{t-1,i}[\Delta\pi_{t-1+h}]$	0.266	0.375	0.424	0.428	0.425	0.429	0.251	0.250	0.257
	***(0.075)	***(0.073)	***(0.064)	***(0.064)	***(0.063)	***(0.064)	***(0.077)	***(0.077)	***(0.076)
$E_{t,i}$[ΔRGDP]	0.512						0.444	0.482	0.454
	***(0.137)						***(0.165)	***(0.160)	***(0.166)
$E_{t,i}$[INF]		0.135					0.051	0.039	0.044
		**(0.058)					(0.064)	(0.064)	(0.065)
$\Psi(\text{RGDP}_{TY})$			-0.032						
			(0.049)						
$\Psi(\text{RGDP}_{NY})$				0.249			0.183		0.163
				***(0.046)			***(0.055)		***(0.058)
$\Psi(\text{INF}_{TY})$					0.167			0.238	
					**(0.065)			***(0.061)	
$\Psi(\text{INF}_{NY})$						0.192			
						***(0.063)			
$\Psi(\text{INF}_{NY})^{\perp}$									0.179
									**(0.090)
const.	-0.430	-0.437	-0.089	-0.087	-0.089	-0.088	-0.519	-0.514	-0.509
	***(0.091)	***(0.152)	**(0.013)	***(0.013)	***(0.013)	***(0.013)	***(0.133)	***(0.133)	***(0.133)
R^2_{COR}	0.36	0.29	0.34	0.34	0.34	0.34	0.37	0.37	0.37
$J-$Stat.	64.85	62.63	67.46	62.27	63.83	63.26	64.66	65.38	65.66
df	70	70	68	68	68	68	72	72	72
p-value	(0.65)	(0.72)	(0.50)	(0.67)	(0.62)	(0.64)	(0.72)	(0.70)	(0.69)
Test $\Delta\epsilon_t$ for AR(2)	1.570	0.675	-0.012	0.598	0.082	0.187	1.948	1.851	1.98
p-value	(0.12)	(0.50)	(0.99)	(0.55)	(0.94)	(0.85)	(0.05)	(0.06)	(0.05)
# Instr.	73	73	71	71	71	71	77	77	78
N	116	114	126	126	126	126	114	114	114
T	1,639	1,575	1,999	1,999	1,999	1,999	1553	1553	1,553

of "only" 40 basis points of the dependent variable, i.e. expected term premium changes. Thus, a rise of one standard deviation in expected real output growth has an effect that makes up for about 50% of the standard deviation of expected term premium changes and the other two determinants still have an impact of about 7%-12% relative to a typical movement in the dependent variable. Thus, expected real output growth has a rather large impact on expected term premium changes, whereas uncertainty is still economically significant but clearly less important.[21]

We also report Pseudo R^2s and a couple of diagnostic statistics. We see that R^2s are around 35% in specifications including uncertainty and/or output growth expectations and are somewhat lower if only inflation expectations are included. The J-test is far from rejecting the overidentifying restrictions and residuals seem largely free from autocorrelation (we test for second-order autocorrelation since we have a fixed-effects setting), except for the last three specifications which are significant at the 10%-level only.

1.5.3 Yield curve factors and *CP*-factor

Given the prominence of yield curve factors in the literature, we next look at the relation of level, slope, and curvature (obtained as in Diebold and Li, 2006) with our proxy for term premium expectations.[22] We also include the *CP Factor*, which has been proposed by Cochrane and Piazzesi (2005) to forecast excess returns of bonds of different maturities. Given that subjective term premium expectations have predictive power, they are also related to future bond returns. Hence, the CP-Factor should be able to explain expected changes in the term premium to some extent.

A plot of the four factors is shown in Figure 1.3. The plot shows the decline of the level of yields

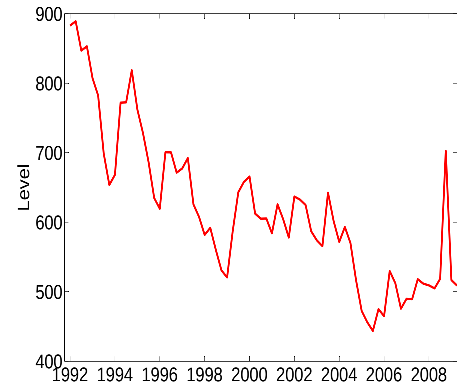
[21] As a robustness check, we provide results for specifications with a recession dummy (Table A.1) and for regressions where we use expectations for annual horizons, i.e. $h = 4$, in Table A.2 in the appendix. It can be seen from these robustness tests that our results are not driven by events of the recent financial crisis.

[22] Note that the Diebold and Li procedure results in a "slope" factor that has an almost perfectly negative correlation with the term spread. Thus, we multiply our slope factor with -1 so that a high slope means a steep yield curve.

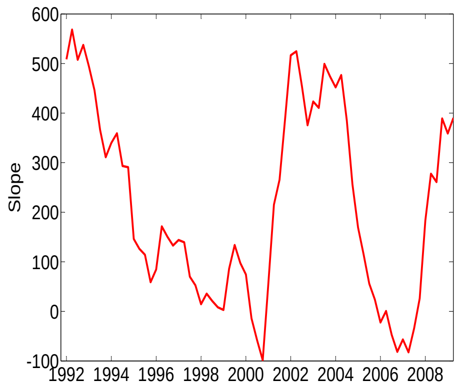
during the 1990s and 2000s (Panel (a)), the inverted yield curves prior to the last two recessions (Panel (b)), and the curvature factor in Panel (c), which is similar to the average subjective term premium expectations in Figure 1.2. In fact, curvature and term premium expectations have a positive correlation of about 67%. This result seems especially noteworthy in the light of findings in Cochrane and Piazzesi (2008), who report that curvature is linked to *future* expected returns (as opposed to current term premia). This is exactly what our expected term premium proxy ought to capture as well. Finally, the CP-Factor in Panel (d) seems to be rather unrelated to the three other yield factors, as already motivated in Cochrane and Piazzesi (2005).

Next, we include the four bond yield factors in our dynamic panel regression. It is well-known that level, slope, and curvature span most macro information relevant for bond yields, so it seems interesting to see whether they drive out our proxy of expected term premium changes as well. Also, since information in the term structure is related to the business cycle (see Estrella and Hardouvelis, 1991; Ang, Piazzesi, and Wei, 2006, among many others) and since the CP factor is informative about future macro conditions (Koijen, Lustig, and Van Nieuwerburgh, 2010), we present results from joint specifications where we include macro expectations, uncertainty, and bond factors in Table 1.3. These results aim for a closer investigation of possible relationships between yield-related and macro factors and are reported in Table 1.3.

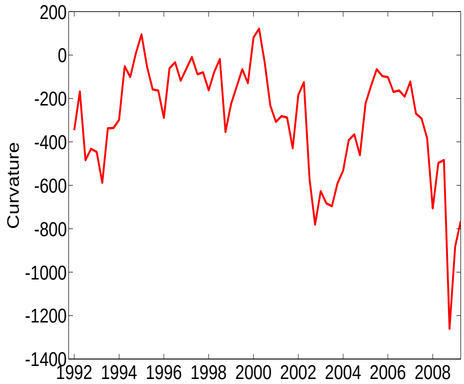
Table 1.3 shows that level, slope, curvature, and the CP factor are significantly different from zero in all specifications. The estimated signs of factors seem to make sense when comparing them with earlier literature. For example, Diebold, Rudebusch, and Aruoba (2006) find that the *level* factor captures *inflation* (also see Rudebusch and Wu, 2008). To the extent that forecasters have mean-reverting expectations anchored at some level of inflation, one would expect a high level factor (i.e. high inflation) to be accompanied by high contemporaneous term premia but lower



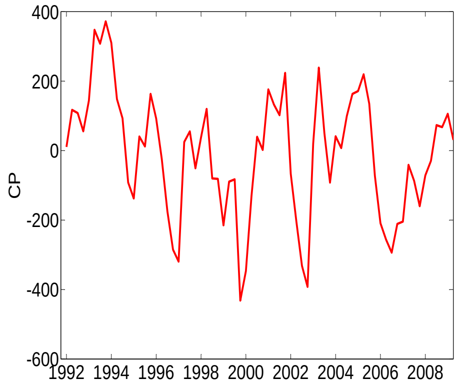
(a) Level factor



(b) Slope factor



(c) Curvature factor



(d) Cochrane-Piazzesi factor

Figure 1.3: Bond yield factors

This figure shows time-series plots of level, slope, and curvature based on Diebold and Li (2006) and the bond forecasting factor of Cochrane and Piazzesi (2005). Note that we have multiplied the slope factor with minus one so that higher readings of "slope" correspond to a steeper yield curve. The scaling of the graphs is in basis points.

term premia expectations for the future (which imply high expected excess returns).[23] A similar argument may be made for the *slope*, for which Diebold, Rudebusch, and Aruoba (2006) argue that it may be interpreted as a proxy for *real activity*. While Diebold, Rudebusch, and Aruoba (2006) find that *curvature* seems rather unrelated to macro factors, our results and the discussion above suggest that curvature is highly correlated with expectations about future bond risk premia. We also see this positive relation in the panel regressions.

Finally, the CP factor is negatively related to expectations about future term premia, i.e. positively related to expected excess returns as in Cochrane and Piazzesi (2005) which further validates our term premium proxy. Cochrane and Piazzesi (2005), Ludvigson and Ng (2009) and others find strong evidence that *return* risk premia are countercyclical. In this essay, we show that this *counter*cyclical nature of return risk premia corresponds to a *pro*cyclical behavior of term premia expectations: as shown above, high GDP growth expectations today are associated with term premia expected to increase in the future. In the same vein, it also is reassuring to see the CP regression-based results reflected in the actual expectations of individual investors.

Interestingly, we find that level and slope both drive out aggregate uncertainty (whereas curvature and CP do not), suggesting that these two factors also capture uncertainty about real and nominal variables. This result seems novel to the literature and may shed some more light on the economic forces underlying these popular yield curve factors. It is also worth noting that expected real GDP growth is not driven out by any combination of other factors and even remains significant in the full specification (v). This underlines the role of expected output growth in the expectation formation with respect to movements in term premia.

[23] We provide additional evidence on this later in the chapter.

Table 1.3: Combining macro expectations, uncertainty and bond factors

This table reports panel regression results where expected risk premium changes are regressed on standard yield curve factors (level, slope, and curvature) and the bond forecasting factor of Cochrane and Piazzesi (2005), denoted CP. Jackknifed standard errors are provided in parentheses. Asterisks denote the level of significance, ***: 0.01, **: 0.05, *: 0.10.

	(i)	(ii)	(iii)	(iv)	(v)
$E_{t-1,i}[\Delta\pi_{t-1+h}]$	0.264	0.207	0.228	0.262	0.234
	***(0.078)	***(0.075)	***(0.084)	***(0.081)	***(0.083)
$E_{t,i}[\Delta\text{RGDP}]$	0.444	0.428	0.300	0.448	0.313
	***(0.144)	***(0.156)	*(0.169)	***(0.169)	**(0.159)
$E_{t,i}[\text{INF}]$	0.071	0.025	-0.009	0.036	0.019
	(0.055)	(0.059)	(0.063)	(0.064)	(0.056)
$\Psi(\text{RGDP}_{NY})$	0.095	0.083	0.102	0.169	0.045
	(0.089)	(0.122)	(0.142)	*(0.098)	(0.186)
$\Psi(\text{INF}_{NY})^{\perp}$	-0.014	0.076	0.306	0.120	0.096
	(0.095)	(0.120)	**(0.120)	(0.101)	(0.143)
Level	-0.117				-0.083
	***(0.038)				***(0.031)
Slope		0.077			0.025
		***(0.011)			(0.024)
Curvature			0.051		0.037
			***(0.017)		***(0.013)
CP				-0.023	
				*(0.013)	
const.	0.134	-0.308	-0.136	-0.506	0.295
	(0.239)	**(0.126)	(0.205)	***(0.138)	(0.243)
R^2_{COR}	0.43	0.47	0.45	0.38	0.51
$J-$Stat.	66.34	65.54	62.82	66.72	61.72
df	72	72	72	72	72
p-value	(0.67)	(0.69)	(0.77)	(0.65)	(0.80)
Test $\Delta\epsilon_t$ for AR(2)	1.524	1.469	1.034	1.942	0.943
p-value	(0.13)	(0.14)	(0.30)	(0.05)	(0.35)
# Instr.	79	79	79	79	81
N	114	114	114	114	114
NT	1,553	1,553	1,553	1,553	1,553

1.5.4 Real-time macro factors and expected term premium changes

As a final test, we also include real-time macro factors in our regressions to find out whether focusing on *expected* macro conditions yields additional insights relative to relying on *current* macro conditions. We rely on real-time vintage data and include growth rates of industrial production, GDP growth, CPI inflation, and real money growth (M2). Results for various specifications are collected in Table 1.4.

Our estimates show that current real-time CPI inflation has a significantly *negative* impact on term premium expectations at the micro-level, i.e. higher inflation raises expected excess returns on government bonds. This is in contrast to our findings above where *expected* inflation has a positive impact on expected term premium changes. This result is rather counterintuitive but may be understood by forecasters' reliance on mean-reversion and anchored inflation expectations. To the extent that relatively high inflation leads forecasters to expect lower inflation in the future, this negative coefficient is in line with our finding that high expected inflation increases term premium expectations as shown above. This finding, however, underlines the importance of investigating forward-looking drivers of term premia rather than determinants mirroring the current state of the economy, as these two approaches may yield very different results.

Having said this, we find that output growth (growth of industrial production and GDP) has a significantly positive impact on expected term premia, just as our measure of expected output growth does. Thus, relying on expected as well as actual macro conditions leads to similar results. However, our estimates also reveal that actual, real-time output growth does not drive out expected output growth and the latter is still highly significant in all specifications examined in Table 1.4. Once again, these results emphasize that there is a role for forward-looking macro factors when modeling term premia over and above the information contained in the current state of the economy.

Table 1.4: Combining macro expectations, uncertainty, and real-time macro factors

This table reports panel regression results where expected risk premium changes are regressed on lagged macro expectations, macro uncertainty, and real-time macro factors. As additional macro factors we consider growth rates in CPI inflation (Δ CPI), Industrial Production (Δ IP), GDP (Δ GDP), and M2 (Δ M2). Jackknifed standard errors are provided in parentheses. Asterisks denote the level of significance, ***: 0.01, **: 0.05, *: 0.10.

	(i)	(ii)	(iii)	(iv)	(v)
$E_{t-1,i}[\Delta\pi_{t-1+h}]$	0.263	0.211	0.227	0.249	0.217
	***(0.083)	**(0.100)	***(0.086)	***(0.082)	**(0.086)
$E_{t,i}[\Delta\text{RGDP}]$	0.451	0.411	0.433	0.460	0.368
	**(0.176)	**(0.176)	***(0.165)	**(0.189)	**(0.176)
$E_{t,i}[\text{INF}]$	0.062	0.014	0.015	0.046	0.033
	(0.069)	(0.069)	(0.063)	(0.068)	(0.068)
$\Psi(\text{RGDP}_{TY})$	0.121	0.151	0.107	0.147	0.115
	(0.138)	**(0.070)	(0.080)	(0.164)	(0.098)
$\Psi(\text{INF}_{TY})$	0.229	0.129	0.190	0.155	0.213
	**(0.116)	(0.108)	(0.119)	(0.136)	(0.154)
Δ CPI	-0.023				-0.042
	(0.017)				**(0.019)
Δ IP		0.021			0.025
		***(0.007)			***(0.007)
Δ GDP			0.053		
			***(0.018)		
Δ M2				-0.002	
				(0.011)	
const.	-0.487	-0.455	-0.584	-0.509	-0.369
	***(0139)	***(0.139)	***(0.134)	***(0.172)	***(0.137)
R^2_{COR}	0.37	0.39	0.40	0.37	0.41
$J-$Stat.	62.40	66.19	67.30	68.71	62.71
df	72	72	72	72	72
p-value	(0.78)	(0.67)	(0.64)	(0.59)	(0.77)
Test $\Delta\epsilon_t$ for AR(2)	1.837	1.39	1.56	1.856	1.26
p-value	(0.07)	(0.17)	(0.12)	(0.06)	(0.21)
# Instr.	79	79	79	79	80
N	114	114	114	114	114
NT	1,553	1,553	1,553	1,553	1,553

1.5.5 Predictive regressions

Our results in the previous sections deal with individual expectations about future term premium movements and the impact of macro expectations and uncertainty on these risk premium expectations. While we believe that this approach provides valuable insights into how macro factors affect term premia, it is also of interest to see whether our term premium expectations are actually related to future bond returns or whether forecasters' expectations are merely an unimportant sideshow for bond markets. A link between future bond excess returns and expectations of forecasters with respect to term premium movements would clearly strengthen the case for our findings. To shed some light on this issue, we run predictive regressions as in Cochrane and Piazzesi (2005) or Ludvigson and Ng (2009)

$$rx(m)_{t+h} = \alpha_h + \beta_h \overline{e}_t + \varepsilon_{t+h} \tag{1.16}$$

of future bond excess returns $rx(m)$ on current average term premium expectations $\overline{e}_t$, i.e. we use the average forecast across individuals discussed in Table 1.1 and Figure 1.1 above. The forecast horizon h varies from one to four quarters and we match the forecast horizon of returns with the forecast horizon of subjective term premium expectations. m denotes the maturity of the bonds underlying the excess returns and we also include average excess returns across all maturities (denoted $rx(avg)$). We report t-statistics based on Newey and West (1987) standard errors (with h lags for robustness) and also based on Hodrick (1992) standard errors which were shown to have better size properties when forecasting with persistent regressors (see Ang and Bekaert, 2007).[24]

If term premium expectations matter for bond markets, we would expect to see a significant

[24] Average term premium expectations have an autocorrelation of "only" 70%, see Table 1.1, which is not very high relative to other predictors such as dividend yields in stock markets. Thus, we expect finite-sample biases (Stambaugh, 1999) to be fairly mild in our sample.

impact of expectations on future bond returns, i.e. that the coefficient β_h is significant in Eq. (1.16). More specifically, we would expect to find a negative coefficient since higher term premia in the future imply that future bond yields must rise (relative to the short-rate) so that actual bond excess returns have to be lower.

Results from these predictive regressions for maturities of $m = 1, 2, \ldots, 5, 10$ years and the average excess return over all maturities $rx(avg)$ are provided in Table 1.5. Note that we only include data until 2007Q2 since there are enormous return movements due to the subsequent financial crisis and these outliers drive much of our result given that we have a relatively short time-series.[25] We thus limit our analysis to "normal" situations and exclude extreme events.

Given this caveat, our results show that term premium expectations forecast bond excess returns with rather low R^2s of up to 4% at a quarterly forecast horizon, but with R^2s of up to 22% at an annual forecast horizon. The R^2s as well as the levels of statistical significance (even when based on Hodrick (1992) standard errors) tend to increase with longer forecast horizons of up to four quarters. Predictive R^2s are largest for excess returns over maturities between one to three years but we also find significant predictability at longer maturities. At an annual forecast horizon, expected term premium changes forecast average bond excess returns across maturities with an R^2 of around 13% and predictability is stronger for short horizons with R^2s as high as 22% for one-year maturities. While other papers (Cochrane and Piazzesi, 2005) find much higher R^2s (of up to 45%) for annual horizons (Cochrane and Piazzesi, 2005; Ludvigson and Ng, 2009) in longer samples, it should be noted that our factor is available in real-time and not estimated as in other papers. We will provide more details on this issue below.

Furthermore, we find a consistently negative predictive coefficient across forecast horizons and

[25]More precisely, our sample is short relative to sample sizes usually employed for predictive regressions. This fact is important, since actual returns are noisy and it is thus difficult to estimate expected returns from actual returns with sufficient precision. Thus, we choose not to include the extremely unusual market movements of the financial crisis in our regressions since these data points would swamp our results.

Table 1.5: Predictive regressions

This table reports predictive regressions of future bond excess returns $rx(m)$ on our proxy for expected term premium changes $E_t[\Delta\pi_{t+h}]$. Excess returns are based on CRSP bond returns for maturities of $m = 1, \dots, 5, 10$ years and the average return over all maturities minus the return to holding a three month T-bill. Panels A – D show results for forecast horizons h of one to four quarters and we match forecast horizons with the horizon of our proxy for expected term premia. We report t-statistics based on Newey-West (1987) standard errors (t_{NW}) as well as based on Hodrick (1992) standard errors (t_H).

	$rx(avg)$	$rx(1Y)$	$rx(2Y)$	$rx(3Y)$	$rx(4Y)$	$rx(5Y)$	$rx(10Y)$
Panel A: Forecast horizon $h = 1$ quarter							
const.	0.25	0.09	0.14	0.21	0.29	0.33	0.46
t_{NW}	[1.19]	[2.63]	[1.27]	[1.12]	[1.14]	[1.05]	[1.20]
t_H	[1.33]	[3.01]	[1.43]	[1.25]	[1.26]	[1.15]	[1.32]
$E_t[\Delta\pi_{t+1}]$	-1.09	-0.19	-0.77	-1.20	-1.47	-1.60	-1.33
t_{NW}	[-1.38]	[-1.53]	[-1.72]	[-1.60]	[-1.50]	[-1.36]	[-1.00]
t_H	[-1.32]	[-1.53]	[-1.65]	[-1.52]	[-1.42]	[-1.27]	[-0.98]
R^2	0.02	0.04	0.04	0.03	0.02	0.01	0.00
Panel B: Forecast horizon $h = 2$ quarters							
const.	0.53	0.17	0.31	0.48	0.63	0.69	0.91
t_{NW}	[1.54]	[3.02]	[1.66]	[1.52]	[1.51]	[1.37]	[1.47]
t_H	[1.52]	[3.40]	[1.75]	[1.54]	[1.48]	[1.30]	[1.42]
$E_t[\Delta\pi_{t+1}]$	-1.96	-0.38	-1.29	-1.95	-2.53	-2.91	-2.70
t_{NW}	[-1.91]	[-2.22]	[-2.18]	[-2.02]	[-1.99]	[-1.90]	[-1.52]
t_H	[-1.57]	[-2.06]	[-1.94]	[-1.69]	[-1.62]	[-1.50]	[-1.28]
R^2	0.05	0.10	0.08	0.06	0.06	0.05	0.02
Panel C: Forecast horizon $h = 3$ quarters							
const.	0.82	0.26	0.49	0.75	0.98	1.07	1.35
t_{NW}	[1.76]	[3.06]	[1.74]	[1.67]	[1.72]	[1.59]	[1.70]
t_H	[1.60]	[3.58]	[1.86]	[1.65]	[1.57]	[1.38]	[1.45]
$E_t[\Delta\pi_{t+1}]$	-2.31	-0.49	-1.51	-2.20	-2.87	-3.34	-3.43
t_{NW}	[-1.98]	[-2.57]	[-2.26]	[-1.98]	[-1.98]	[-1.93]	[-1.71]
t_H	[-1.59]	[-2.25]	[-2.00]	[-1.69]	[-1.61]	[-1.51]	[-1.35]
R^2	0.06	0.13	0.09	0.06	0.06	0.05	0.04
Panel D: Forecast horizon $h = 4$ quarters							
const.	0.86	0.31	0.53	0.80	1.04	1.11	1.38
t_{NW}	[1.62]	[2.93]	[1.51]	[1.47]	[1.54]	[1.42]	[1.64]
t_H	[1.24]	[3.09]	[1.49]	[1.29]	[1.22]	[1.04]	[1.10]
$E_t[\Delta\pi_{t+1}]$	-3.63	-0.73	-2.22	-3.36	-4.43	-5.23	-5.80
t_{NW}	[-3.17]	[-3.65]	[-3.17]	[-2.95]	[-3.07]	[-3.11]	[-3.10]
t_H	[-2.05]	[-2.68]	[-2.39]	[-2.13]	[-2.06]	[-1.97]	[-1.82]
R^2	0.13	0.22	0.15	0.12	0.12	0.12	0.11

maturities as expected. Hence, our results suggest that forecasters' expectations contain relevant information for future bond returns and that movements in expected discount rates matter for bond excess returns, especially at the shorter end of the maturity spectrum.

The question remains whether our proxy for term premium expectations captures the same information as other bond predictors known from the literature. As a comparison, we re-estimate our predictive regressions with a real-time (i.e. recursively estimated) CP-factor instead of our term premium expectations $E_t[\Delta\pi_{t+1}]$. Results are reported in the appendix (see Table A.5). We find that the CP factor works best for longer maturities and short forecast horizons (where it clearly dominates our factor) during our sample period whereas our factor performs best for longer forecast horizons and shorter maturities (where it outperforms the CP factor). Hence, our proxy for term premium expectations seems to capture pieces of information which complement the insights that can be gained by the usage of the CP factor.[26] The results we have discussed in the previous sections are therefore not only relevant to describe patterns of the (potentially irrational and subjective) expectation formation of professional forecasters, but may improve our understanding of risk premia movements in bond markets more generally.

1.6 Robustness

We briefly summarize results for some robustness checks relating to the main results of this essay. We only describe these results here and provide detailed tables with all results in the appendix.

First of all, we have re-estimated our main result and include a dummy for NBER recessions to see whether such a dummy contains information not captured by our benchmark macro factors. Table A.1 in the appendix reports results for this specification. We find (in specification (i))

[26]We also find that our factor is different when we compare it to real-time measures of growth in industrial production. Ludvigson and Ng (2009) show that their real macro factor is related to industrial production growth so that this comparison again suggests that expected term premium expectations are different.

that times of recession indicate significantly lower expected term premium changes, i.e. higher expected excess returns, which makes intuitive sense. However, we also find that the impact of the recession dummy turns insignificant once we include our benchmark macro expectations and uncertainty factors. Hence, our results seem robust to this.

Second, we report our main result for a forecast horizon of four quarters. As noted in Section 1.3 above, our proxy of expected term premium changes can be constructed for horizons of one to four quarters based on SPF data. However, for the sake of brevity, we focus on a forecast horizon of one quarter in most of our results above. We show in Table A.2, though, that our results are robust to using a longer forecast horizon of 4 quarters. We also obtain similarly robust results for horizons of two or three quarters.

Third, we provide results based on a simplified proxy for expected term premium changes which does not rely on a long-run forecast of short-term interest rates. More specifically, we drop the last term in Eq. (1.6) when computing our proxy. Hence, our proxy is computed as

$$E_t[\Delta\pi_{t+1}] = E_t[\pi_{t+1}] - \pi_t = E_t[y^n_{t+1}] - y^n_t \tag{1.17}$$

and we are effectively leaving out the long-run forecast of future short-term interest rates which may be hard to compute with high precision anyway. We report results for this simplified proxy in Table A.3 in the appendix and find that our results in the main text are robust to this modification.

Finally, we check for robustness of another component of our proxy for expected term premium changes. In order to compute expected term premium changes, Eq. (1.6), which we repeat here for convenience,

$$E_t[\Delta\pi_{t+1}] = E_t[y^n_{t+1}] - y^n_t - \frac{1}{n}\left(E_t[y^1_{t+n}] - y^1_t\right),$$

tells us to compute the difference between expected bond yield and current zero-coupon bond yields $E_t[y_{t+1}^n] - y_t^n$. As discussed in Section 1.3 above, we have approximated these yields with expected and actual yields of coupon bonds with a maturity of ten years. However, since 10-year coupon bonds have a duration of approximately 7 seven years over our sample period, we re-estimate our main results with a proxy based on coupon bond yields with a duration of seven years. Results are shown in Table A.4 in the appendix and corroborate our findings in the main text.

1.7 Conclusions

We analyze *individual* expectations about term premium movements in a panel of forecasters and relate these individual expectations to expected real and nominal macro variables, to aggregate uncertainty about real and nominal macro variables, as well as to further control variables, such as term structure factors, risk-related factors, and real-time macro developments. A novel aspect of our analysis is our focus on the impact of inherently forward-looking macro factors on expectations about term-premia in a panel approach which allows for heterogeneity across forecasters. We find that individual forecasters' macro expectations are strongly related to expectations about bond risk premia, and we find the largest impact for real output growth and uncertainty about real output growth. Thus, there is a strong link between macro developments and term premia in bond markets.

Furthermore, our results suggest that curvature of the term structure is strongly related to subjective expectations about term premia, while the level and slope factors seem to capture information similar to that contained in our uncertainty measures about future real output growth and inflation. We also show that focusing on expected *future* macro conditions can lead to different results than analyzing the impact of *current* macro conditions on risk premia, and that expected macro conditions contain information for term premia over and above the information contained in current (real-time) macro conditions. Finally, an aggregate measure of term premium expectations forecasts future bond returns over horizons of up to one year in a way that is consistent with the idea that our proxy for expected term premium changes forecasts future changes in discount rates.

2. Using expectations to study the exchange rate forecasting puzzle†

2.1 Introduction

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

Our motivation rests on the notion that the relationship between exchange rates and fundamentals is quite complex, for several reasons. First, the asset market approach to exchange rates

†This chapter is an earlier version of joint work with Lukas Menkhoff and Ronald MacDonald. An even earlier version has appeared as a discussion paper entitled *Individual Exchange Rate Forecasts and Expected Fundamentals* (henceforth Dick, MacDonald, and Menkhoff, 2011).

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

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

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

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

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

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

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

We are unaware of researchers using the procedures proposed in this essay before. Nevertheless, this research is based on, and related to, a number of earlier studies which we selectively overview in Section 2.2. Our study is based on the Centre for European Economic Research's (ZEW, Mannheim) monthly survey among financial market professionals, who give their forecasts about several variables, including exchange rates, interest rates and other macroeconomic fundamentals. As responses are marked by a personal identification number, every single forecast response during the 18-year history of the survey can be related to a concrete individual. We decided to include individuals with a minimum of 10 responses, i.e. considering holidays etc. equal to about one year. This leaves us with more than 1,050 professionals and more than 63,000 responses.

This chapter is structured as follows. Section 2.2 introduces related literature, Section 2.3 presents data used and Section 2.4 documents our measurement of forecasting performance. Results are discussed in Section 2.5. Section 2.6 presents robustness exercises and Section 2.7 concludes.

2.2 Literature

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

Subsequent to the result of Meese and Rogoff (1983), which showed the underperformance of exchange rate models in comparison to a random walk model, the linkage of exchange rates to fundamentals has now been demonstrated to hold at very short and long horizons: at very short-term horizons, exchange rates systematically react to fundamentals or to observable order flow containing fundamental information (e.g., Andersen, Bollerslev, Diebold, and Vega, 2003; Iwatsubo and Marsh, 2011), while at long-term horizons, exchange rates are attracted to the purchasing power parity level and, related to this, seem to be tentatively in line with the monetary model (e.g., Mark, 1995; MacDonald and Marsh, 1997; Taylor and Taylor, 2004). Thus, it is the medium-term horizon where it is most difficult to show a clear relationship between fundamentals and exchange rates (Rogoff, 2007).

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

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

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

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

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

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

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

2.3 Data

Microdata of forecasts. We consider USD/EUR exchange rate forecasts by financial professionals as collected in a unique panel spanning 18 years of individual forecasts made in the context of the Financial Market Survey by the Centre for European Economic Research (ZEW) in Mannheim, Germany. These forecasters work in various areas of the financial industry or in financial departments of industrial companies. The forecasts collected in the ZEW Financial Market Survey have been used in various recent empirical studies in finance and macroeconomics, such as Schmeling and Schrimpf (2011) or Schmidt and Nautz (2012). The reason for the popularity of this data set lies in the relatively high frequency of the survey point (monthly), and the relatively high number of responses per point: the data set comprises 216 survey points from 12.1991 to 11.2009, with an average number of responses of 307; hence, the microeconomic panel is both relatively long and broad, summing up to a total of more than 1,700 forecasters and 66,000 observations. As a meaningful measurement of forecasting performance requires a certain minimum number of responses per forecaster, we omit forecasters with less than 10 USD/EUR forecasts. This reduces the sample to 1,056 forecasters. Table 2.1 provides more details on the structure of the survey responses. The US Dollar forecasts are of a qualitative nature; i.e., forecasters indicate whether the USD is expected to appreciate, remain unchanged or depreciate compared to the Euro within the subsequent six months.[27]

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

Table 2.1: Structure of survey responses

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

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

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

Exchange rates. The period of interest between 12.1991 and 11.2009 includes the transition from national currencies to the Euro. We therefore consider the US Dollar (USD) with respect to the D-Mark (DM, before 01.1999) and the Euro (EUR, after 01.1999). Hence, we convert the DM/USD exchange rates into USD/EUR rates for the period before 01.1999.[28] We consider both spot exchange rates as well as the one-month forward exchange rates on a daily basis. We replace missing exchange rates (e.g. from weekends) with those recorded on the preceding trading day.

2.4 Forecasting performance

For the measurement of forecasting performance, we follow several authors who have argued that forecasts about marketable assets should be evaluated from an investor's perspective by a zero net investment trading rule (Leitch and Tanner, 1991; Anatolyev and Gerko, 2005; Jordà and Taylor, 2012). Accordingly, we translate the qualitative forecasts of respondents into a long/short position, i.e., we translate an appreciation expectation into a buy etc.

Measuring forecasting performance with respect to exchange rates. Regarding foreign exchange, we follow Elliot and Ito (1999) who formulate a trading strategy in which sophisticated investors take a long USD position using the forward market when they expect the US Dollar to appreciate, such that $F_{t,k} > E_{i,t}[S_{t+k}]$, and take a short USD position when they expect the US Dollar to depreciate, such that $F_{t,k} < E_{i,t}[S_{t+k}]$, where $E_{i,t}[S_{t+k}]$ represents the subjective expectation of forecaster i.[29]

The usage of trading rules is easily adaptable in the context of monthly qualitative forecasts. In

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

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

the underlying survey, the professional forecasters have to respond to the question: do they expect a foreign currency to appreciate or depreciate compared to the Euro with the current *spot* rate as reference point. A natural trading strategy, T_{ind}, triggers a trade in the forward market according to the expected direction of change of spot exchange rates. The one-month forward contract will then be settled one month later in the spot market, and a new trade will be made in the forward market according to the new forecast made in the current month. As forward rates are linked to interest rates differentials through covered interest rate parity, the log returns of the trading rule take account of refinancing costs.[30] We consider the log returns of T_{ind} based on the prediction of forecaster j, i.e.

$$r_{j,t,t+k} = I_t(s_t > E_{j,t}[s_{t+1}])(f_{t,1} - s_{t+1}) + I_t(s_t < E_{j,t}[s_{t+1}])(s_{t+1} - f_{t,1}) \tag{2.1}$$

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

Compared to alternative measures, there are important advantages to using trading rules as a forecast performance measure: first, conventional statistical measures (such as the mean squared error) underlie narrow assumptions about a forecasters' loss function (e.g., quadratic).[31] Second, the trading rule-approach avoids the loss of information by a categorization of continuous realizations of exchange rate movements into an *appreciate*, a *constant* and a *depreciate* range. Third, we are able to compute the average profit and the Sharpe ratio for each forecaster. The latter is relevant in cross sectional analysis as profits from trading strategies typically depend on their risk,

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

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

Table 2.2: Average exchange rate forecasting performance in the cross section: mean returns and Sharpe ratios of T_{ind}

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

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

which may be different for several forecasters.[32] Sharpe ratios can also be linked to other studies on exchange rate models (Jordà and Taylor, 2012; Rime, Sarno, and Sojli, 2010) or carry trade strategies (Burnside, Eichenbaum, Kleshchelski, and Rebelo, 2011; Menkhoff, Sarno, Schmeling, and Schrimpf, 2011). For example, Jordà and Taylor (2012) compare Sharpe ratios in their analysis of carry trades to the Sharpe Ratio for the S&P 500 of 0.4. For the sake of comparability with our results, we also provide monthly Sharpe ratios in Table 2.2.

It can be seen that the annual Sharpe ratio of the median forecaster amounts to 0.114, which is rather low. This indicates that a trading strategy based on some average exchange rate forecast is unlikely to be profitable in practice, in particular as transaction costs are not yet taken into

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

account. However, the annual Sharpe ratio for the forecaster at the 95% percentile amounts to 1.159, which is substantial. Table 2.2 also shows that Sharpe ratios of greater than 0.4 can be achieved by the forecasts of almost 30% of the forecasters. Overall, these statistics demonstrate the heterogeneity in forecasting performance across the sample, which is central to the strategy followed in our analysis.[33]

Measuring forecasting performance with respect to fundamentals. Unlike currencies, macroeconomic fundamentals are not tradeable assets. As performance measures based on trading rules are not available, we rely on a measure of *forecast errors* by comparing forecasts with their respective realizations. For this purpose, the directional forecasts (e.g., the interest rate rises, stays constant, or decreases)[34] are coded for simplicity in $X^e_{i,t+6} \in \{1, 0, -1\}$, an approach also applied by, for example, Souleles (2004). Likewise, the realizations (observed interest rates, inflation rates, growth rates of industrial production) are also categorized into three corresponding groups. It has to be noted, however, that the latter step depends on the choice of threshold values for a no-change category. We choose symmetric threshold values such that, over the entire time span, the share of observations in the no-change category for *realizations* is equally large as the share of *forecasts* in this category.[35] In this setting, forecasters can be wrong to two different extents: they make a *small* error when they predict an unchanged variable, whereas the actual outcome is an increase, but a *severe* error if they predict a decline. We take account of the severity of these errors by computing absolute forecast errors by $|_t\varepsilon_{i,t+6}(X)| = |_tX^e_{i,t+6} -_t X_{t+6}|$, which

[33]Elliot and Ito (1999) present their results in terms of t-values, a performance measure closely related to the Sharpe ratio, which we also report in the appendix, Table B.1.

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

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

takes on 2 for a severe error, 1 for a small error and 0 for a correct prediction.

Table 2.3 presents the cross-section of average absolute forecast errors, $|\varepsilon(\bar{X}_{j,t})|$ for different macroeconomic fundamentals, including U.S. and Eurozone interest rates. It can be seen that the forecasters tend to commit less severe forecast errors for the interest and inflation rate in the Eurozone compared to the United States, while this is reverse for industrial production.

Table 2.3: Macroeconomic fundamentals: average absolute forecast errors

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

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

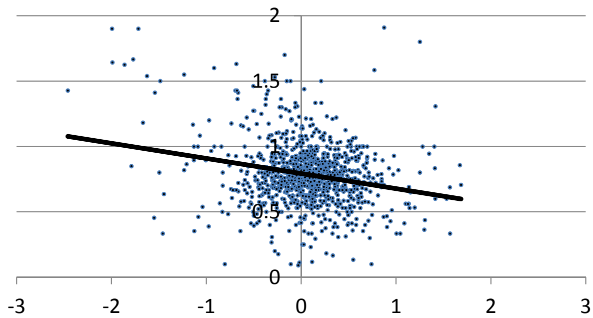
2.5 Empirical analysis

This section presents results starting with describing the fundamental relationship between (forecasting performance with respect to) fundamentals and exchange rates (Section 2.5.1). We then test whether this relation holds in a panel approach (Section 2.5.2), whether an implication holds (Section 2.5.3) and whether it can be revealed from forecasters' implicitly expected relation between interest rate and exchange rate forecasts (Section 2.5.4).

2.5.1 Exchange rate and fundamentals

This paragraph shows the fundamental relationship that we find throughout various analyses of our data: a positive link between forecast performance for exchange rates and for an important fundamental; namely, interest rates. As introduced above, the measurement units for the respective performance measures are the *average return* of T_{ind} for exchange rate forecasts, and *absolute forecast errors* for interest rate forecasts. Figure 2.1 illustrates the average performance for each of the 1,056 forecasters in our sample with respect to U.S. interest rate forecasts and USD/EUR-forecasts.

Figure 2.1: Illustration of the link of average forecast performance, sorted by forecaster



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

Figure 2.1 shows a negative relationship between the interest rate forecast errors (on the y-axis) and the returns earned from their exchange rate forecasts (on the x-axis), which underlines that performance is positively related across the forecasted variables. In fact, the correlation coefficient of -0.23 is statistically significant at any conventional level. Also a negative, although weaker relationship is found between forecast errors with respect to Eurozone interest rates and U.S. dollar forecast performance; the corresponding correlation coefficient is -0.08, which is significant at the 5% level.

2.5.2 Panel analysis

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

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

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(i^{EUR})| + \beta_2|\varepsilon_{j,t}(i^{USD})| + \gamma\Phi_{j,t} + \delta\Psi_{j,t} + \epsilon_{j,t}. \tag{2.2}$$

By following the fixed effects methodology, we rule out that unobserved heterogeneity across forecasters drives our results, such that we can attribute a change in exchange rate forecast performance (compared to an individual forecaster's average performance) to changes in $|\varepsilon_{j,t}(i^{EUR})|$,

$\Phi_{j,t}$ or $\Psi_{j,t}$. In line with this idea, the Breusch-Pagan tests reject the null of no individual-specific effects particularly for the simpler specifications (i.e. (i)-(iv) from Table 2.4). The Hausman tests confirm that a fixed effects estimator should be applied, as random effects are inconsistent for virtually all specifications.[36]

In Eq. (2.2), we regress the return from a trading strategy (which evaluates the performance of exchange rate forecasts) on a contemporaneous performance measure with respect to interest rates ($\varepsilon_{j,t}(i)$) or, as control variables, with respect to other fundamentals (in $\Phi_{j,t}$). While this setting allows us to focus on the connection between interest rate and exchange rates forecasts, it generates a potential endogeneity problem, as it is not *a priori* clear that interest rate forecast errors cause errors in exchange rate forecasts and not vice versa: for example, if exchange rates and fundamentals are related, there could be a third factor affecting both the USD/EUR exchange rate as well as the interest rate in one of these countries. To eliminate this problem, we rely on IV estimation using the first lagged value of the forecasting errors with respect to interest rates and other fundamentals as external instruments for forecast errors; this IV approach is preferable to an estimator without instruments according to the results from Davidson and MacKinnon (1989)'s test in the majority of specifications.[37]

The effect of interest rate forecasts. Table 2.4 reports the results of the fixed effects regression of the return earned from T_{ind} (i.e., our forecasting performance measure) on the absolute forecast error with respect to interest rates as well as various control variables: *negative* coefficients for the error variables $|\varepsilon(i)|$ indicate that *more severe* errors in the predictions of interest rates are associated with *lower* success in predicting exchange rates.

Specifications (i) and (ii) only consider the influence of absolute interest rate forecast errors on

[36]See Table B.2 in the appendix for detailed results.

[37]See also Table B.2 in the appendix for further details.

Table 2.4: Panel fixed effects regression

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

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

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

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

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

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

As columns (iii) and (iv) in Table 2.4 show, the coefficients for the interest rate forecast errors remain virtually unchanged when further fundamentals are controlled for. The results are also stable and even more pronounced when we additionally control for year dummies in specifications (v) to (vii). We also find a relatively robust negative relationship between forecasting errors made for European inflation rates and exchange rate forecasting performance, while the coefficient estimates for the remaining fundamental forecast errors are mostly insignificant with the exception of U.S. production forecasts - see specifications (iii) to (vii).

2.5.3 Exchange rate and fundamentals: interactions in different market phases

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

Grimaldi, 2006). Finally, large interest rate differentials may have an impact, as they signal an exchange rate readjustment according to uncovered interest rate parity (or they invite carry trades, which would tend to reduce the role of fundamentals). We define market phases on the basis of the prevailing market conditions.

Defining market phases. When the nominal exchange rate deviates strongly from its PPP value, the exchange rate can be expected to revert to its fundamental value. Thus, we capture such *value phases* by a dummy variable labeled FUND_t. More specifically, following the concept of real exchange rates, we compute a ratio of the CPI in Germany compared to the CPI in the United States,[38] i.e. (in logs)

$$q_t = s_t + p_t^{EUR} - p_t^{US}, \tag{2.3}$$

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

We consider the size of the trend of the USD/EUR exchange rate over the previous 30 days as a signal for a prevailing *momentum phase*. Again, we carry out a recursive approach and classify past absolute trends into three equally large subgroups: a phase in which the prevailing trend is relatively low (“low-momentum-phase", belonging to the lowest 33 percent during the 10 years prior to the respective date), a “normal momentum phase" and a “high-momentum-phase" (belonging to the top 33 percent).[39] We capture these phases by dummy variables D^L and D^H which are one for low and high momentum phases, respectively, and zero otherwise (the normal

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

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

momentum phase will be considered the benchmark).

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

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

$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(i)| + \beta_2\mathrm{SIG}_{j,t} + \beta_3\left(|\varepsilon_{j,t}(i)| \times \mathrm{SIG}_{j,t}\right) + \epsilon_{j,t}, \tag{2.4}$$

where $\mathrm{SIG}_{j,t}$ represents the signal for the respective market phase; we conduct the regressions for $|\varepsilon_{j,t}(i^{EUR})|$ and $|\varepsilon_{j,t}(i^{USD})|$ separately and without instruments. Controlling for different states of the value, momentum or interest rate differential phases, respectively, we focus on the estimate of the marginal effect of an interest rate forecast (error) on the return earned by the exchange rate forecast, i.e. $\frac{\partial r}{\partial|\varepsilon(i)|} = \hat{\beta}_1 + \hat{\beta}_3 \times \mathrm{SIG}_{j,t}$.[40]

Forecasting fundamentals depending on value phases. We model interaction effects of the absolute interest rate forecast error in dependence of the value market phase by setting $\mathrm{SIG}_{j,t} = \mathrm{FUND}_t$ in Eq. (2.4). Table 2.5 shows the coefficient estimates and the computed marginal effects.

Table 2.5, (i)-(ii), shows that the negative marginal effects of an interest rate forecast error are larger when $\mathrm{FUND}_t = 1$, i.e. when the exchange rate deviates substantially from its fundamental

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

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

Table 2.5: Interaction model: signals for value trade phases

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

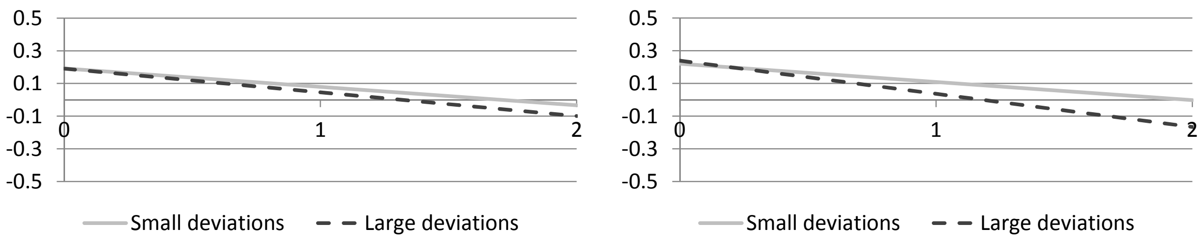
$$r_{j,t,t+1} = \mu_j + \beta_1|\varepsilon_{j,t}(X)| + \beta_2\text{FUND}_t + \beta_3\left(|\varepsilon_{j,t}(X)| \times \text{FUND}_t\right) + \epsilon_{j,t}.$$

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

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

value according to PPP: the marginal effect of an error with respect to Eurozone interest rates is almost twice as large in these market phases with fundamental mispricing. The average return from T_{ind} decreases by 20 basis points for each increase in error points with respect to U.S. interest rates when currencies are fundamentally mispriced; in contrast, this effect only amounts to 13 basis points in market phases when exchange rates are more aligned to fundamental values. To illustrate this finding, Figure 2.2 shows predictions of returns conditional on the forecast error and the degree of deviation of the current nominal exchange rate from its PPP level.

Figure 2.2: Expected effects of fundamental forecast errors under different value phases



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

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

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

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

While these findings suggest that it is more important to understand *interest rates* in times in which a severe mispricing of exchange rates calls for value strategies, it is worth noting that a similar effect can be documented for industrial production, whereas there is a mixed pattern for inflation rates, see Table 2.5, (iii)-(vi).

Forecasting fundamentals depending on momentum phases. Similarly, we model interaction effects of the absolute interest rate forecast error in dependence of the momentum market phase by setting $\text{SIG}_{j,t} = \left(D^H_{j,t}\; D^L_{j,t}\right)'$ and $\beta_2 = (\beta_{21}\; \beta_{22})$ and $\beta_3 = (\beta_{31}\; \beta_{32})$ in Eq. (2.4).[41]

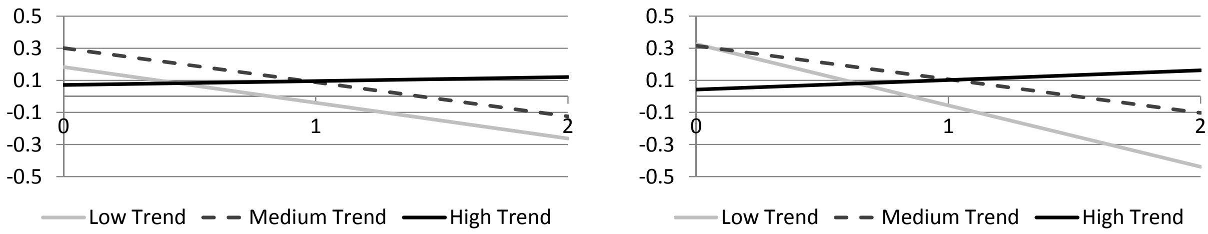
Table 2.6, (i) and (ii), shows that the marginal effects of interest rate forecast errors vary substantially across momentum phases: they matter most when the momentum is not particularly pronounced.

The marginal effect of a deterioration of a Euro interest rate forecast by one error point corresponds, on average, to a decline of the monthly trading return of 0.213 percentage points when the forecasts were made in normal momentum phases (see (i)). This value is not far away from the marginal effect in low momentum phases (-0.223), but differs substantially from the marginal effects observed in high momentum phases (0.025). While the former two marginal effects are significantly different from zero, this is not the case for the latter. These results indicate that a good prediction of European interest rates helps improve the exchange rate forecasts unless momentum trading dominates markets. To illustrate this issue further, Figure 2.3 depicts predictions of returns conditional on the forecast error and the momentum phase.

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

$$\left(Var(\hat{\beta_1}) + (D^L)^2 Var(\hat{\beta_{31}}) + (D^H)^2 Var(\hat{\beta_{32}}) + 2(D^L)Cov(\hat{\beta_1}, \hat{\beta_{31}}) + 2(D^H)Cov(\hat{\beta_1}, \hat{\beta_{32}})\right)^{\frac{1}{2}}.$$

Figure 2.3: Expected effects of fundamental forecast errors under different momentum phases



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

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

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

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

Figure 2.3(a) shows that returns decrease with increasing Euro interest rate forecast error for both low and normal momentum phases, leading to a positive expected return if the interest rates are predicted correctly, and to a negative expected return if the interest rates are anticipated in a (severely) wrong way. In contrast, the expected return is positive in high momentum phases regardless of the quality of the Euro interest rate forecast. As can be seen from the marginal effects in Table 2.6, (ii), and from subfigure 2.3(b), the results are very similar (and maybe even more pronounced) when the relationship between the forecast of the U.S. interest rate and the exchange rate forecasting performance is considered.

For comparison, Table 2.6 also shows that the marginal effects of the other fundamental forecast errors (w.r.t inflation, industrial production) show a similar pattern across momentum phases but are smaller in absolute value compared to those of the interest rate forecast errors: to mention the most pronounced effect, an increase of one error point with respect to the forecast of the European industrial production (see (v) in Table 2.6) leads to a return decrease of 0.155 percentage points in low momentum phases.

Table 2.6: Interaction model: signals for momentum trade phases

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

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

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

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

Forecasting fundamentals and interest differential phases. Finally, we also consider interaction models of the absolute forecast error with interest differential phases; hence, we set $\text{SIG}_t = |i_t^{USD} - i_t^{EUR}|$, and we focus on the marginal effects, i.e. $\frac{\partial r}{\partial|\varepsilon_{j,t}(i)|} = \hat{\beta}_1 + \hat{\beta}_3 \times |i_t^{USD} - i_t^{EUR}|$. Table 2.7 presents the coefficient estimates as well as the marginal effects evaluated at the average absolute interest rate differential over the sample period.

For this particular value, there are relatively large negative effects of prediction errors in interest rates forecasts (see (i) and (ii)). Figure 2.4 shows the state-dependent marginal effects in more detail.

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

For comparison, Table 2.7, (iii)-(vi), also reports similar exercises for the other fundamental forecasts besides interest rates. The findings for interest rate forecasting errors are mainly confirmed by growth forecast errors but not by inflation forecast errors as Figure 2.4, (c)-(f), illustrates. As for the analysis of value phases, the contribution of good inflation forecasts to good exchange rate forecasts does not fit well into the pattern. One may speculate whether a possible impact of inflation (forecasts) on exchange rates is overruled by very obvious, relatively shorter-term economic forces, i.e. short-term interest rates and business cycle considerations.

Table 2.7: Interaction model: interest rate differential phases

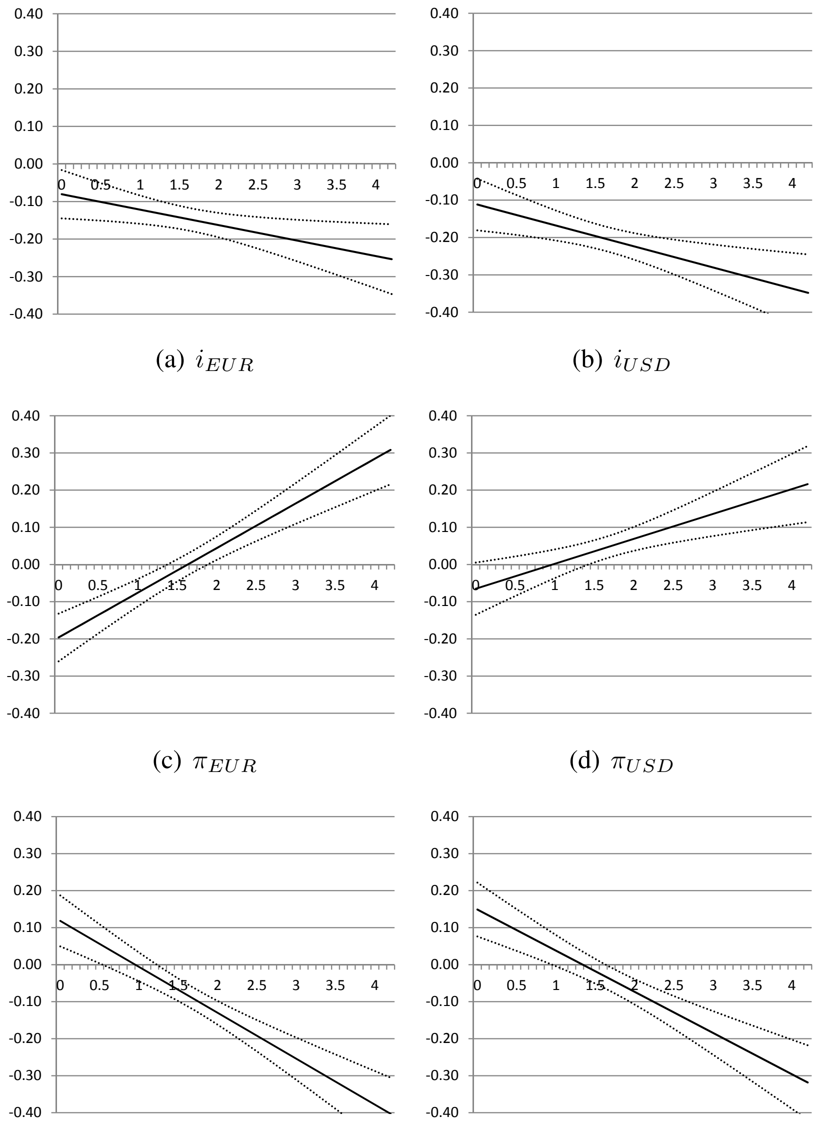
This table reports the results of a panel regression with individual fixed effects of the trading rule T_{ind}'s period forecast return, $r_{j,t,t+1}$ (based on the forecast of the forecaster j in t), on a fundamental forecast error (in absolute terms) $|\varepsilon_{j,t}(X)|$, the absolute differential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

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

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

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

Figure 2.4: Marginal effects of forecast errors depending on absolute size of the interest rate differential



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

(c) π_{EUR} (d) π_{USD}

(e) y_{EUR} (f) y_{USD}

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

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

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

2.5.4 The expected relation between interest rate and exchange rate changes

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

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

$$E_t[\Delta s_{t,t+6}] = \beta_0 + \beta_1 [E_t[\Delta i^{EUR}_{t,t+6}] - E_t[\Delta i^{US}_{t,t+6}]] + \epsilon_t \tag{2.5}$$

If the difference between the expected change in Eurozone interest rates and the expected change in the U.S. interest rates ($E_t[\Delta i^{EUR}_{t,t+6}] - E_t[\Delta i^{US}_{t,t+6}]$) determines expected changes in foreign exchange rates, we would expect the parameter β_1 to be different from zero. We estimate Eq. (2.5) based on the individual exchange rate and interest rate forecasts with a fixed-effects regression,[42] and report the coefficient estimates in Table 2.8, Panel A.

Table 2.8: Exchange rate forecasting models and their usage to predict actual exchange rate changes

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

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

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

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

As Table 2.8, (i), demonstrates, $\hat{\beta}_1$ is found to be significantly larger than zero; consequently, the forecasters expect, on average, the USD to depreciate against the Euro ($\Delta s_{t,t+6} > 0$) when the

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

differential of Eurozone interest rates vs. U.S. interest rates increases. As there are more candidate influencing factors beyond interest rates, we also augment Eq. (2.5) by $E_t[\Delta\pi^{EUR}_{t,t+6}] - E_t[\Delta\pi^{US}_{t,t+6}]$, i.e., the difference in the expected changes in inflation. Table 2.8, (ii), illustrates that nevertheless, the relative interest rate expectations continue to have a strong effect whereas the inflation differential also has an effect, albeit a smaller one. Hence, we conclude that expected interest rate differentials are indeed a dominant determinant of forecasters' exchange rate expectations, and hence we continue to consider Eq. (2.5) as a parsimonious representation of the forecasters' model.

To look into this in more detail, we analyze whether good forecasters rely on a different model than bad forecasters. To do so, we divide the total set of forecasters into three different groups according to their overall (*ex post*) forecasting performance (measured by average returns of a forecaster j) and reestimate Eq. (2.5) for these subgroups (high performer, medium performer, and low performer) separately. It can be seen from Table 2.8, (iii)-(v), that relative interest rate expectations matter regardless of whether we consider low, medium, or high performers, respectively: the coefficient estimates are found to be significantly positive for all groups.

In a second step, we check whether the individual interest rate forecasts are suited to predict *actual* exchange rate changes, given that the forecasters follow a model with the above mentioned structure (i.e., $E_t[\Delta s_{t,t+6}]$ and $E_t[\Delta i^{EUR}_{t,t+6}] - E_t[\Delta i^{US}_{t,t+6}]$ are *positively* related). In particular, we regress ex post exchange rate changes ($\Delta s_{t,t+6}$) on the RHS variables of Eq. (2.5) and estimate $\hat{\beta}_0$ and $\hat{\beta}_1$ for the groups of low, medium, and high performers separately. Table 2.8, Panel B, displays the results. Strikingly, the estimates for $\hat{\beta}_1$ are significantly *negative* for the low and medium performers (see (vi)-(vii)): this shows that on average, the USD has *appreciated* after an increase of the differential of Eurozone interest rates change vs. U.S. interest rates change expectations of these groups. This is contrary to the forecasters' models' implication and will lead to misguided forecasts, on average. In contrast, $\hat{\beta}_1$ carries the correct (positive) sign for the group of high performers (see (viii)); more often than not, an increase of the differential of Eurozone interest rates change vs. U.S. interest rates change expectation by this group is associated with USD *depreciation*, as is implied by the forecasters' model.

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

2.6 Robustness

This section documents some of our robustness calculations showing that the main findings are not unique to the USD/EUR exchange rate (Section 2.6.1) and do not depend on the specific trading rule (Section 2.6.2) or on the usage of trading rules as a performance measure in general (Section 2.6.3). Finally, Section 2.6.4 demonstrates that our main results are robust to the chosen estimator.

2.6.1 Further currencies

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

As introduced in Eq. (2.2), we run fixed effects regressions of the type

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

i.e., we regress the return of a trading rule based on an individual's forecasts of the GBP/EUR rate (and separately, the JPY/EUR rate) on the forecast error with respect to the European interest rate and the foreign (i.e. British or Japanese) interest rate $i^{\star}$ and corresponding control variables. Table 2.9 displays the results. Strikingly, the negative and significant coefficients of absolute interest rate forecast errors remain a common feature in all specifications, while there are larger differences across currencies and specifications for the other fundamentals considered control variables.

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

Table 2.9: Robustness: GBP/EUR and JPY/EUR exchange rates

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

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

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

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

2.6.2 Different specifications of the trading rule

So far, we have used a market-based loss function T_{ind} (see Eq. 2.1) for the evaluation of an individual's forecasting performance, which we repeat here for convenience:

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

This rule implies that the investor uses the forward market when taking a long/short position, which is (through covered interest rate parity) equivalent to borrowing in one currency and investing the same amount in the other currency at market interest rates. While this approach is natural for an investor, it has to be noted that we observe exchange rate forecasts expressed in terms of changes of *spot rates* (and not *forward rates*, which incorporate spot rates and *and* the current levels of refinancing costs (i.e., the interest rate differential). Hence, $E_t[s_{t+1} - f_t^1]$ is not directly observable nor can it be backed out indirectly (due to the directional nature of the considered forecasts). To deal with two potential objections on these grounds, this section presents two alternative trading rules as robustness checks: first, the measured return could be driven by changes in the refinancing costs rather than exchange rates (and hence we replace $f_{t,1}$ in Eq. (2.1) with s_t for an alternative trading rule $T_{ind}(1)$). Second, trades which are made according to Eq. (2.1) could be *ex ante* unprofitable if $s_t > E_{j,t}[s_{t+1}]$ but $f_t^1 \leq E_{j,t}[s_{t+1}]$ (and hence we consider a trading rule $T_{ind}(2)$ in which a trade according to Eq. (2.1) is not made unless either $E_{j,t}[s_{t+1}] > s_t \geq f_t^1$ or $E_{j,t}[s_{t+1}] < s_t \leq f_t^1$ holds). Intuitively, this latter trading rule is more conservative (in which forecasters only trade when forward rates "predict" a different exchange rate change according to UIP than the forecasters' own forecasts), whereas the former trading rule is a gross trading rule which ignores the costs and revenues of borrowing and investing in different currencies. Table 2.10 presents the estimates. Table 2.10 confirms the general results from the main part. The alternative

Table 2.10: Robustness: panel fixed effects regression with alternatively specified trading rules

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

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

and

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

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

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

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

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

Average absolute forecasting errors. This paragraph documents that our findings do not depend on the use of trading rules to measure exchange rate forecast performance; in contrast, the main insights are similar when the analysis is based on absolute forecasting errors $|\varepsilon_{j,t}(FX)|$ instead (computed as above for the interest rate forecasts).[43] These two measures are negatively related, as a *large* error corresponds to *poor* forecasting performance, which implies low returns. In fact, there is a negative correlation coefficient of -0.8 when considering the entire panel of data over time for all forecasters.

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

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

i.e. the probability of making a correct exchange rate forecast in dependence of $|\varepsilon_{j,t}(i)|$;[44] as we are interested in phase-dependent effects of interest rate forecasts on exchange rate forecasts, we specify the models with interaction terms (as also done in Eq. (2.4)), i.e.

$$\varepsilon^{\star} = \beta' X = \beta_1 |\varepsilon_{j,t}(i)| + \beta_2 \text{SIG}_{j,t} + \beta_3 \left(|\varepsilon_{j,t}(X)| \times \text{SIG}_{j,t} \right) + \epsilon_{j,t}, \tag{2.6}$$

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

Results. Table 2.11 displays the results from the ordered probit regressions, where the probability of making a correct forecast $P(|\varepsilon_{j,t}(FX)| = 0)$ is computed by $\Phi(\kappa_1 - \beta' X)$, with $\Phi(\cdot)$ being the cumulative standard normal density.

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

Table 2.11: Robustness: absolute forecast errors

This table reports the results from an ordered-probit regression of the type $\varepsilon^\star = \beta' X = \beta_1 |\varepsilon_{j,t}(i)| + \beta_2 x_1 + \beta_3 (|\varepsilon_{j,t}(X)| \times x_1) + \epsilon_{j,t}$ where the respondents' FX forecast errors $|\varepsilon_{j,t}(FX)|$ are related to the unobserved $\varepsilon^\star$ with the threshold parameters κ_1 and κ_2. $|\varepsilon_{j,t}(i)|$ represents the absolute interest rate forecast error, x_1 is a short-cut for the variables that $|\varepsilon_{j,t}(i)|$ is interacted with, e.g. the dummy variables for a fundamental mispricing according to PPP (FUND$_t = 1$ if mispriced), low or high trend phases D^L and D^h, respectively, or the interest rate differential $|i_t^{USD} - i_t^{EUR}|$.
Marginal effects of an interest rate forecast error on the probability of making a correct FX forecast ($\frac{\partial P(|\varepsilon(FX)|=0)}{\partial|\varepsilon_{j,t}(X)|}\Big|_{\varepsilon_{j,t}(X)=1}$) are computed by $-\phi(\kappa_1 - \beta' X) \times [\beta_1 + \beta_3 x_1]$, whereas the corresponding standard errors are obtained by the delta method. Standard errors are provided in parentheses. Significance: ***:1%, **: 5%, *: 10%.

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

The marginal effects of an interest rate forecast error on the probability of a correct exchange rate forecast are computed by $-\phi(\kappa_1 - \beta' X) \times [\beta_1 + \beta_3 x_1]$ (with $\phi(\cdot)$ being the standard normal density). Table 2.11 also presents these marginal effects, where columns (i) and (ii) contain the interaction models with momentum signals. The marginal effects of interest rate forecasts observed in the low and normal momentum phases are significantly negative for both the U.S. and Eurozone interest rates (while the effects are more pronounced for the U.S. interest rates), indicating that a worse interest rate forecast decreases the probability of making correct exchange rate forecasts. In high trend phases, these effects are smaller in absolute size or even insignificant, confirming our results from the main section that the relationship between interest rates and exchange rate forecasting performance breaks down when the signals for momentum strategies are strong. Columns (iii) and (iv) show the results from the interaction models including the interest rate differential phase, taking two different levels of absolute interest rate differentials as illustrative examples. As in the baseline analysis above, it can be seen that higher forecast errors decrease the probability of making a good exchange rate forecast and that this effect is more pronounced when interest rate differentials are larger. Columns (v) and (vi) show that the probability of making a correct USD forecast decreases more strongly with more severe interest rate errors when the exchange rate deviates substantially from its fundamentally fair value according to PPP.

2.6.4 Different estimators

As described in more detail in Section 2.5.2, we conduct panel IV fixed effects regressions. Our main result, i.e. a significantly negative relationship between short term interest forecast errors on exchange rate forecasting performance, however, is also found when using pooled OLS with (Table B.3) or without (Table B.4) instruments or fixed effects without instruments (Table B.5). We also demonstrate that our results are qualitatively unaffected by autocorrelation in the panel.

To show this, we report the estimates from the fixed effects estimation technique put forth by Baltagi and Wu (1999) to deal with AR(1) disturbances (Table B.6). Moreover, we obtain qualitatively similar results when we consider an alternative IV strategy (Table B.7): instead of using lagged values, we use the absolute forecast errors with respect to the interest rates in the *UK* and in *Japan* as exogenous instruments for the forecast errors with respect to the *U.S.* and the *Eurozone*. Likewise, we use the absolute forecast errors with respect to the inflation rate and industrial production in these countries as instruments for the U.S. and Eurozone inflation and industrial production, respectively.[45]

2.7 Conclusions

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

The starting point of our research is the hypothesis that expected fundamentals determine exchange rates. Accordingly, we rely on a large data set of individual expectations on fundamentals and exchange rates. Analyzing these expectations shows enormous heterogeneity, a fact that is well documented in the literature and it demonstrates therefore that in this sense our data are conventional. In order to learn about the formation of exchange rates, we make use of the hetero-

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

geneity with respect to forecasting performance. Given the supposition that individuals who can forecast exchange rates should have a correct understanding about exchange rate determinants, we investigate whether the quality of fundamental forecasts is related to the ability to predict exchange rates. As interest rates can be seen as the most important determinant of exchange rates over medium-term horizons, we analyze the connection between interest rate and exchange rate forecast performance. We find that good exchange rate forecasting performance is robustly related to good interest rate forecasts. This main result also holds when we consider individual fixed effects in the panel approach, controlling for general exchange rate forecasting ability, when we use an IV approach to test causality and when we control the main relation for further potential determinants.

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

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

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

3. Using expectations to inform chartist-fundamentalist exchange rate models [‡]

3.1 Introduction

There is ample research about 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, until today there has been no direct evidence combining these two strands of literature: How do professionals, who state to be 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; Manzan and Westerhoff, 2007; De Grauwe and Grimaldi, 2006). 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 instable 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.

[‡]The chapter is an earlier version of a joint work with Lukas Menkhoff with the title *Exchange Rate Expectations of Chartists and Fundamentalists*. It has also appeared as a discussion paper, see Dick and Menkhoff (2012)

Third, the existence of various groups in financial markets implicitly assumes that all these groups operate successfully in the long run. The efficient market hypothesis has stated in this respect 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 and fundamentalists each provide a basis for profitable trading strategies.

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 rests on the Financial Market Survey conducted on a monthly basis by the Centre for European Economic Research (ZEW) in Mannheim, Germany, among 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 asked three times, i.e., 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, until September 2011. We classify forecasters into the categories of chartists, fundamentalists, and the remaining 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 frequently than fundamentalists. (2) Regarding forecasting dynamics, chartists tend to revise the direction of their exchange rate forecasts more frequently than fundamentalists, confirming a frequent 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. 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 equally good at longer horizons, which nicely fits the preferred short (long) horizon of chartists (fundamentalists) (Taylor and Allen, 1992).

All these findings conform with 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 3.2. In this sense, we provide supportive evidence complementing earlier approaches, which often relied on indirect tests. In detail, however, we also obtain evidence that is less conclusive with 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).

This essay is structured as follows: Section 3.2 briefly discusses relevant literature in order to embed our study in earlier work and to carve out our own contribution. Section 3.3 reports the comprehensive dataset. Section 3.4 presents results of our research in several steps, Section 3.5 contains robustness tests. Conclusions are provided in Section 3.6.

3.2 Literature and hypotheses

This section shows the relation of our research to various strands of earlier literature, which we can cover only selectively. There are studies about *exchange rate expectation formation* and the *use of charts and fundamentals* which have heavily influenced 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 an instability of prices. Finally, our work is related to studies about the *performance* of chartist and fundamentalist trading.

Exchange rate expectation formation. In the standard economic models about exchange rate formation, representative agents perfectly understand macroeconomic fundamentals so that the present price always and fully reflects the available information. The empirical test of such models shows, however, that these stylized rational expectations models seem to be too stylized to adequately explain exchange rate formation (e.g., Meese and Rogoff, 1983; Cheung, Chinn, and Garcia-Pascual, 2005). A useful starting point to explain the existence of such a gap between models and reality is the high degree of heterogeneity among foreign exchange professionals, which has been found in seminal studies by Frankel and Froot (1990) or Ito (1990) and has later been reconfirmed by, e.g., MacDonald and Marsh (1996).

While heterogeneity as such is not a problem for models with representative agents, the heterogeneity in foreign exchange does not seem to be normally distributed. Instead, several kinds of patterns in heterogeneity have been revealed over the years, some of which are of interest for our research. In one of the first studies examining exchange rate expectations, Frankel and Froot (1987) state that the formation of exchange rates follows bandwagon expectations over short horizons and regressive expectations over longer horizons. This finding already contains the core ingredient of chartist-fundamentalist models, i.e. the co-existence of trend-following and mean-reverting expectations. This core insight has been steadily confirmed and refined in later studies (for surveys, see MacDonald (2000) or Jongen, Verschoor, and Wolff (2008)), e.g., by considering the fact that forecasters rely on mean-reversion in a non-linear fashion (e.g., Menkhoff, Rebitzky, and Schröder, 2008; Reitz, Rülke, and Stadtmann, 2012), an aspect we also consider in this study.

Use of charts and fundamentals. Another line of research initiated by Taylor and Allen (1992) has explicitly asked foreign exchange dealers about their use of technical and fundamental analysis when forecasting exchange rates. Dealers state that they indeed mostly use both kinds of analysis, but that they use charts at shorter horizons than fundamentals. This result has also been replicated in many studies and could be extended to fund managers (see survey by Menkhoff and Taylor, 2007).

Chartist-fundamentalist models. All this provides clear motivation to model foreign exchange markets where both, chartists and fundamentalist, co-exist and interact. An early version of such a chartist-fundamentalist model has been formulated by Frankel and Froot (1990) and has been much refined by De Grauwe and Grimaldi (2006). The basic idea is that there are two groups in the market, i.e. chartists and fundamentalists, who follow different investment strategies. Chartists usually dominate the market with their trend-following behavior, which generates its own kind of risk for fundamentalists. When, however, 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; this also provides a motivation for foreign exchange interventions (e.g., Beine, De Grauwe, and Grimaldi, 2009). As long as exchange rates are not obviously misaligned such that there is less certainty about their true fundamental rate, chartists are relatively stronger. It should be noted that De Grauwe and Grimaldi (2006) define chartists as being ignorant of fundamental information. In contrast, Manzan and Westerhoff (2007) assume, for instance, that both groups are equally informed about fundamental information, but that only chartists consider technical analysis to also be relevant, whereas fundamentalists do not.

We use the results discussed so far as guiding hypotheses for our research. Complementing earlier evidence, we demonstrate that the professional forecasters' self-assessment regarding their forecasting tools enables us to classify them as chartists, fundamentalists, or intermediates.

Next, we test whether chartists' and fundamentalists' forecasting behavior does differ as expected. As a common core chartist-fundamentalist models often assume that chartists base their forecasts on prevailing market trends by following these trends. In reality, however, there is a large variety of ways to construct a technical trading rule (see, e.g. Neely and Weller, 2011) so that the focus on trend-following strategies is less than obvious. As a consequence, we investigate whether chartists can in fact be characterized by a strong use of trend-following strategies which is, in particular, stronger than for fundamentalists (*Hypothesis 1*). In order to quantify trend-following we rely on simple momentum rules, although we acknowledge that trend-extrapolation could be done in more sophisticated ways in reality, as experimental evidence suggests (Rötheli, 2011).

The characterization of chartists needs to be complemented by a characterization of fundamentalists. Fundamental models basically assume a mean reverting forecasting behavior, such that a long-run moving average indicating purchasing power parity provides the hypothetical mean. Thus, we investigate whether the orientation at PPP is more pronounced for fundamentalists (*Hypothesis 2*). This hypothesis has been tested in a related fashion for an earlier sample of the ZEW data with a supportive result (Menkhoff, Rebitzky, and Schröder, 2008). However, this earlier paper has only used information about the use of more or less fundamental information, but did not examine *chartists* as an own category in comparison.

Heterogeneous agents' models. A core element of chartist-fundamentalist models in foreign exchange is the dynamics between groups. Several mechanisms have been suggested for these dynamics in the heterogeneous agents' literature. Some models rely on segmented investors, such as sophisticated α-investors and purely trend-following β-investors introduced by Day and Huang (1990), such as Chiarella, Dieci, and Gardini (2002), or segmented markets, such as in Westerhoff (2004). The results of these simulation studies are largely consistent with highly stylized facts of financial markets and observations in experimental asset markets, where, usually, students form expectations about future asset prices and operate in a dynamic market setting (see, e.g., Sonnemans, Hommes, Tuinstra, and Van De Velden, 2004; Haruvy, Lahav, and Noussair, 2007; Bloomfield, Taylor, and Zhou, 2009; Hommes, 2011). Results are also consistent with models from behavioral finance, such as Barberis, Shleifer, and Vishny (1998), where investors believe in two states of the world, i.e. a trend regime and a mean-reverting regime. Finally, heterogeneous agents have been linked to the dispersion of expectations in foreign exchange. Menkhoff, Rebitzky, and Schröder (2009) demonstrate in a somewhat abstract framework that switching between chartists and fundamentalist positions may explain forecast dispersion. Jongen, Verschoor, Wolff, and Zwinkels (2012) show in more detail how the switching between a chartist, a fundamentalist and a carry trade position can explain expectation dispersion.

In particular Brock and Hommes (1997, 1998) model a switching mechanism: 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 the notion by Brock and Hommes (1997) that switching between chartists and fundamentalists occurs through the comparison of ex post profits. This has been applied to exchange rate expectations by Jongen, Verschoor, Wolff, and Zwinkels (2012). In contrast, Lux (1998) allows both the comparison of ex post profitability as well as contagion to induce switching between different trading rules. A third explanation for switching between strategies is given by Dieci and Westerhoff (2010), who assume that all traders are familiar with both technical and fundamental trading rules, and opt for one of them based on the expected future performance rather than the ex post performance. According to this view, the agents tend to move from chartist to fundamental strategies when the deviation between fundamental value and exchange rate becomes large.

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 (e.g., Brock and Hommes, 1998; Farmer and Joshi, 2002); this idea has already been formalized earlier by, e.g., De Long, Shleifer, Summers, and Waldmann (1990), albeit in a different way. A source of instability is these agents' willingness to often switch their positions. Applied to our case, one would expect that chartists show instable behavior by switching between appreciation and depreciation expectations (motivating long and short positions in a currency) more frequently than fundamentalists (*Hypothesis 3*). Regarding the concrete motivation for switching, the concept by Brock and Hommes (1997) suggests that agents evaluate alternative strategies on the basis of their ex-post profitability. Accordingly, 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*).

In a somewhat forward-looking modification of this rule, it is often assumed that the influence of fundamentalism increases when the exchange rate deviates more clearly from its fundamental equilibrium (e.g., Bauer, De Grauwe, and Reitz, 2009). In line with recent empirical exchange rate modeling, De Grauwe and Grimaldi (2006) introduce transaction costs to incorporate a non-linear response of exchange rates to changes in fundamentals (e.g. Dumas, 1993; Taylor, Peel, and Sarno, 2001; Kilian and Taylor, 2003). This implies that a greater deviation from the fundamental value decreases the perceived risk of following a fundamental strategy, and 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 continuous line of studies examining the profitability of chartist trading in foreign exchange. Profitability is a crucial issue because it justifies the existence of chartists in competitive financial markets. Since the 1970s many studies have found that simple trading rules applied to a set of exchange rates seem to generate considerable excess returns. This main result has been confirmed by later studies which extend the analysis to different forms of technical analysis and to various methodological refinements (e.g. Okunev and White, 2003; Qi and Wu, 2006; Park and Irwin, 2007; Neely, Weller, and Ulrich, 2010).

A shortcoming of these studies in assessing chartists' performance is that they can only analyze *simulated* trading rules and do not calculate real-world returns. Another shortcoming is that a *comparative* analysis of forecasting performance by chartists and fundamentalists has been neglected almost completely 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 superior or inferior to fundamentalists: earlier heterogeneous models, such as Day and Huang (1990) tend to model the non-fundamental traders in a way that they call "*buy high and sell low*", i.e., these traders lose money until they learn how fundamental strategies work. De Grauwe and Grimaldi (2006), in contrast, suggest that chartists are generally more profitable than fundamentalists. Ultimately, the performance of forecasts based on chartist and fundamental information as well as their profitability is an empirical issue. 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*).

However, there are two caveats to be made: first, in some analyses we seemingly reduce chartism to *momentum trading* which is, of course, not the same. The difference may be important in our study, because we cover the major exchange rates over the last decade, i.e. a case where earlier studies show that simple momentum trading does not work profitably (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). On the one hand carry trading may be seen as a form of "chartism" in the sense of mechanically conditioning investment decisions on interest rates. On the other hand chartists may be expected to execute not only carry trades but to (also) follow different considerations.

Overall, we examine six hypotheses derived from a rich literature. The starting assumption on the existence of chartists and fundamentalists only provides the ground 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; regrading the remaining hypotheses, our study enters new ground.

3.3 Data

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

Microdata of 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 we 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, i.e. in 2004.01, 2007.04 and 2011.09, and a part of the forecasters has responded to more than one of these special surveys. 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 from 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 of directional nature, i.e. 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 special surveys in 2004.01, 2007.04 and 2011.09 ask the forecasters to attach percentage figures to their use of fundamental analysis, technical analysis and the analysis of order flows. Table 3.1 summarizes the cross sectional means and standard deviations of the answers to this question.

Table 3.1: Weighting of forecasting tools

This table reports the self-assessment of professional forecasters with respect to their preferred forecasting tools. In special surveys 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	57.6	28.6	13.8	57.4	27.4	15.2
SD	21.6	19.8	11.9	20.3	17.1	12.7	22.0	18.0	14.1
N	237	237	237	247	247	247	198	198	198

The table reveals that, on average, the proportion of the analytical tools remains relatively constant. Analysts attribute an average share of almost sixty percent to fundamental analysis, and below thirty percent to technical analysis. Over the years, the importance of order flow analysis for exchange rate forecasting appears to increase slightly, although it remains minor compared to the other sources. Hence, we concentrate on fundamental and technical analysis in the remainder of this chapter.

These responses can be directly compared to those reported in Menkhoff and Taylor (2007, Table 3) as the identical survey question has been applied. The foreign exchange dealers, who are also located in Germany (and Austria), give charts a weight of 35 percent to 45 percent, whereas international fund managers give a weight of 36 percent to 37 percent. These figures are markedly higher than for our sample of professional forecasters with 27 percent to 30 percent, although the difference between our analysts and the fund managers is not very large. Accordingly, the weight of fundamentals is much higher in our sample, in particular compared to dealers.

Chartists and fundamentalists. In particular, we make use of the information given in the special surveys to form groups of fundamentalists and chartists, respectively. For the choice of our groups, we take into account that most forecasters indicate to apply both fundamental and technical analysis for their forecasts at least to some extent, while fundamental analysis dominates in quantitative terms for the majority of forecasters. To obtain groups of forecasters with diverging forecasting techniques, we define the two groups in a pragmatic way reflecting the kind of data they use. There are two criteria forecasters need to meet in order to be classified as *chartists*: first, they give a relatively larger weight to technical analysis than to fundamental analysis (or order flow analysis), and second, their weight 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 give a weight of at least 80 percent to fundamental analysis. The remaining forecasters are called *intermediates*, but we realize that their forecasting behavior will be largely characterized by reliance on fundamentals. For those forecasters who have responded to the special questions more than once, we compute the average response.

Table 3.2 shows that our chosen groups of forecasters represent a relatively sharp selection: only 60 and 65 forecasters are classified as chartists and fundamentalists, respectively, while the large majority of the total of 396 forecasters, i.e. 271 persons, is classified as intermediate. The

Table 3.2: 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 special surveys, 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	65	88.8	8.4	80.0	100.0	7.2	7.7	0.0	20.0
intermediates	271	58.3	12.1	20.0	78.3	27.3	10.3	0.0	50.0
chartists	60	30.4	10.3	0.0	45.0	55.8	11.7	40.0	92.5

fundamentalists only attach a weight of 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 used forecasting methods, 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 equivalently use technical information. This result follows mainly from our definition of the two groups, which is asymmetric, and should not be interpreted as a particular group behavior. 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).

Persistence and representativeness. 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 3.3 show that the broad majority of respondents continues 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 (i.e., 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.

Furthermore, the considered set of forecasters (those who have provided us with a self-assessment of preferred forecasting tools at the special surveys) is representative of the entire set of forecasters in terms of their predictions: as Table 3.4 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 3.3: 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 3.2 for each of the three special surveys 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 special survey 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 special survey is independent from the classification in the other special survey. (***: 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 3.4: 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	

Exchange rates and inflation data. We use the USD/EUR exchange based on the exchange rate XUDLERD issued by the Bank of England with daily frequency. This time series has the advantage of also comprising a synthetically-computed exchange rate for the time before 1999.01, which we need, e.g., 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.[46] Where needed, we consider the Consumer Price Index in the Eurozone and the United States obtained from Datastream.[47]

3.4 Empirical results

This section documents examination results about exchange rate expectations of chartists and fundamentalists in three steps. First, we show results on forecasting behavior (Section 3.4.1), then results on forecasting dynamics (Section 3.4.2) and finally results on forecasting performance (Section 3.4.3).

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

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

[47] Datastream Mnemonics: USCONPRCE, EMCONPRCF.

tend to be more in line with trend-following strategies compared to those made by fundamentalists (see our *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. 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, i.e.

$$E[\Delta s_{t,t+h}] = \phi^{(k,DD)} \Delta s_{t-DD,t} \text{ with } \phi^{(k,DD)} > 0. \tag{3.1}$$

As we know from Section 3.3 that chartists also use fundamental prediction tools in addition to chartist rules, it is unlikely that their forecasts correspond to those from Eq. (3.1) at all time. Compared to fundamentalists' predictions, however, one could still expect a higher level of association of 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. (3.1), i.e.

$$\text{SHARE}_i^{DD} = \frac{\text{number of forecasts by } i \text{ in line with trend-following strategy}}{\text{number of all forecasts by } i} \tag{3.2}$$

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 all time periods in line with a forecasting rule which extrapolates the trend over the previous DD days. 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 3.5 summarizes the correlation coefficients of SHARE_i^{DD} with the percentage figure attributed by i to fundamental and technical analysis, respectively.

Table 3.5: 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 about 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	***-0.16	***-0.14	-0.08	-0.07	-0.08
techn. analysis (in %)	*0.11	**0.12	*0.09	0.03	0.01	0.08

Table 3.5, Panel A, shows that SHARE_i^{DD} decreases with the 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 3.6 compares the average SHARE^{DD} for the groups of chartists and fundamentalists.

Table 3.6, 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 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 overall demonstrate that *revealed* trend-following and the *stated* preference for technical analysis is closely linked. This result does not only confirm *Hypothesis 1*, but also ultimately underlines the credibility of the self-assessment in the special surveys.

While the results above on average hold across prevailing trends of different sizes (which also

Table 3.6: 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).

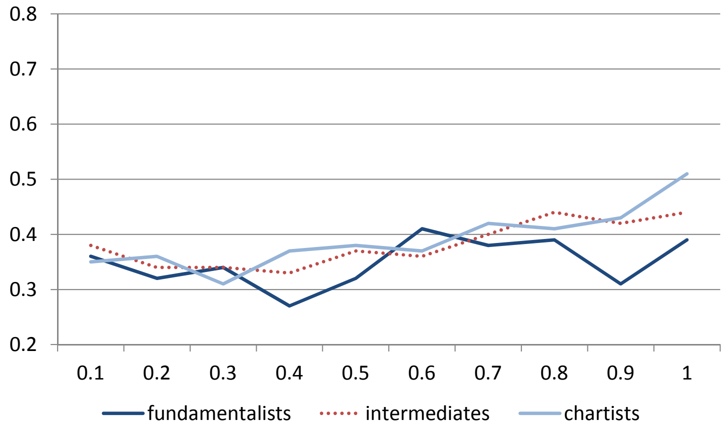
	Panel A					**Panel B**
	SHARE^{10}	SHARE^{30}	SHARE^{60}	SHARE^{90}	SHARE^{180}	SHARE^{PPP}
fundamentalists	0.34	0.34	0.35	0.37	0.37	0.33
intermediates	0.38	0.38	0.39	0.39	0.39	0.35
chartists	0.39	0.39	0.40	0.40	0.41	0.33
t-test fund. vs. chart.	**2.26	**2.54	**2.26	1.16	1.02	0.08

includes 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 into ten intervals according to deciles (i.e, the first interval including the periods with only little movement of exchange rates and the tenth interval including the periods with large exchange rate movements), and compute the average SHARE^{30} separately for each of these intervals. Figure 3.1 displays the results for chartists and fundamentalists, respectively.

Figure 3.1 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 and intermediates, as they remain relatively unimpressed by momentum compared to the other groups: for chartists, SHARE^{30} is on average 0.35 for the lowest interval, while it is 0.51 for the highest interval. In contrast, SHARE^{30} only rises to 0.44 for the group of fundamentalists.

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

Figure 3.1: Observed momentum-following, depending on size of previous trends



This plot represents a set of cross-sectional averages (for each fundamentalists, chartists, and intermediates separately) of the proportion of individual forecasts which are in line with momentum-following behavior (based on the trend observed in the last 30 days). The graph in this figure illustrates the averages in dependence of the market phases, i.e. the absolute size of the trend of the previous 30 days. The x-axis displays the intervals according to deciles (0.1 representing the lowest 10 percent of observed trends (0-10%), 1 representing the highest 10 percent (90-100%)). The y-axis represents the proportion of forecasts which are in line with momentum strategy (e.g., $0.4 = 40\%$). The solid dark line represents the group of fundamentalists, the solid light line the group of chartists, and the dotted line the group of intermediates.

(see Cheung and Chinn, 2001; Cheung, Chinn, and Marsh, 2004), and 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 our *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

$$q_t = s_t + ln(CPI_t^{EUR}) - ln(CPI_t^{US}) \tag{3.3}$$

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

$$E\Delta s_{t,t+k} = \phi^{(PPP)}(\bar{q}_t - q_t) \;\text{ with } \phi^{(PPP)} > 0 \tag{3.4}$$

Similarly to the measure SHARE_t^{DD} introduced in Eq. (3.2), 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 into the same direction as the forecast made by Eq. (3.4), i.e.

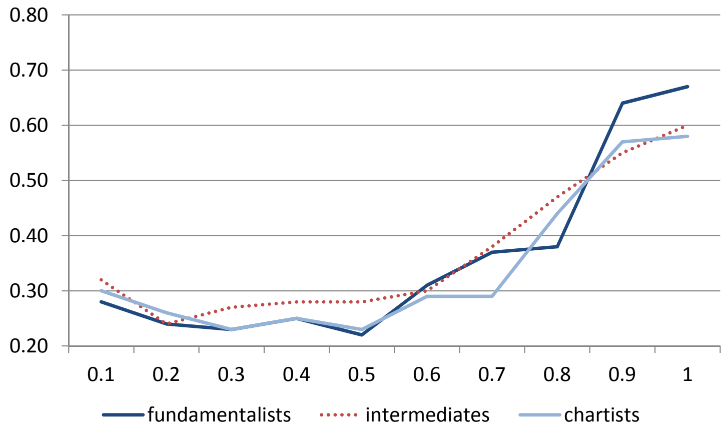
$$\text{SHARE}_i^{PPP} = \frac{\text{number of forecasts by } i \text{ in line with PPP orientation}}{\text{number of all forecasts by } i} \tag{3.5}$$

Table 3.5 and 3.6 (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, which 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 here for the sake of simplicity.

To see how PPP orientation differs depending on the degree of fundamental misalignment, we sort the periods of survey responses into ten intervals according to the deciles of the absolute size of $|\bar{q}_t - q_t|$, and present the averages separately for each of these intervals in Figure 3.2.

Figure 3.2 shows that the orientation at PPP (SHARE^{PPP}) dramatically increases from 0.33 to 0.57 (for intermediates) with increasing misalignment of interest rates. This holds qualitatively true for chartists, intermediates, and fundamentalists. For fundamentalists, this effect appears to be slightly more pronounced, as the average SHARE^{PPP} even increases from 0.27 to 0.63. Overall, the steep increase of SHARE^{PPP} in the five upper deciles is consistent with the view of

Figure 3.2: Observed PPP-orientation, depending on size of fundamental misalignment



This plot represents a set of cross-sectional averages (for each fundamentalists, chartists, and intermediates separately) of the proportion of individual forecasts which are in line with PPP-oriented behavior (based on the deviation of the real exchange rate from its 10-year moving average). The graph in this figure illustrates the averages in dependence of the market phases, i.e. the absolute deviation. The x-axis displays the intervals according to deciles (0.1 representing the lowest 10 percent of observed trends (0-10%), 1 representing the highest 10 percent (90-100%)). The y-axis represents the proportion of forecasts which are in line with PPP orientation (e.g., $0.4 = 40\%$). The solid dark line represents the group of fundamentalists, the solid light line the group of chartists, and the dotted line the group of intermediates.

a non-linear influence of PPP on exchange rate movements (e.g., Taylor, Peel, and Sarno, 2001). The fact that all groups of forecasters exhibit similar behavior in that respect (with only a gradual difference between chartists and fundamentalists) underlines that fundamental analysis is well present in the information set of our group of chartists, a result which again reconfirms the stated preferences by this group.

3.4.2 Results on forecasting dynamics

This section looks at changes in forecasting behavior in two ways. First, we analyze the probability of professionals to switch the *direction* of their exchange rate expectations. Second, we analyze *transitions* from chartist to fundamentalist behavior (and reverse) 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 that technical traders typically provide less stable predictions than fundamentalists (see our *Hypothesis 3*). Agent based models (e.g., by Brock and Hommes, 1998; Farmer and Joshi, 2002; Westerhoff, 2004) adopt this view in their modeling assumptions, such that it is typically a group of "chartists" which - due to its changes in expectations and thus trading positions - is responsible for volatility in the markets. As we discuss below in more detail, our evidence supports this idea.

Table 3.7: Switching probability, correlations and mean

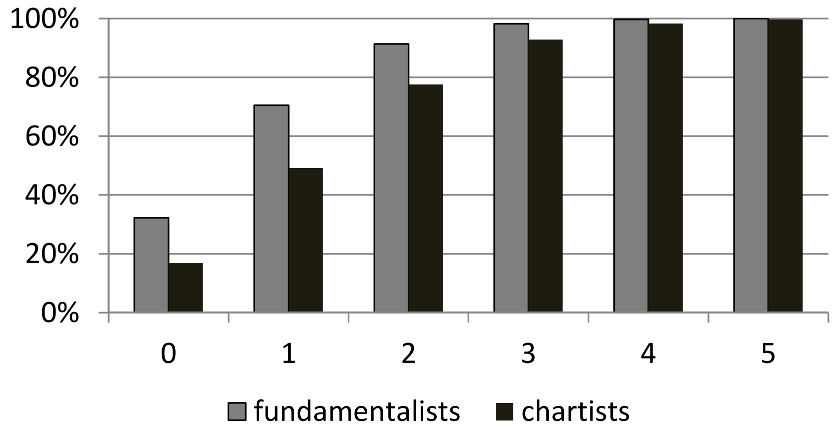
Panel A reports Pearson correlation coefficients for the correlation of the individual probability of switching the direction of an USD/EUR forecast from one month to the next with with the individual survey response about the weights (in percent) attributed to fundamental and technical analysis, respectively. 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 %)	***-0.16
technical analysis (in %)	***0.16
Panel B	Mean switching probability, by group
fundamentalists	0.09
intermediates	0.11
chartists	0.14
t-test fund. vs. chartists	2.35**

We measure the switching probability of an individual forecaster by the relative frequency with which a forecaster changes the direction of his USD/EUR forecast within two subsequent survey months, i.e. 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 3.7, Panel A).

In addition, Table 3.7, 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

Figure 3.3: 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.

difference becomes more visible when translated into probabilities of changes in an annual perspective (see Figure 3.3): 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, which lends support to *Hypothesis 3*.

Explaining the dynamics. The change of expectations may be induced by a switch of strategies, e.g by shifts from fundamental to chartist strategies or reverse. Reasons for such shifts are at the core of our *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. (3.1). 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, i.e.

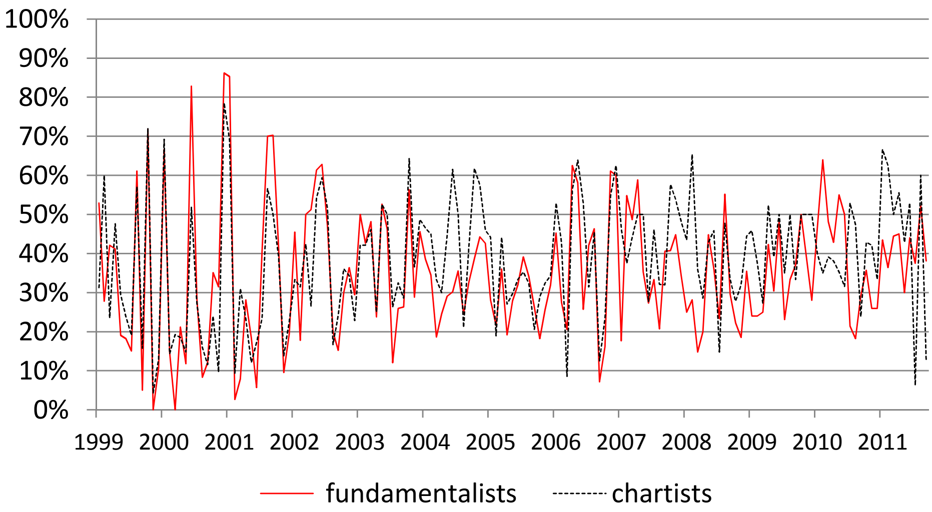
$$\text{SHARE}_t^{30} = \frac{\text{number of forecasters in period } t \text{ in line with trend-following strategy}}{\text{number of all forecasters in period } t} \tag{3.6}$$

Figure 3.4 illustrates how this proportion fluctuates over time, separately for the groups of chartists and fundamentalists. The two graphs show that there are substantial short-term fluctuations in these proportions; it can also be seen that the dynamics are similar, albeit not identical, for chartists and fundamentalists. 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

$$\Delta\text{SHARE}_t^{30} = a_0 + a_1\Delta\text{SHARE}_{t-1}^{30} + a_2\Delta X_t + e_t \tag{3.7}$$

$\Delta\text{SHARE}_t^{30}$ 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, $\Delta\text{SHARE}_{t-1}^{30}$ a lagged

Figure 3.4: Proportion of forecasters in line with momentum following behavior



This plot represents the proportion of forecasters whose forecasts are in line with a momentum-following strategy which follows the trend of the previous 30 days. The graph plots separate lines for fundamentalists and chartists, respectively.

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 at monthly frequency), 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 (our *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 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

$$r_t^{expost(30)} = |f_{t-1}^1 - s_t| \tag{3.8}$$

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 (3.7) as a variable of interest; we refer to changes in returns between two months because we want to explain changes in the share of participants following trends also over two months. Given the idea of our *Hypothesis 4*, we expect to find significantly positive coefficients. Table 3.8, (i), displays the results.

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 size 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 observe very closely if a past momentum strategy -which has been chosen based on the information set a period ago- 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

Table 3.8: 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 into 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 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).

	(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

is the most recent monthly return of an investment decision which was made one month earlier according to Eq. (3.1) based on the trend observed at that time, i.e.,

$$r_t^{TR30} = I_{t-1}(s_{t-1} > E_{t-1}^{(1)}[s_t])(f_{t-1}^1 - s_t) + I_{t-1}(s_{t-1} < E_{t-1}^{(1)}[s_t])(s_t - f_{t-1}^1) \qquad (3.9)$$

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. (3.1). When we include $\Delta r_t^{TR30} = r_t^{TR30} - r_{t-1}^{TR30}$ on the RHS of Eq. (3.7), the coefficient for Δr_t^{TR30} is not significantly different from zero (see Table 3.8, (ii)). Thus, according to this result it is not the behavior described in Eq. (3.9) 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*). We confirm this assumption on the basis of our data; 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, i.e. $|q_t - \bar{q}_t|$ (see Eq. (3.3)) 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 gives stronger weight to observations for which the misalignments are more pronounced. In particular, in the framework of the time series regression as in Eq. (3.7), 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 3.8, (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 substantially large. This result is in line with the earlier finding in Menkhoff, Rebitzky, and Schröder (2008) which is derived by 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 is in line with the notion of non-linearity of the relationship between exchange rates and fundamentals, and confirms our *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 more into the details of the non-linear influence of fundamental misalignment on the forecasting dynamics, we reconsider our *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 our *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 our *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. (3.7) for both states separately, i.e.,

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

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 3.9, Panel A, displays the results.

Table 3.9, (i) and (iv), show that the coefficient for $\Delta r_t^{expost(30)}$ is not significantly different from zero at any conventional significant 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 into 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 forth) standard deviation. Thus, the effects of our *Hypothesis 4* matter more when fundamental misalignment is small.

Unexpectedly, Table 3.9, specification (ii), demonstrates that $\Delta|q_t - \bar{q}_t|$ carries even 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 large 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 3.8), and why only $\Delta|q_t - \bar{q}_t|^2$ reveal the effects as postulated by our *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

Table 3.9: 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 into 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 3.8, 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

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 these two groups separately. We then conduct the regressions introduced by Eq. (3.7). Table 3.10 present the results for chartists and fundamentalists, respectively.

Table 3.10: Explaining switching into momentum strategies, time series regressions by groups

This table reports the results of a regression of the type described in Table 3.8. The regressions are conducted separately for chartists and fundamentalists. (***: 1%, **: 5%, *: 10% significance level).

	Fundamentalists	Chartists
ΔSHARE^{30}	-0.385	-0.488
	***(0.074)	***(0.068)
$\Delta r_t^{expost(30)}$	2.232	1.846
	**(0.873)	**(0.882)
$\Delta\lvert q_t - \bar{q}_t\rvert$		
$\Delta(q_t - \bar{q}_t)^2$	-6.433	-4.496
	***(1.917)	**(1.795)
ΔSHARE^{PPP}	0.324	-0.030
	*(0.176)	(0.171)
ΔSHARE^{CT}	-0.076	0.075
	(0.179)	(0.162)
const.	0.002	0.001
	(0.010)	(0.009)
T	150	150
R^2	0.28	0.30
adj. R^2	0.26	0.28

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 fundamental misalignments are pronounced. 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 that they additionally 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 to its fundamental value. This finding is also in line with intuition.

3.4.3 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 none of our groups is superior in terms of forecasting performance (our *Hypothesis 6*). We illustrate that this holds generally true, albeit chartists appear to be rather 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), and we thus measure *trading* performance with these measures.[48]

For both measures, we follow the concept introduced in Dick, MacDonald, and Menkhoff (2011) and translate the individual forecasts into trading strategies, going long USD (in the forward market) when they expect the USD to appreciate, and short when they expect the opposite.

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

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 six-month-ahead forecast, it is natural to focus on investments with a six-months-horizon ($k = 6$), but we will in addition also consider different investment horizons, i.e. one-, two-, three-, twelve-, 24, and 36-month horizons. Formally, the trading rule is given by

$$r_{t,t+k}^{TR_{IND,k}} = I_t(s_t > E_t^{(IND)}[s_{t+k}])(f_{t,k} - s_{t+k}) + I_t(s_t < E_t^{(IND)}[s_{t+k}])(s_{t+k} - f_{t,k}) \tag{3.10}$$

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 well as the annualized Sharpe ratios. Table 3.11 shows the averages for the groups of fundamentalists and chartists, respectively.

Taking first a 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 which are different from six months. However, we do observe gradual changes in the relative average

Table 3.11: 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).

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%	0.14%	0.09%	0.10%	0.09%
t-values fund. vs. chart.	**2.34	*1.81	0.94	0.44	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	0.45	0.14	0.37	0.11	0.27

performance of chartists and fundamentalists: in fact, Table 3.11 suggests that chartists' forecasts lead to more profitable trading strategies than fundamentalists' forecasts when their forecasts are translated into investments on the one-month-horizon. The average monthly returns are 0.21 percent on average for chartists, and only 0.06 percent for fundamentalists; the Sharpe ratios amount to 0.25 for chartists compared to 0.06 for fundamentalists. The significance of the difference is more pronounced for average returns than for Sharpe ratios, but chartists are also superior according to the latter criterion at least at the ten-percent significance level. On a two-month horizon, the average returns based on FX predictions of chartists are also significantly superior to those based on predictions made by fundamentalists; however, the corresponding difference is not significant any more as far as Sharpe ratios are concerned. For investments at 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 at very short horizon trading strategies. In contrast, the forecasts made by fundamentalists are somewhat better suited to make predictions at intermediate- and long-term horizons than short term horizons, which can be seen in the increasing Sharpe ratios for this group. Our findings corroborate the idea that fundamentalists and chartists forecast on different horizons (e.g. Taylor and Allen, 1992), and it is thus perceivable that fundamentalists might be rather long-term oriented investors and their forecasts may not be meant to be evaluated at short-term horizons such as one month. For longer horizons, in contrast, fundamentalists and chartists appear to be comparably profitable, which supports *Hypothesis 6* and underlines the efficiency of FX markets in this important respect.

3.5 Robustness

This section informs about several robustness tests we have performed; they do not qualitatively affect our findings. (i) 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 (ii) controlling for volatility and (iii) without including the autoregressive term in Eq. (3.7). (iv) Finally, we test the robustness of our approach by substituting the trading strategy as a measure of performance by a measure of forecast accuracy.

Controlling for alternative trading rules. So far and throughout this study, our LHS variable in Eq. (3.7) 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 with certainty *based* on that particular rule. In this paragraph we address the possibility that forecasters have made their forecasts on a different, i.e. PPP-oriented trading rule or carry trade rule.

To ensure that our results in the main part are not driven by the coincidence between the predictions from alternative rules, 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.[49] We compute the proportion of forecasters whose forecasts are in line with those strategies, i.e. 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. (3.7).

Table 3.8, (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 alter any of the other coefficients in a substantial way. Overall, the main results for our *Hypotheses 4* and *5* are also confirmed in this setting.

Controlling for volatility. We also test whether our results in Section 3.4.2 hold when we control for volatility. A positive association between turbulence in markets and the use of chartist rules has been postulated by, e.g., De Grauwe and Grimaldi (2006). More specifically, we compute the standard deviation of daily returns during the 30 days before an individual forecast has been made, and take the cross-sectional mean of these values for each survey period t, henceforth $\sigma_t^{(30)}$. A survey period characterized by high average volatility measures is interpreted to be particularly turbulent, and we consider changes in volatility $\Delta\sigma_t^{(30)}$ as a variable of interest in our regression Eq. (3.7).

[49]The PPP rule follows the concept from Eq. (3.4), 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.

As Table 3.8, (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. (3.7), which captures a lagged dependent variable. As a robustness check, we also reconsider the dynamics with a specification without an AR(1) term, i.e.,

$$\Delta\text{SHARE}_t^{30} = a_0 + a_2 \Delta X_t + e_t \tag{3.11}$$

Table 3.12 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* do thus not depend on the inclusion of a lagged dependent variable into the time series regressions.

Table 3.12: 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 into 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 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 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).

	(i)	(ii)	(iii)	(iv)	(v)
$\Delta r_t^{expost(30)}$	2.526				2.568
	***(0.868)				***(0.745)
$\Delta r_t^{TR(30)}$		-0.637			
		-0.747			
$\Delta\|q_t - \bar{q}_t\|$			-0.767		
			-0.881		
$\Delta(q_t - \bar{q}_t)^2$				***-5.039	***-4.984
				-1.782	-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	0.06	0.01	0.01	0.06	0.13
adj. R^2	0.06	0	0	0.06	0.12

Forecast errors. To illustrate that the results of our discussion of *Hypothesis 6* are not driven by the way how 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 (e.g., 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

Table 3.13: 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

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.[50] It has to be noted that forecasters can be mistaken to two different extents: 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 3.13 presents the average absolute forecast errors for the groups of chartists and fundamentalists.

Table 3.13 shows very similar results as 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) forecast 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.

[50]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.

3.6 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 root 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 been 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 at 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. This research is the first - to the best of our knowledge - 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, e.g., favoring longer horizons than foreign exchange traders. Regarding the chartist-fundamentalist models, these are highly stylized and reduce market behavior in drastic ways: e.g., chartist behavior is more than trend-following and fundamental behavior reaches beyond PPP-orientation. This may be considered more explicitly in future research.

4. Using expectations to study the uncovered equity parity

4.1 Introduction

In addition to agents in the real economy, exchange rates also matter to *financial investors* who build their equity portfolio internationally: their portfolio weights of foreign assets do not only fluctuate due to stock market movements, but also due to movements in exchange rates. Traditional (macroeconomic) exchange rate models primarily consider exchange rate movements being determined by the real economy (and not by financial investors), however, with little empirical success in predicting patterns of exchange rate movements (e.g., Meese and Rogoff, 1983; Cheung, Chinn, and Garcia-Pascual, 2005). In contrast, a set of more recent articles shift their attention to the role of investors, either by incorporating a *valuation channel* into models of international imbalances (in addition to traditional *trade channels*) (Gourinchas and Rey, 2007), or by partial equilibrium models which ignore good markets and exclusively focus on the responsibility of capital markets for exchange rate movements (Hau and Rey, 2004, 2006).

This essay follows the logic of the approach by Hau and Rey (2006) and investigates the connection between exchange rate movements, capital flows, and stock market returns. Unlike Hau and Rey (2006), we take a more explicit focus on investors' *expectations*, in particular with respect to the correlation between exchange rates and stock market returns. Hau and Rey (2006) demonstrate theoretically that exchange rate movements incorporate an automatic (partial) hedge against risk from foreign equity. Their argument can be summarized as *uncovered equity parity* and runs as described here: when the foreign investment increases in value relative to domestic investments, investors readjust the portfolio weights of foreign assets accordingly by selling some of these; hence, they have to convert foreign currency into domestic currency, which decreases the value of the foreign currency. Inversely, the price of foreign currency increases when foreign stock market returns are low. Hau and Rey (2006) show empirically that foreign currency depreciation and higher returns on foreign equity are in fact related as predicted by their model. In contrast, they obtain rather mixed empirical results with respect to the correlation coefficient between capital flow and exchange rate movements, which is supposed to be in positive territory according to the theoretical model.[51]

This essay studies the *expectations* about the link between future exchange rate movements and relative foreign stock market returns (i.e., returns on foreign equity minus returns on domestic equity) in a time varying framework.[52] This aspect is important as changes in the *perceived* correlation between foreign exchange and foreign equity returns have implications for portfolio allocation: a negative correlation coefficient (as implied by Hau and Rey, 2006) leads *ceteris paribus* to higher foreign investment due to the hedging properties. As a consequence there should be portfolio rebalancing when the expected correlation changes; in this vein, equity flows depend (at least in theory) on the perceived strength of the relationship between relative returns and exchange rates. Hence, we consider these perceptions explicitly in order to learn in which periods the mechanisms suggested by portfolio rebalancing models are most dominant.

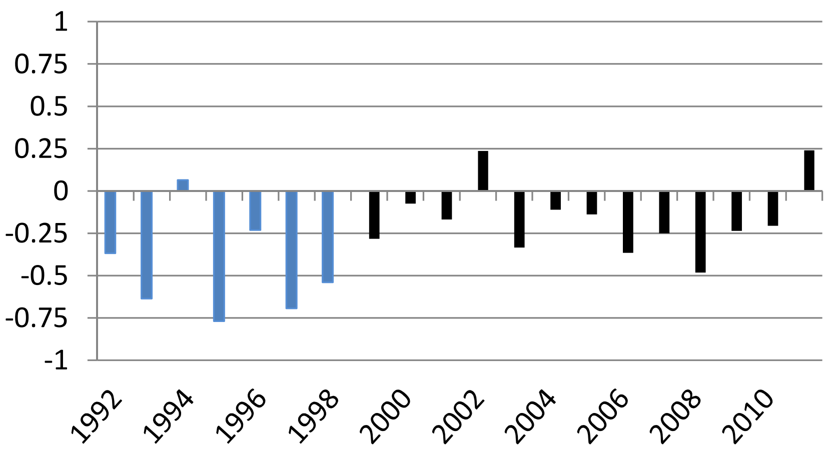
It has to be noted that, *within* the framework of the model by Hau and Rey (2006), the correla-

[51]In fact, Hau and Rey (2006) find insignificant correlation coefficients between -0.09 and 0.12 for the country pair U.S and Germany. Nevertheless, these authors interpret their findings to be supportive of their prior: they point out that the results appear more in line with the theoretical prediction when attaching a stronger weight to more recent observations and pooling data of 17 currency pairs (OECD countries and the U.S.).

[52]More specifically, we consider the country pair of the U.S.A. and Germany; to remain consistent with the article by Hau and Rey (2006), we refer to the U.S. as the "domestic" and Germany as the "foreign" country, regardless of the fact that from the perspective of the examined forecasters, Germany is the home country.

tion between relative foreign stock market returns and foreign exchange rate appreciation should be perfectly negative ($\rho = -1$) at all times. By our specific focus on time-varying expectations, we abandon this paradigm for two reasons: first, this result arises from the assumption that, in the model, exchange rate movements and return differences are solely due to different dividend shocks in the respective countries. This restrictive assumption does not need to hold in reality, such that influences from *outside* the model can also be present. Second, Figure 4.1 shows that the correlation between relative foreign stock market returns and foreign exchange rate appreciation varies over time when looking at realizations (albeit reassuringly, being most of the time negative). Given that experience, it is perceivable that also the expected relationship between relative returns and exchange rates (an *implicitly expected correlation*) fluctuates over time.

Figure 4.1: Exchange movements and relative stock market returns: correlation over time



This figure displays the correlation coefficients between changes in the USD/EUR (since 1999) or the USD/DM (before 1999) rate (e.g., $\Delta FX_t > 0 \Rightarrow$ US- Dollar depreciation) and relative stock market returns ($\Delta r_t = r_t^{DAX} - r_t^{DOW}$), computed with monthly data for each year separately.

To study implicitly expected correlations, we rely on a unique data set of individual expectations collected by the Centre of European Economic Research (ZEW) in Mannheim, Germany. The dataset contains macroeconomic and financial expectations by professional forecasters located in Germany. It is particularly well suited for our research agenda as we are able to connect exchange rate and stock market expectations for each individual forecaster separately, and thus study to what extent (in the cross-section) forecasters expect foreign exchange rate depreciation and relative foreign stock market returns to coincide. Due to the location and professional experience of the forecasters, we conjecture that their predictions are most accurate for the German market as well as the U.S. market. Hence, we focus on the exchange rate, capital flows, and relative stock market returns between the U.S. and Germany. We demonstrate that the implicitly expected correlation is only negative in the period 1992 to fall 1998, whereas it is fluctuating in positive territory afterwards. While we acknowledge that this may be due to additional mechanisms (beyond the one sketched by Hau and Rey, 2006) in the minds of the forecasters, we further investigate to what extent the implicitly expected correlation has an impact on the relationship of *realized* stock market returns or capital flows at the one hand and exchange rate movements at the other.

Over the last decades, potential links between exchange rates and stock market returns have been discussed in literature under changing paradigms. A more traditional view studies the exchange rate exposure of companies, through which exchange rate movements alter the companies' competitive position and, ultimately, affect stock prices. In seminal articles, Adler and Dumas (1983, 1984) suggest to determine a company's exchange rate exposure by the means of a regression of the stock return on the market return and on changes in the exchange rates. Jorion (1990) follows this idea and finds that US companies with foreign operations exhibit a stronger heterogeneity in foreign exchange rate risk exposure than purely domestically-operating firms. However, more recently, Bartram and Bodnar (2010) summarize a variety of empirical papers on exchange rate exposure, which show in general only limited support for the idea of exposure, and highlight that corporations have financial and operative hedging tools which they use in dependence on their degree of international orientation. In contrast, a more recent line of literature stresses that the link between exchange rates and stock returns originates in financial investors' actions rather than goods markets. This literature focuses on *portfolio rebalancing decisions* of financial investors who buy or sell in the foreign stock market for their internationally diversified portfolio. This line of literature corresponds to an increased interest in the determinants of international asset trade, such as equity investment across countries (Portes and Rey, 2005; Lane and Milesi-Ferretti, 2008). As a stock is denominated and traded in a specific currency, an international investment involves currency risk unless it is entirely hedged by further financial instruments. Similarly to earlier papers on *exchange risk* in an international portfolio theory (e.g., Dumas and Solnik, 1995; De Santis and Gérard, 1998), Hau and Rey (2006) assume that investors cannot fully hedge against exchange rate risk and thus bear risk both from exchange rate and equity price volatility when investing internationally. In an additional analysis, Hau and Rey (2004) use a novel identification approach of the variance matrix to analyze conditional correlations which are implied by portfolio balancing models. Francis, Hasan, and Hunter (2006) also argue that it is portfolio rebalancing which links equity and foreign exchange markets, but these authors describe a more indirect mechanism of how it becomes effective: they stress that portfolio rebalancing is private information of the respective international investor in the first place, but that a dynamic interdependence between equity and currency markets arises as information spreads (observable through order flow) to all market participants. This idea goes back to Evans and Lyons (2002), who introduce their portfolio shift model to explain the informational content of order flow for exchange rate determination without referring explicitly to returns in equity markets. Our research is also conceptualized under the paradigm that financial investors, and not agents in good markets, are primarily responsible for the link between exchange rates and stock market returns; our contribution even goes in a sense further to that direction by investigating to what extent these investors' *expectations* matter.

In line with previous literature, our empirical analysis reconfirms the negative association between realized relative foreign stock market returns and foreign exchange rate appreciation. However, this result is only pronounced for an earlier period (1992-1998), and much weaker for a later period (1999-2011). We demonstrate that for the later period, the negative association is much stronger when the implicitly expected correlation is controlled for in an interaction model. We interpret these results in the following way: the conjectured negative relation between exchange rate movements and relative stock market returns (due to portfolio rebalancing) is in fact present in markets, but is complemented by further mechanisms from outside the model. Hence, the negative relation only materializes if these other mechanisms are not dominant; the inclusion of expectations about that relation helps us to determine when this is the case. In a similar vein, we investigate whether the implicitly expected correlation helps to reestablish the positive relationship between capital flows in the foreign country and exchange rate appreciation of that country, which is implied by Hau and Rey (2006)'s model, but not reconfirmed empirically by these authors for the U.S. and Germany. Based on our analysis, however, it has to be noted that this cannot be shown unambiguously.

The remainder of this chapter is organized as follows: Section 4.2 sketches our approach to identify the implicitly expected correlation between relative stock market returns and foreign exchange movements. Section 4.3 discusses the data sources in more detail. Section 4.4 presents the empirical results of this study. Section 4.5 concludes.

4.2 Implicitly expected correlation

Methodology. While most empirical strategies used in our analysis are standard, our approach to measure the *implicitly expected correlation* between relative stock market returns and exchange rate movements deserves clarification. We base our analysis on a dataset of individual qualitative forecasts of both exchange rates and stock market changes which is described in more detail in Section 4.3. These forecasts are issued on a monthly basis, such that we obtain a panel with a relatively large N (on average, about 300 forecasters per wave). More specifically, we have information about whether a forecaster expects the USD to appreciate/remain constant/depreciate against the Euro, and about whether they expect the DAX and the Dow Jones to increase/remain constant/decrease over the next six months. To operationalize this, we code a stock market increase (decrease) to equal unity (minus unity), and a USD depreciation (appreciation) to equal unity (minus unity); the latter convention is chosen as we consider the exchange rate of the USD in terms of one unit of Euros, which implies $\Delta FX_t > 0$ to correspond to a dollar depreciation. For all variables, the no-change variable is coded zero; hence, the directional forecasts are mapped into the $\{-1, 0, 1\}$ -space. In the following, $r_{t,i}^{e,DAX}$ and $r_{t,i}^{e,DJ}$ denote the expected DAX and Dow Jones return, respectively, and $\Delta FX_{t,i}^{e}$ the expected USD depreciation; the subscript t refers to the period in which the forecast is made for the subsequent six months, the subscript i to the individual forecaster.

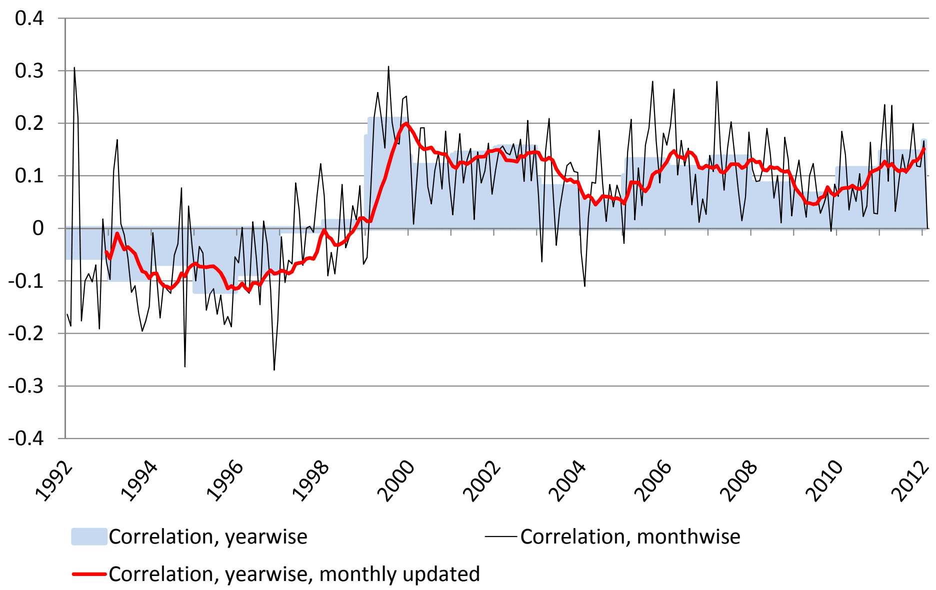
Central for our interest is the *association* between these three variables, i.e., does a forecaster predict a Dollar appreciation (first variable) when they expect the DAX (second variable) to outperform the Dow Jones (third variable)? The two stock-market-related variables can easily be conceptually combined by taking the difference $\Delta r_{t,i}^{e} = r_{t,i}^{e,DAX} - r_{t,i}^{e,DJ}$, which we refer to as the *expected relative stock market returns*. While Δr_t^e can be interpreted as an expectations-based equivalent to the relative stock market returns $\Delta r_{t,i} = r_{t,i}^{DAX} - r_{t,i}^{DJ}$ considered in the Hau and Rey (2006)-framework, it is mapped into the $\{-2, -1, 0, 1, 2\}$-space. However, it has to be noted that $\Delta r_{t,i}^{e}$ is (due to the qualitative character of our forecasts) only sensitive to pronounced differences between DAX and Dow Jones returns, which only allows us to identify expected relative stock market returns in a relatively rough grid. As a consequence, $\Delta r_{t,i}^{e}$ equals zero in 66 percent of the observations in the panel; strong expected divergences of these two stock markets (i.e., $\Delta r_{t,i}^{e} = \{-2, 2\}$: an expected increase of one market and an expected decrease of the other market) are only present in 6 percent of the observations.

Ultimately, we are interested in the association between the expected relative stock market returns $\Delta r^e_{t,i}$ and the expected USD depreciation $\Delta FX^e_{t,i}$. As we observe the corresponding expectations for each forecaster individually (which we are able to link to each other), we are also able to identify the pattern of how these forecasts relate to each other. As a measure of association, we compute Spearman's correlation coefficients $\tau_t = \text{Corr}_t(\Delta r^e_{t,i}, \Delta FX^e_{t,i})$ for each survey wave across the cross-sectional units i. Note that τ_t is negative if an expected dollar appreciation is associated with the U.S. stock returns being expected to be lower than the German stock returns; this is equivalent to the stylized facts (in terms of realizations) documented by Hau and Rey (2006).

Some first results. As described above, we compute τ_t based on the expectations in our dataset from 1992 to 2011. The thin black line in Figure 4.2 illustrates how τ_t fluctuates over time.

For a smoother picture, Figure 4.2 also provides correlation coefficients estimated within yearly (instead of monthly) intervals. These measures illustrate that a negative correlation coefficient has been implicitly expected from 1992 to fall 1998, whereas the expected correlation is positive ever since. Nevertheless, there are also fluctuations of τ_t in that latter period, with the correlation coefficients at some points falling below the 0.1 threshold. Given that realized correlations are typically negative (see Figure 4.1), the positive value of τ_t after 1998 is somewhat surprising. Therefore, we also investigate whether these results arise from the use of the expected DAX returns, which do not need to be the relevant reference after the introduction of Euro. However, as Figure 4.3 demonstrates, the picture also holds true for expected relative stock market returns computed on the basis of Eurostoxx expectations, which are available since 1999.01.

Figure 4.2: Time-varying expected correlations



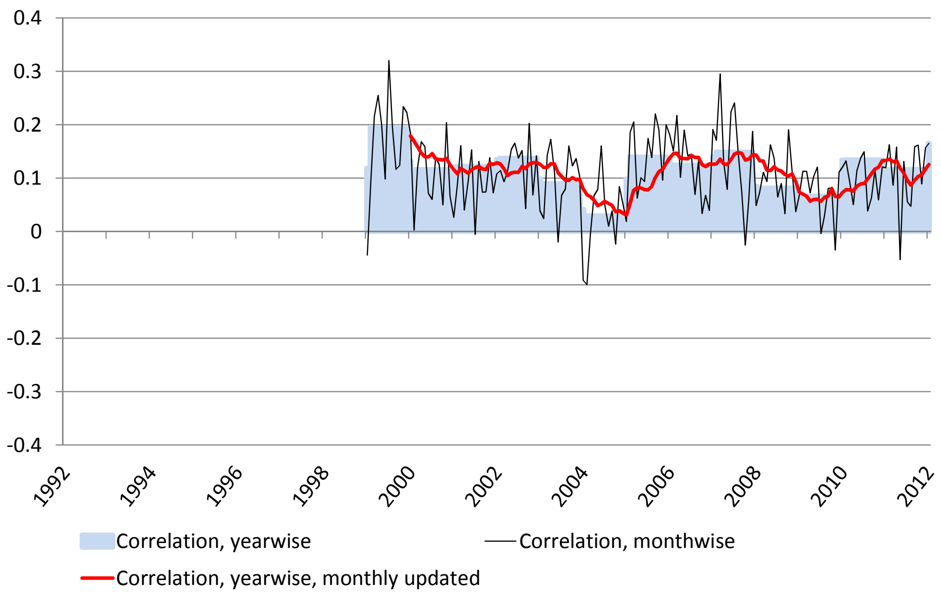
The figure presents how the cross-sectional correlation τ_t between expected relative stock market returns ($\Delta r^e_{t,i}$) and expected USD depreciation ($\Delta FX^e_{t,i}$) fluctuates over time. The considered stock markets are the German stock market (captured by the DAX) and the U.S. stock market (captured by the Dow Jones). The thin line represents τ_t (computed for each survey wave). The blue bars represent the correlation coefficients computed for the respective calendar year (based on all survey waves of the respective year). The red line represents the correlation coefficient computed on the basis of all survey waves from $t - 12$ to t.

4.3 Data and variable description

This section describes in more detail the micro data of expectations mentioned above. Furthermore, we introduce data on capital flow, stock market returns, and exchange rates.

Data on financial expectations. The micro dataset on financial expectations is collected by the Centre for European Economic Research (ZEW) in Mannheim from its monthly Financial Market Survey among about 300 financial professionals in the German financial industry. This dataset contains expectations from 1991.12 to 2012.01. For the purposes of our analysis, these data are particularly useful as they include both exchange rates and stock market expectations,

Figure 4.3: Time-varying expected correlations, with Eurostoxx expectations



The figure presents how the cross-sectional correlation τ_t between expected relative stock market returns ($\Delta r^e_{t,i}$) and expected USD depreciation ($\Delta FX^e_{t,i}$) fluctuates over time. The considered stock markets are the European stock market (captured by the Eurostoxx 50) and the U.S. stock market (captured by the Dow Jones). The thin line represents τ_t (computed for each survey wave). The blue bars represent the correlation coefficients computed for the respective calendar year (based on all survey waves of the respective year). The red line represents the correlation coefficient computed on the basis of all survey waves from $t - 12$ to t.

the latter for the stock market indices of several countries, including the DAX and the Dow Jones. More specifically, the forecasters are asked "*In the medium-term (6 month) the DAX/the Dow Jones will increase/ not change/ decrease*" and "*In the medium-term (6 months) the USD compared to the Euro will appreciate/ stay constant/ depreciate*", hence, the forecasts in our dataset are of directional nature, which are operationalized as described in Section 4.2.

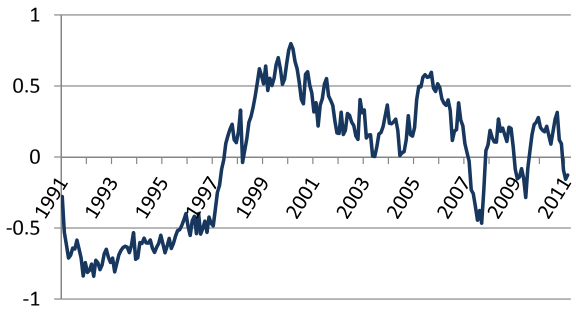
Figure 4.4 illustrates that the overall exchange rate expectations are characterized by only few, long-standing phases in which either an appreciation or a depreciation was dominant. In the earlier years considered in this analysis (1992 to 1997), the USD was clearly expected to appreciate, whereas in most of the time period between 1999 and 2007, the USD was expected to depreciate against the Euro. Since the beginning of the financial crisis, there are two cycles with changing expectations.

Figures 4.5 (a) and (b) illustrate that the overall-level of stock market expectations is on average larger than zero. This corresponds to the notion of that (unconditional) expected stock market returns are positive (the risk free rate plus a risk premium). Figure 4.6 shows that the balances for the DAX are on average larger than the balances for the Dow Jones, which does not exclude that the opposite expectations may be prevailing at the individual level for some forecasters.

Exchange rates and national stock market indices. Exchange rates and national stock market indices for the U.S. and Germany (i.e., the Dow Jones and the DAX) are obtained on a daily basis since 1991 (i.e., the year when the survey among financial professionals has been launched). It has to be noted that we consider the USD/DM exchange rate until 1998.12, and the USD/EUR exchange rate ever since; Figure 4.7 depict these exchange rates, denoted in USD per unit of DM or EUR, respectively.

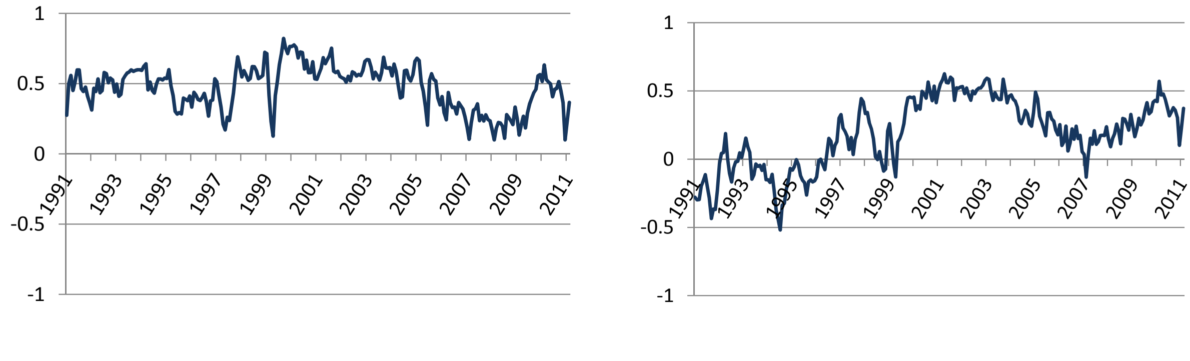
We transform the Dow Jones and DAX data into a monthly series of (monthly) returns (r_t^{DAX} and r_t^{DOW}); this allows to consider the aggregate stock market returns in the U.S. and Germany over time (see Figure 4.8, (a) and (b)). We also compute the return differential $\Delta r_t = r_t^{DAX} - r_t^{DOW}$, which is displayed in Figure 4.8, (c).

Figure 4.4: Exchange rate expectations



This table illustrates the balance statistics for the exchange rate expectations of the professional forecasters surveyed within the framework of the ZEW Financial Market Survey. Before 1999.01, expectations are collected w.r.t. the USD/DM exchange rate. The balance statistic is computed by taking the difference between the percentage share of forecasters who expect the EUR (DM) to appreciate compared to the USD minus the percentage share of forecasters who expect the EUR (DM) to depreciate compared to the USD.

Figure 4.5: Stock market expectations

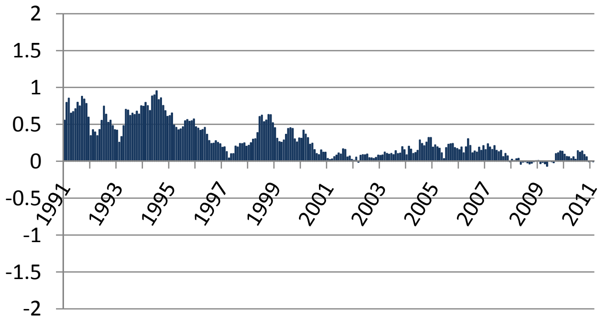


(a) DAX expectations

(b) Dow Jones expectations

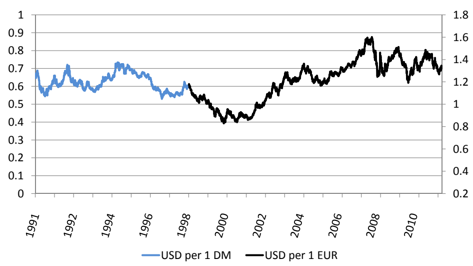
This table illustrates the balance statistics for the stock market expectations of the professional forecasters surveyed within the framework of the ZEW Financial Market Survey. The balance statistic is computed by taking the difference between the percentage share of forecasters who the respective stock market index to incease minus the percentage share of forecasters who expect the stock market index to decrease.

Figure 4.6: Cross-country differences in stock market expectations



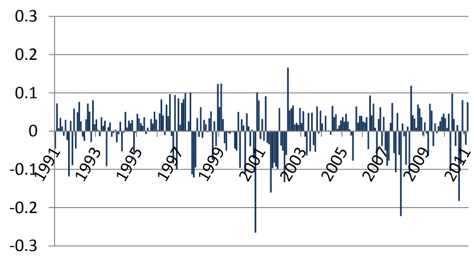
This table illustrates the balance statistics for the stock market expectations of the professional forecasters surveyed within the framework of the ZEW Financial Market Survey. Before 1999.01, expectations are collected w.r.t. the USD/DM exchange rate. The balance statistic is computed by taking the difference between the percentage share of forecasters who expect the respective stock market index to increase minus the percentage share of forecasters who expect the stock market index to decrease.

Figure 4.7: Exchange rate of the USD w.r.t DM and EUR

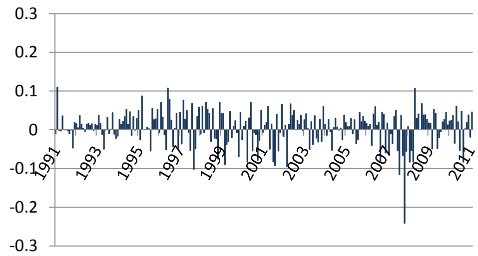


This figure displays the graphs of the foreign exchange rate, given in terms of USD per unit of EUR and DM, respectively. It has to be noted that the left y-axis corresponds to the USD/DM exchange rate (line in blue color), whereas the right y-axis corresponds to the USD/EUR exchange rate (line in black color).

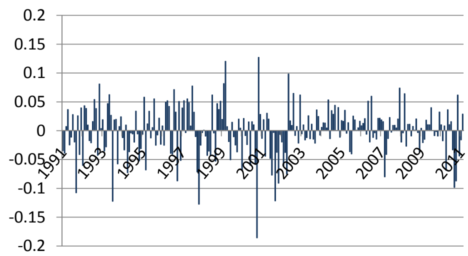
Figure 4.8: Stock market returns of the DAX, the Dow Jones, and return differentials



(a) r_t^{DAX}



(b) r_t^{DOW}

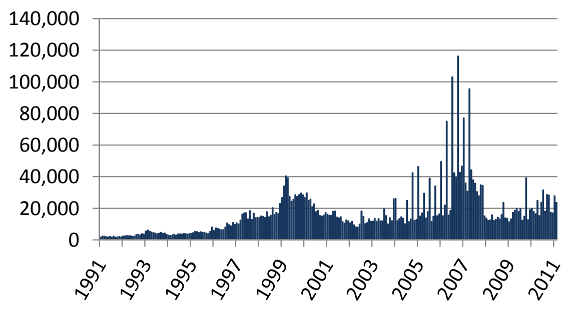


(c) $\Delta r_t = r_t^{DAX} - r_t^{DOW}$

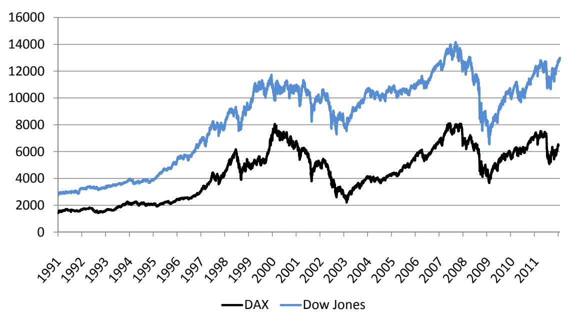
These figures present monthly series of monthly returns (over the past 30 calendar days) of the DAX and the Dow Jones, respectively, in (a) and (b). (c) presents the return differential of these returns, i.e., $\Delta r_t = r_t^{DAX} - r_t^{DOW}$.

Capital flow. Finally, we follow Hau and Rey (2006) and make use of the data on capital flows offered by the (U.S.) Treasury International Capital System (henceforth TIC-data), which has been described in detail by Griever, Lee, and Warnock (2001). These data collect information about aggregate capital flows between the U.S. and other countries. For our purposes, we consider the equity capital flows between the U.S. and Germany; more specifically, we observe purchases of U.S. and foreign corporate stocks by U.S. residents from foreign residents, and sales of U.S. and foreign corporate stocks made by U.S. residents to foreign residents. The sum of these trades carry information about the degree of financial interconnectedness, and is typically referred to as *bilateral gross equity flow*. Figure 4.9, (a), shows that bilateral gross equity flows between the U.S. and Germany have increased over the past two decades, and have locally peaked in times of bullish stock markets (i.e., 2000 and 2007, see Figure 4.9, (b)).

Figure 4.9: Bilateral gross equity flows



(a) Bilateral gross equity flow

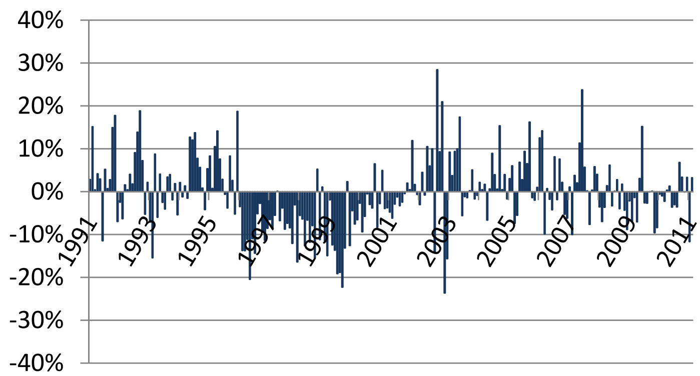


(b) Stock markets

Figure (a) illustrates the bilateral gross equity flows between the United States and Germany from 12.1991 to 01.2012, denoted in millions of USD. Bilateral gross equity flows are the sum of the purchases of US stocks and German stocks by US residents from foreigners plus the sum the purchases of US stocks and German stocks by foreigners from US residents. (b) represents the DAX and the Dow Jones over time.

However, for the analysis of the relationship between portfolio reallocation and exchange rates, the variable of interest is not interconnectedness, but relative equity flows, i.e., *net capital inflow in the foreign country*. This balance is given by the difference between *net purchases of foreign equity* (i.e., purchases of German equity by U.S. residents from foreign residents minus sales of German equity by U.S. residents to foreign residents) and *net sales of U.S. equity* (i.e., sales of U.S. equity by U.S. residents to German residents minus purchases of U.S. equity by U.S. residents from German residents). We follow the convention by Hau and Rey (2006) and scale the net capital inflow in the foreign country by *bilateral gross equity flow* to obtain a relative flow measure which is unaffected by the overall degree of interconnectedness of financial markets. In the following, the scaled net capital inflow into the foreign country will be denoted by $dK_t^f - dK_t^h$. Figure 4.10 plots $dK_t^f - dK_t^h$.

Figure 4.10: Net capital inflow into Germany by U.S. investors



This figure illustrates the net capital inflow from United States to Germany from 12.1991 to 01.2012, denoted in percent of the bilateral gross equity flows (see Figure 4.9). The net capital inflow from United States to Germany is defined as the difference between the net purchases of German stocks by US residents minus the net sales of US stocks to German residents.

4.4 Empirical Analysis

In the following, we detail our empirical analysis. In particular, we investigate whether or not exchange rate changes are related to relative stock returns, and whether or not exchange rate changes systematically react to capital flows. Our empirical analysis is partly based on models which incorporate our measure of implicitly expected correlations introduced in Section 4.2.

4.4.1 Exchange rates and relative stock returns

In the following paragraphs, we first present our empirical model which reconsiders the relationship between relative stock market returns and exchange rates, with and without incorporating the role of implicitly expected correlations. Second, we discuss the properties of the time series which are needed for our analysis. Finally, we present and discuss the results.

Empirical model. In a first step, we follow Hau and Rey (2006) and relate contemporaneous changes in exchange rates ΔFX_t to relative stock market returns Δr_t by both correlation analysis and regression techniques. In particular, we conduct the regression

$$\Delta FX_t = \alpha + \beta \Delta r_t + \epsilon_t \tag{4.1}$$

and consider both the significance of $\hat{\beta}$ as well as the R^2 to determine the strength of the relationship. Going beyond Hau and Rey (2006) in a second step, we estimate an interaction model

$$\Delta FX_t = \alpha + \gamma_1 \Delta r_t + \gamma_2 \tau_t + \gamma_3 (\Delta r_t \times \tau_t) + \epsilon_t \tag{4.2}$$

in which the implicitly expected correlation at t, τ_t, enters. The idea of this approach is to investigate whether the expected correlation alters the effect which the relative stock market return has on exchange rate movements, i.e. $\frac{\partial \Delta FX_t}{\partial \Delta r_t}\Big|_{\tau_t}$.

Both the analysis from Eqs. (4.1) and (4.2) will be done separately for the time period before the introduction of the Euro in 1999, and afterwards. Also, we consider movements and returns both at a monthly frequency (looking at the past 30 days from the 15th of each month) and at a quarterly frequency (looking at the past 90 days from the 15th of month in the middle of a quarter).

Stationarity tests. The empirical approach sketched above requires stationary time series, .i.e. monthly and quarterly data on exchange rate movements (ΔFX_t), relative stock returns (Δr_t), and the implicitly expected correlation measure (τ_t). Table 4.1 shows the results from Dickey-Fuller-tests. The null hypothesis of a unit root in the data can be convincingly rejected for the considered variables.

Results. Table 4.2 presents the results of the regressions based on Eqs. (4.1) and (4.2). On the left hand side (Panel A), the table displays the correlation between ΔFX_t and Δr_t. It can be seen from the upper part that, for the period before the introduction of the Euro (1992-1998), the correlation between these two series is strongly negative (with -0.47 for monthly and even -0.61 for quarterly data). The idea that relative stock returns and currency movement are correlated in that fashion is also underlined by the estimates for $\hat{\beta}$ for Eq. (4.1): the coefficient is negative and strongly significant at all conventional significance levels, both for monthly as well as quarterly data. In addition, the R^2 is substantial with 0.22 and 0.38 for monthly data and quarterly data, respectively. These results confirm the findings by Hau and Rey (2006), who demonstrate that this relationship is strong between 1991 and 2001.

In contrast, the correlation as well as the estimated parameter is remarkably lower for the period

Table 4.1: Dickey- Fuller tests

This table represents Dickey Fuller test. The null hypothesis is that the respective time series contains a unit root. The null can be rejected if the test statistic exceeds the critical value in absolute size.

Variable	Period	Frequency	Test statistic	1%	5%	10%
ΔFX_t (USD/DM)	1992-1998	monthly	-7.915	-3.534	-2.904	-2.587
		quarterly	-5.909	-3.736	-2.994	-2.628
ΔFX_t (USD/EUR)	1999-2011	monthly	-11.861	-3.491	-2.886	-2.576
		quarterly	-6.518	-3.579	-2.929	-2.600
Δr_t	1992-1998	monthly	-9.315	-3.534	-2.904	-2.587
		quarterly	-5.186	-3.736	-2.994	-2.628
	1999-2011	monthly	-11.775	-3.491	-2.886	-2.576
		quarterly	-4.507	-3.577	-2.928	-2.599
τ_t	1992-1998	monthly	-6.575	-3.534	-2.904	-2.587
		quarterly	-3.646	3.736	-2.994	-2.628
	1999-2011	monthly	-9.250	-3.491	-2.886	-2.576
		quarterly	-6.805	-3.579	-2.929	-2.600
$dK_t^f - dK_t^h$	1992-1998	monthly	-5.481	-3.534	-2.904	-2.587
		quarterly	-2.433	3.743	-2.997	-2.629
	1999-2011	monthly	-9.239	-3.492	-2.886	-2.576
		quarterly	-4.733	-3.580	-2.930	-2.600

from 1999-2011: the correlation is -0.14 for monthly data and -0.15 for quarterly data, which is only significantly different from zero for monthly data. The same holds true for $\hat{\beta}$, and the R^2 of these regressions are at the 0.02 level. It appears that, according to the estimates from Eq. (4.1), the negative correlation between exchange rate movements and relative stock returns is very weak.

Panel B draws a different picture when reporting the results of the regression according to Eq. (4.2): for the time period 1999-2011, the $\hat{\gamma}_1$ coefficient is strongly significant, and also the $\hat{\gamma}_3$ coefficient is significant at least at the ten percent level (for both monthly and quarterly data). The R^2 of these regressions increases substantially. When considering the marginal effects of a change in relative stock market returns on exchange rate movements, we have to consider $\hat{\gamma}_1 + \tau_t \times \hat{\gamma}_3$. Thus, the marginal effect is most negative when τ_t is small; in fact, the smallest value of τ_t is around zero in that time period, such that it corresponds to the -0.29 measured for the earlier

Table 4.2: Relation between foreign exchange movements and relative stock market returns

This table summarizes statistics to illustrate the relation between changes in the USD/EUR rate (e.g., $\Delta FX_t > 0 \Rightarrow$ US- Dollar depreciation) and relative stock market returns ($\Delta r_t = r_t^{DAX} - r_t^{DOW}$) with respect to the Dow Jones and the DAX. We consider monthly data of changes over the previous 30 calendar days, and quarterly data of changes (mid quarter) over the previous three months alternatively. We proceed in two steps: Panel A represents the analysis similar to the one by Hau and Rey (2006), which collects the Pearson correlation coefficients between ΔFX_t and Δr_t (over the indicated time span), $Corr(\Delta FX_t, \Delta r_t)$, and estimates $\Delta FX_t = \alpha + \beta \Delta r_t + \epsilon_t$. Panel B displays the coefficient estimates and measures of fit for an interaction model, $\Delta FX_t = \alpha + \gamma_1 \Delta r_t + \gamma_2 \tau_t + \gamma_3 (\Delta r_t \times \tau_t) + \epsilon_t$, in which τ_t represents the implicitly expected correlation at time t. We split the considered period into subperiods from 1992-1998 (where the USD/DM rate is considered) and from 1999-2011 (where the USD/EUR rate is considered). (***: 1%, **: 5%, *: 10% significance level)

	Panel A $\Delta FX_t = \alpha + \beta \Delta r_t + \epsilon_t$				Panel B $\Delta FX_t = \alpha + \gamma_1 \Delta r_t + \gamma_2 \tau_t + \gamma_3 (\Delta r_t \times \tau_t) + \epsilon_t$				
1992-1998	$Corr(\Delta FX_t, \Delta r_t)$	$\hat{\beta}$	R^2	R^2_{adj}	$\hat{\gamma_1}$	$\hat{\gamma_2}$	$\hat{\gamma_3}$	R^2	R^2_{adj}
monthly	-0.47***	-0.29	0.22	0.21	-0.31	-0.04	-0.31	0.24	0.22
		***(0.06)			***(0.06)	*(0.02)	(0.52)		
quarterly	-0.61***	-0.39	0.38	0.35	-0.40	-0.04	-0.22	0.38	0.30
		***(0.11)			***(0.10)	(0.07)	(1.04)		
1999-2011	$Corr(\Delta FX_t, \Delta r_t)$	$\hat{\beta}$	R^2	R^2_{adj}	$\hat{\gamma_1}$	$\hat{\gamma_2}$	$\hat{\gamma_3}$	R^2	R^2_{adj}
monthly	-0.14*	-0.10	0.02	0.01	-0.29	-0.03	1.47	0.04	0.02
		*(0.05)			***(0.10)	(0.03)	*(0.81)		
quarterly	-0.15	-0.12	0.02	0.00	-0.30	-0.27	1.67	0.18	0.13
		(0.08)			***(0.074)	***(0.07)	**(0.67)		

period by Eq. (4.1). In contrast, at the largest τ_t (which was around the 0.2 level in that period), the marginal effect is about zero.

How can we interpret these results? It appears that the negative correlation between realized exchange rate and relative stock market returns is most pronounced in the period in which the prevailing *expectations* were in line with this relationship as well (i.e., 1992-1998, see Figure 4.1). Or put it differently: if ever there were additional mechanisms in the markets which could link exchange rate and relative stock market returns in an opposite way compared to the Hau and Rey (2006)-model, these mechanisms were believed to be inactive at these times. The realized correlations indicate that such believes were in fact reasonable. In contrast, the fact that the implicitly expected correlation remain in positive territory in the later period (1999-2011) can be interpreted as a signal for the presence of such (out-of-the-model) mechanisms. As a consequence, the conjectured relation can only be seen in *realizations* after controlling for *expectations*, as the latter also capture further prevailing mechanisms.

4.4.2 Exchange rates and net capital inflow in the foreign country

In the following paragraphs, we investigate whether there is a positive relationship between a foreign currency appreciation and capital inflows into that foreign country, again for the country pair of the U.S.A and Germany. This relationship is postulated by the portfolio rebalancing theory, albeit not unambiguously found in the empirical part in Hau and Rey (2006)'s article.

Empirical model. As in the analysis above, we analyze a relationship between net capital inflow into the foreign country ($dK_t^f - dK_t^h$) and the appreciation of the foreign currency (ΔFX_t) unconditionally, i.e., by the regression equation

$$\Delta FX_t = \alpha + \beta(dK_t^f - dK_t^h) + \epsilon_t \tag{4.3}$$

and conditionally on the implicitly expected correlation, i.e., by the regression equation

$$\Delta FX_t = \alpha + \gamma_1(dK_t^f - dK_t^h) + \gamma_2\tau_t + \gamma_3((dK_t^f - dK_t^h) \times \tau_t) + \epsilon_t. \tag{4.4}$$

Stationarity tests. The variables included in the regressions from Eqs. (4.3) and (4.4) have to be stationary. Hence, we conduct Dickey-Fuller tests (shown in Table 4.1) to determine whether this condition holds. The properties of τ_t and ΔFX_t are discussed above. The hypothesis of a unit root in $dK_t^f - dK_t^h$ can be rejected at all conventional significance levels with the exception of quarterly data between 1992 and 1998; the regression results for the latter series should therefore be taken with caution.

Results. Table 4.3 reports the results from the regressions based on Eqs. (4.3) and (4.4). Overall, we do not find a statistically significant relationship between $dK_t^f - dK_t^h$ and ΔFX_t,

Table 4.3: Relation between foreign exchange movements and capital inflow into the foreign country

This table summarizes statistics to illustrate the relation between changes in the USD/EUR rate (e.g., $\Delta FX_t > 0 \Rightarrow$ US- Dollar depreciation) and the scaled net capital flow into the foreign country (Germany) ($dK_t^f - dK_t^h$). We consider monthly data of changes over the previous 30 calendar days, and quarterly data of changes (mid quarter) over the previous three months alternatively. We proceed in two steps: Panel A collects the Pearson correlation coefficients between ΔFX_t and $dK_t^f - dK_t^h$ (over the indicated time span), $Corr(\Delta FX_t, dK_t^f - dK_t^h)$, and estimates $\Delta FX_t = \alpha + \beta(dK_t^f - dK_t^h) + \epsilon_t$. Panel B displays the coefficient estimates and measures of fit for an interaction model, $\Delta FX_t = \alpha + \gamma_1(dK_t^f - dK_t^h) + \gamma_2\tau_t + \gamma_3((dK_t^f - dK_t^h) \times \tau_t) + \epsilon_t$, in which τ_t represents the implicitly expected correlation at time t. We split the considered period into subperiods from 1992-1998 (where the USD/DM rate is considered) and from 1999-2011 (where the USD/EUR rate is considered). (***: 1%, **: 5%, *: 10% significance level)

	Panel A $\Delta FX_t =$ $\alpha + \beta(dK_t^f - dK_t^h) + \epsilon_t$				Panel B $\Delta FX_t =$ $\alpha + \gamma_1(dK_t^f - dK_t^h) + \gamma_2\tau_t + \gamma_3((dK_t^f - dK_t^h) \times \tau_t) + \epsilon_t$				
1992-1998	$Corr(\Delta FX_t, dK_t^f - dK_t^h)$	$\hat{\beta}$	R^2	R^2_{adj}	$\hat{\gamma_1}$	$\hat{\gamma_2}$	$\hat{\gamma_3}$	R^2	R^2_{adj}
monthly	0.09	0.03	0.01	-0.00	0.02	-0.03	0.09	0.02	-0.02
		(0.03)			(0.05)	(0.03)	(0.36)		
quarterly	-0.04	-0.01	0.00	-0.04	-0.03	-0.07	-0.23	0.09	-0.03
		(0.05)			(0.03)	(0.06)	(0.35)		
1999-2011	$Corr(\Delta FX_t, dK_t^f - dK_t^h)$	$\hat{\beta}$	R^2	R^2_{adj}	$\hat{\gamma_1}$	$\hat{\gamma_2}$	$\hat{\gamma_3}$	R^2	R^2_{adj}
monthly	-0.05	-0.02	0.00	-0.00	-0.05	-0.02	0.26	0.01	-0.01
		(0.03)			(0.06)	(0.03)	(0.44)		
quarterly	0.11	0.04	0.01	-0.01	0.08	-0.04	-0.26	0.07	0.01
		(0.04)			**(0.03)	(0.05)	(0.22)		

neither based on correlations, nor based on regression estimates. There is also little systematic evidence that the inclusion of τ_t improves these findings. For quarterly data, the marginal effect $\frac{\partial \Delta FX_t}{\partial (dK_t^f - dK_t^h)}\Big|_{\tau_t}$ becomes more positive with more negative τ_t (i.e., with expectations that are more in line with a portfolio rebalancing relationship), but the interaction coefficient γ_3 is not as such significantly different from zero; furthermore, this pattern is not confirmed on the basis of monthly data. Hence, the empirical results with respect to the relationship of capital flows and exchange rate movements continue to provide little evidence in favor of the portfolio balancing hypothesis.

4.5 Conclusions

This study follows a line of research which investigates the influence of financial investors on exchange rates. According to this approach (which has also been called *uncovered equity parity* (Hau and Rey, 2006)), exchange rates, capital flow and relative stock market returns are endogenously determined based on differential dividend shocks across countries. These shocks affect foreign exchange and stock markets through portfolio rebalancing.

Our research contributes to this literature by incorporating the investors' *expectations* in this reasoning. While we learn from Hau and Rey (2006) that foreign exchange rate appreciation and relative exchange rates should be negatively correlated due to portfolio rebalancing considerations, our approach allows for a time-varying magnitude of this impact. In particular, we investigate whether implicitly expected correlations (which are measured with time-variation) are able to explain why the negative correlation between foreign exchange rate appreciation and relative exchange rates is more pronounced in some periods than in others. We find that this is indeed the case: the negative correlation is most pronounced when forecasters expect the correlation to be negative. Hence, a low *implicitly expected correlation* is a signal that portfolio rebalancing effects are in fact governing exchange rate markets, whereas additional mechanisms (from outside the Hau and Rey (2006)-model) are more active when the *implicitly expected correlation* is high.

We next hypothesize that a positive correlation between capital inflow and currency appreciation (as implied by portfolio rebalancing models by e.g., Hau and Rey (2006)), should be obvious when portfolio rebalancing is the dominant mechanism; similarly to our argumentation above, we therefore test whether our expectation measure also helps to uncover the link between capital flows and exchange rate movements. In contrast to our findings with respect to relative stock market returns, however, we do not find a convincing association between these variables.

Overall, our study indicates that expectations may be useful to capture the time-variation in dominating mechanisms in foreign exchange markets. When controlling for implicitly expected correlations, the relation between relative exchange rates and relative stock market returns (as predicted by portfolio rebalancing models) becomes even more visible. While we believe that this finding strengthens the argument that financial investors are important drivers of exchange rate movements, we have not been able to demonstrate how this responsibility is reflected by capital flow data. Hence, a more thorough investigation of this aspect is left for further research.

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Supplementary Appendix to accompany

Macro Expectations, Aggregate Uncertainty, and Expected Term Premia

Table A.1: Determinants of expected bond risk premia

The setup of this table is identical to table 1.2, but we include an NBER recession dummy. Jackknifed standard errors are provided in parentheses. Asterisks denote the level of significance, ***: 0.01, **: 0.05, *: 0.10.

	(i)	(ii)	(iii)	(iv)	(v)
$E_{t-1,i}[\Delta\pi_{t-1+h}]$	0.332	0.225	0.235	0.233	0.241
	***(0.066)	***(0.087)	***(0.078)	***(0.081)	***(0.080)
$E_{t,i}[\Delta\text{RGDP}]$		0.428	0.411	0.449	0.425
		**(0.199)	**(0.200)	**(0.199)	**(0.206)
$E_{t,i}[\text{INF}]$		0.042	0.047	0.036	0.041
		(0.064)	(0.065)	(0.064)	(0.065)
$\Psi(\text{RGDP}_{NY})$			0.162		0.146
			***(0.056)		**(0.067)
$\Psi(\text{INF}_{NY})$				0.213	
				***(0.076)	
$\Psi(\text{INF}_{NY})^{\perp}$					0.163
					(0.107)
Recession	-0.273	-0.090	-0.079	-0.071	-0.070
	***(0.033)	(0.078)	(0.076)	(0.079)	(0.078)
const.	-0.071	-0.479	-0.478	-0.480	-0.476
	***(0.015)	***(0.147)	***(0.145)	***(0.148)	***(0.145)
R^2_{COR}	0.38	0.37	0.37	0.37	0.38
$J-$Stat.	62.04	65.85	65.40	65.99	66.61
df	68	72	72	72	72
p-value	(0.68)	(0.68)	(0.70)	(0.68)	(0.66)
Test $\Delta\epsilon_t$ for AR(2)	-1.578	0.992	1.432	1.421	1.530
p-value	(0.12)	(0.32)	(0.15)	(0.16)	(0.13)
# Instr.	71	77	78	78	79
N	126	114	114	114	114
NT	1,999	1,553	1,553	1,553	1,553

Table A.2: Determinants of expected bond risk premia, $h = 4$

The setup of this table is identical to table 1.2 but here we investigate expectations for four quarters ahead, i.e. $h = 4$. Jackknifed standard errors are provided in parentheses. Asterisks denote the level of significance, ***: 0.01, **: 0.05, *: 0.10.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
$E_{t-1,i}[\Delta\pi_{t-1+h}]$	0.343	0.418	0.443	0.44	0.452	0.452	0.346	0.354	0.356
	***(0.083)	***(0.096)	***(0.073)	***(0.073)	***(0.071)	***(0.072)	***(0.089)	***(0.087)	***(0.086)
$E_{t,i}[\Delta\text{RGDP}]$	0.165						0.137	0.164	0.144
	**(0.070)						*(0.079)	**(0.076)	*(0.080)
$E_{t,i}[\text{INF}]$		0.113					0.019	-0.002	0.010
		(0.153)					(0.126)	(0.125)	(0.126)
$\Psi(\text{RGDP}_{TY})$			0.098						
			(0.071)						
$\Psi(\text{RGDP}_{NY})$				0.392			0.360		0.325
				***(0.061)			***(0.093)		***(0.095)
$\Psi(\text{INF}_{TY})$					0.407			0.413	
					***(0.098)			***(0.102)	
$\Psi(\text{INF}_{NY})$						0.400			
						***(0.084)			
$\Psi(\text{INF}_{NY})$									0.267
									**(0.125)
const.	-0.546	-0.391	-0.093	-0.093	-0.092	-0.091	-0.522	-0.540	-0.519
	***(0.194)	***(0.409)	***(0.016)	***(0.016)	***(0.015)	***(0.015)	(0.323)	*(0.322)	(0.323)
R^2_{COR}	0.47	0.45	0.48	0.48	0.47	0.48	0.49	0.48	0.49
$J-$Stat.	61.11	62.36	64.05	61.76	62.97	63.05	62.86	62.36	63.02
df	70	70	68	68	68	68	72	72	72
p-value	(0.77)	(0.73)	(0.61)	(0.69)	(0.65)	(0.65)	(0.77)	(0.78)	(0.77)
Test $\Delta\epsilon_t$ for AR(2)	0.922	0.331	0.951	1.331	0.912	1.073	1.246	1.119	1.300
p-value	(0.36)	(0.74)	(0.34)	(0.18)	(0.36)	(0.28)	(0.21)	(0.26)	(0.19)
# Instr.	73	73	71	71	71	71	77	77	78
N	113	112	124	124	124	124	111	111	111
T	1,471	1,432	1,847	1,847	1,847	1,847	1,409	1,409	1,409

Table A.3: Determinants of expected bond risk premia, alternative proxy

The setup of this table is identical to table 1.2 but here we construct our proxy for expected change in risk premia without the difference part of short term interest rates (i.e. we keep the expected change of long yields on the RHS). Jackknifed standard errors are provided in parentheses. Asterisks denote the level of significance, ***: 0.01, **: 0.05, *: 0.10.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
$E_{t-1,i}[\Delta\pi_{t-1+h}]$	0.248	0.354	0.403	0.408	0.405	0.408	0.233	0.232	0.239
	***(0.075)	***(0.075)	***(0.067)	***(0.066)	***(0.066)	***(0.066)	***(0.076)	***(0.075)	***(0.075)
$E_{t,i}[\Delta$RGDP$]$	0.497						0.432	0.466	0.443
	***(0.134)						***(0.161)	***(0.155)	***(0.162)
$E_{t,i}[$INF$]$		0.129					0.045	0.034	0.038
		**(0.058)					(0.064)	(0.063)	(0.064)
$\Psi($RGDP$_{TY})$			-0.022						
			(0.049)						
$\Psi($RGDP$_{NY})$				0.236			0.166		0.146
				***(0.046)			***(0.054)		**(0.057)
$\Psi($INF$_{TY})$					0.171			0.225	
					***(0.064)			***(0.060)	
$\Psi($INF$_{NY})$						0.191			
						***(0.062)			
$\Psi($INF$_{NY})$									0.178
									**(0.087)
const.	-0.373	-0.382	-0.052	-0.050	-0.052	-0.051	-0.448	-0.442	-0.439
	***(0.087)	**(0.150)	***(0.009)	***(0.009)	***(0.009)	***(0.009)	***(0.129)	***(0.128)	***(0.128)
R^2_{COR}	0.34	0.26	0.30	0.31	0.30	0.30	0.34	0.34	0.35
$J-$Stat.	64.21	62.39	67.32	62.85	64.62	64	65.21	62.65	62.10
df	70	70	68	68	68	68	72	72	72
p-value	(0.67)	(0.73)	(0.50)	(0.65)	(0.59)	(0.62)	(0.70)	(0.78)	(0.79)
Test $\Delta\epsilon_t$ for AR(2)	1.471	0.659	0.012	0.608	0.11	0.218	1.849	1.770	1.882
p-value	(0.14)	(0.51)	(0.99)	(0.54)	(0.92)	(0.83)	(0.06)	(0.08)	(0.06)
# Instr.	73	73	71	71	71	71	77	77	78
N	116	114	126	126	126	126	114	114	114
T	1,639	1,575	1,999	1,999	1,999	1,999	1553	1553	1,553

Table A.4: Determinants of expected bond risk premia, proxy based on 7-year duration bonds

The setup of this table is identical to table 1.2 but here we construct our proxy for expected change in risk premia with the current yield of a 7-year-zero-coupon bond (instead of a 10 year bond). Jackknifed standard errors are provided in parentheses. Asterisks denote the level of significance, ***: 0.01, **: 0.05, *: 0.10.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)
$E_{t-1,i}[\Delta\pi_{t-1+h}]$	0.226	0.273	0.290	0.289	0.295	0.291	0.251	0.217	0.222
	***(0.072)	***(0.082)	***(0.080)	***(0.080)	***(0.082)	***(0.081)	***(0.073)	***(0.074)	***(0.074)
$E_{t,i}[\Delta\text{RGDP}]$	0.319						0.299	0.310	0.308
	***(0.115)						**(0.143)	**(0.138)	**(0.143)
$E_{t,i}[\text{INF}]$		0.082					0.009	0.001	-0.001
		(0.052)					(0.062)	(0.060)	(0.062)
$\Psi(\text{RGDP}_{TY})$			-0.007						
			(0.047)						
$\Psi(\text{RGDP}_{NY})$				0.127			0.078		0.047
				***(0.042)			(0.051)		(0.053)
$\Psi(\text{INF}_{TY})$					0.292			0.238	
					***(0.067)			***(0.057)	
$\Psi(\text{INF}_{NY})$						0.239			
						***(0.056)			
$\Psi(\text{INF}_{NY})$									0.299
									***(0.081)
const.	-0.054	-0.073	0.128	0.128	0.126	0.127	-0.065	-0.051	-0.050
	(0.073)	(0.131)	***(0.016)	***(0.016)	***(0.016)	***(0.016)	(0.130)	(0.120)	(0.120)
R^2_{COR}	0.22	0.15	0.22	0.22	0.22	0.22	0.21	0.22	0.23
$J-$Stat.	67.48	62.60	64.45	61.96	60.07	60.81	68.45	71.83	70.20
df	70	70	68	68	68	68	72	72	72
p-value	(0.56)	(0.72)	(0.60)	(0.68)	(0.74)	(0.72)	(0.60)	(0.48)	(0.54)
Test $\Delta\epsilon_t$ for AR(2)	0.533	0.49	0.261	0.644	0.622	0.621	0.890	1.056	0.97
p-value	(0.59)	(0.62)	(0.79)	(0.52)	(0.53)	(0.54)	(0.37)	(0.29)	(0.33)
# Instr.	73	73	71	71	71	71	77	77	78
N	116	114	124	124	124	124	114	114	114
T	1,595	1,531	1,950	1,950	1,950	1,950	1,509	1,509	1,509

Table A.5: Predictive regressions with the CP factor

This table reports predictive regressions of future bond excess returns $rx(m)$ on the bond forecasting factor by Cochrane and Piazzesi (2005). The setup is identical to that of Table 1.5.

	$rx(avg)$	$rx(1Y)$	$rx(2Y)$	$rx(3Y)$	$rx(4Y)$	$rx(5Y)$	$rx(10Y)$
Panel A: Forecast horizon $h = 1$ quarter							
const.	0.48	0.12	0.28	0.44	0.58	0.66	0.77
t_{NW}	[2.84]	[4.64]	[2.98]	[2.76]	[2.76]	[2.59]	[2.75]
t_H	[2.55]	[4.80]	[2.92]	[2.58]	[2.49]	[2.27]	[2.39]
CP	0.00	0.00	0.00	0.00	0.00	0.01	0.01
t_{NW}	[4.74]	[2.62]	[3.51]	[4.18]	[4.60]	[4.83]	[5.34]
t_H	[3.08]	[2.36]	[2.80]	[2.93]	[3.02]	[3.04]	[3.21]
R^2	0.19	0.10	0.14	0.16	0.18	0.19	0.21
Panel B: Forecast horizon $h = 2$ quarters							
const.	0.90	0.24	0.53	0.83	1.09	1.23	1.46
t_{NW}	[2.84]	[4.42]	[2.83]	[2.68]	[2.74]	[2.63]	[2.84]
t_H	[2.47]	[4.81]	[2.87]	[2.51]	[2.42]	[2.19]	[2.31]
CP	0.00	0.00	0.00	0.00	0.01	0.01	0.01
t_{NW}	[4.05]	[1.93]	[2.76]	[3.46]	[3.97]	[4.36]	[4.59]
t_H	[2.50]	[1.70]	[2.18]	[2.31]	[2.41]	[2.45]	[2.73]
R^2	0.17	0.06	0.10	0.13	0.15	0.17	0.21
Panel C: Forecast horizon $h = 3$ quarters							
const.	1.25	0.34	0.75	1.15	1.51	1.70	2.03
t_{NW}	[2.62]	[4.07]	[2.54]	[2.42]	[2.50]	[2.41]	[2.69]
t_H	[2.41]	[4.95]	[2.84]	[2.45]	[2.35]	[2.11]	[2.23]
CP	0.01	0.00	0.00	0.00	0.01	0.01	0.01
t_{NW}	[2.57]	[1.58]	[1.89]	[2.18]	[2.40]	[2.60]	[3.13]
t_H	[2.34]	[1.79]	[2.11]	[2.18]	[2.23]	[2.23]	[2.57]
R^2	0.14	0.06	0.09	0.11	0.13	0.14	0.19
Panel D: Forecast horizon $h = 4$ quarters							
const.	1.63	0.45	0.99	1.51	1.97	2.22	2.64
t_{NW}	[2.54]	[3.83]	[2.39]	[2.31]	[2.41]	[2.35]	[2.71]
t_H	[2.39]	[4.97]	[2.83]	[2.43]	[2.33]	[2.10]	[2.19]
CP	0.01	0.00	0.00	0.00	0.01	0.01	0.01
t_{NW}	[1.87]	[1.38]	[1.45]	[1.57]	[1.70]	[1.82]	[2.35]
t_H	[1.90]	[1.70]	[1.76]	[1.75]	[1.78]	[1.79]	[2.11]
R^2	0.09	0.04	0.05	0.06	0.08	0.09	0.14

Supplementary Appendix to accompany

Individual Exchange Rate Forecasts and Expected Fundamentals

Table B.1: Average FX forecasting performance in the cross section: t-values of T_{ind}

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

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

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

Table B.2: Diagnostics

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

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

We proceed in three steps. In a first step, we conduct Breusch and Pagan (1980)-tests to determine for each specification reported in Table 2.4 whether or not individual-specific effects are present. Under the null, individual-specific effects are absent. In a second step, we compare the fixed effects and random effects estimators by the means of Hausman tests. If the null can be rejected, there are systematic differences between the coefficient estimates, indicating that random effects does not estimate consistently and hence, fixed effects should be used. Ultimately, we perform regressions in which we take the lagged variables to instrument for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$ and make use of Davidson and MacKinnon (1989)'s test of the null hypothesis that OLS can consistently estimate the model (i.e. there is no need to instrument for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$).

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

Table B.3: Panel pooled OLS regression, no instruments

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

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

Depending on the specification (i) to (ix), $\Phi_{j,t}$ includes forecast errors with respect to other fundamentals than interest rates, i.e. inflation ($|\varepsilon(\pi)|$) and industrial production growth forecast errors $|\varepsilon(y)|$. Unlike in Table 2.4, we do not use instruments for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$. $\Psi_{j,t}$ represents purely exogenous control variables such as year specific dummy variables. Significance: ***:1%, **: 5%, *: 10%.

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

Table B.4: Panel pooled OLS regression, with instruments

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

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

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

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

Table B.5: Panel fixed effects regression, no instruments

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

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

Depending on the specification (i) to (ix), $\Phi_{j,t}$ includes forecast errors with respect to other fundamentals than interest rates, i.e. inflation ($|\varepsilon(\pi)|$) and industrial production growth forecast errors $|\varepsilon(y)|$. $\Psi_{j,t}$ represents purely exogenous control variables such as year specific dummy variables. Unlike in Table 2.4, we do not use instruments for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$. Significance: ***:1%, **: 5%, *: 10%.

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

Table B.6: Panel fixed effects regression with AR(1) correction, no instruments

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

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

Depending on the specification (i) to (ix), $\Phi_{j,t}$ includes forecast errors with respect to other fundamentals than interest rates, i.e. inflation ($|\varepsilon(\pi)|$) and industrial production growth forecast errors $|\varepsilon(y)|$. $\Psi_{j,t}$ represents purely exogenous control variables such year specific dummy variables. Unlike in Table 2.4, we do not use instruments for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$. We control for first-order autocorrelation by the fixed-effects method proposed by Baltagi and Wu (1999). Significance: ***:1%, **: 5%, *: 10%.

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

Table B.7: Panel fixed effects regression, alternative instruments

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

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

Depending on the specification (i) to (ix), $\Phi_{j,t}$ includes forecast errors with respect to other fundamentals than interest rates, i.e. inflation ($|\varepsilon(\pi)|$) and industrial production growth forecast errors $|\varepsilon(y)|$. $\Psi_{j,t}$ represents year specific dummy variables.
Unlike in Table 2.4, we use *alternative* instruments for $|\varepsilon_{j,t}(i^{EUR})|$, $|\varepsilon_{j,t}(i^{USD})|$ and $\Phi_{j,t}$, which are correlated with these variables but uncorrelated with the unexplained portion of Eq. (2.2). Doing so, we make use of the facts that: (i) our dataset covers a broader set of countries than the US and the Eurozone, i.e. the UK and Japan; and that, (ii), skills in predicting macroeconomic series persist across countries. We thus employ the absolute forecast errors with respect to the interest rates in the *UK* and in *Japan* as exogenous instruments for the forecast errors with respect to the *US* and the *Eurozone*. Likewise, we use the absolute forecast errors with respect to the inflation rate and industrial production in these countries as instruments for the US and Eurozone inflation and industrial production, respectively. These instruments are valid for two reasons: first, it can be shown from our data that skills in predicting these macroeconomic series are correlated across countries: for example, the cross-sectional correlation between average absolute errors with respect to Eurozone and UK interest rates is 0.51. In the panel context, there still remains a positive correlation of absolute forecast errors with respect to these two series of 0.25. Secondly, there is no theoretical reason to believe that errors in predicting the macroeconomic circumstances in Japan should have a systematic impact on the USD/EUR exchange rate predictions which is not yet covered by the forecast error with respect to the fundamentals in the United States or the Eurozone; hence, the instruments are exogenous.
Significance: ***:1%, **: 5%, *: 10%.

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

Wissenschaftlicher Werdegang des Autors:

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