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MSc Financial Economics

FORWARD LOOKING EXPECTATIONS IN THE FOREIGN EXCHANGE MARKET

ABSTRACT:

In this paper, we examine the foreign exchange rate expectation of agents participating in Consensus Forecast survey of the euro rate. Participants in this survey are asked to reveal their inflation forecast along with the forecasts of foreign exchange rates. We question whether the survey participants, in forming the financial expectations, make use of their personal expectations on the relative price levels. We find that expectations of currency analysts do include components of expected future inflation. Hence, we propose that agents have forward looking expectations. We furthermore show that dispersion in fundamental expectations can significantly explain the agent heterogeneity.

Keywords: Exchange rate expectations, heterogeneity, dispersion of beliefs, survey data, rational expectation hypothesis

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I. INTRODUCTION

One of the major objectives in international finance is to explain the large trading volume and volatility in the foreign exchange rate markets. Currently, the exchange rate market trade volume by far exceeds the trade volume of goods and services. In 2008, the world trade volume of goods and services totaled 19.5 trillion[1] dollars. By contrast, the estimated average daily turnover in the global foreign exchange market amounted to staggering 3.98 trillion[2] dollars.

This issue is complemented with the large misalignment between the volatility of the exchange rates and that of macroeconomic indicators. Halwood and MacDoanld (2000) suggests that it is difficult to explain this large volatility using the standard set of fundamental models given the low frequency, and relatively low volatility which is characteristic of the fundamental series. The issue of excess volatility coincides with the forward premium puzzle, whereby the large body of empirical literature finds forward rates to be a biased predictor of the future spot rate, which is in contradiction with the rational expectation hypothesis. These problems call for alternative approaches to studying the exchange rate market, with a focus on market microstructure and the behavior of the market agents. As a result, some of the recent literature has deviated from the fundamental story.

An attractive route for explaining the exchange rate puzzles is offered by availability of survey data on exchange rate expectation. Frankel and Froot (1987) have suggested a framework which allows for modeling expectations under three basic processes; extrapolative, adaptive and regressive. The Frankel and Froot’s model has found an extensive support in the empirical literature.

The survey-based literature initially relied on the representative agent assumption, but the recent availability of disaggregated data on survey expectations allows for relaxing this assumption. Increasingly popular is the view that exchange rates should be modeled taking into account the interaction and differences among heterogeneous agents. The test heterogeneity of expectations has been proposed by Ito (1990) and followed by MacDonald and Marsh (1996), Bénassy-Quéré et al.(2003) and Jongen et al. (2009). This line of literature suggests that agents tend to hold differing beliefs about the future spot rate.

The models in survey-based literature typically assume that agents form expectations only on the basis of past price levels or realized spot rates. This is in contrast to the asset pricing view on exchange rates, whereby agents are assumed to derive expectations from future expected price levels. This calls for

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1 As estimated by World Trade Organization.

[2] Estimated by the Bank of International settlements for 2007.

extending the Frankel and Froot's model using information on expected future fundamentals, such as expected inflation rates.

However, such an extension is not easily implemented empirically, particularly if agents are heterogeneous. In practice, the fundamental expectations of analysts are typically dispersed and unobservable. Yet, *Consensus Forecast* recently begun publishing disaggregated survey data on analyst expectations of exchange rates, which are issued in parallel with inflation expectations of the same analyst. This allows for matching the individual exchange rate and inflation beliefs and thus modeling expectations under an asset pricing perspective.

This study builds up on the existing survey-based literature in two steps. Fist, we hypothesize that agents are forward looking in the sense they employ expected future fundamentals in forming exchange rates expectations. To test for this proposition, we match the individual specific data on inflation and exchange rate expectations from two parallel *Consensus Forecast* publications and study whether currency analysts exploit their personal forecast of inflation. We do find evidence of forward looking content in expectations of the euro rate.

For our second hypothesis, we assume that the currency analysts have dispersed expectations about future price levels. Therefore, we can study whether the dispersion effect in the fundamental beliefs can explain the dispersion in the exchange rate expectations. We hypothesize that the dispersion in fundamental beliefs may significantly contribute to the agent heterogeneity.

The paper is structured as follows. The next chapter presents the literature overview and some key theoretical concepts applied in this paper. In chapter 3 and 4, we discuss the data and methods, which is followed by Chapter 5, where we analyze the results. Finally, the concluding remarks are presented in Chapter 6.

2. THE LITERATURE REVIEW

2.1 Literature on Survey of Expectations

The theory of rational expectations in the sense of Muth (1961) maintains that the forward rate is an unbiased and optimal predictor of the futures spot rate, if agents are rational and markets are efficient. Much of the attention has been focused on testing the concept of rational expectations, yet, the majority of studies fails to provide clear support for rationality and a large body of empirical literature finds the foreign exchange forward rate to be a biased predictor of the future spot rate. A number of studies, including Bilson (1981), Longworth (1981) and Fama (1984) moreover find that the forward rate can be negatively related to the future spot rate, which suggests that the market is wrong about the direction of exchange rate change.

The interpretation of the rationality tests results is not straightforward, due to the potential time varying risk premium component in the forward rate. The prospect of the time varying premium means that the standard rationality tests are formulated as a joint hypothesis on REH and that of risk premium. Therefore, in earlier literature, the existence of the time varying risk premium has offered a favorable explanation for the rejection of rationality. To test the single hypothesis, a researcher requires an independent measure of currency expectations. Several authors, including Dominguez (1986), Frankel and Froot (1987), Cavaglia at al. (1993), Chinn and Frankel (1994), propose to exploit expectations data available from survey publications. This line of literature generally confirms the rejection of the traditional formulation of the rational expectations. (Hallwood and MacDonald 2000)

The rejection of the standard formulation of REH, calls for alternatives in explaining price determination in the exchange rate markets. Such an alternative is offered by Frankel and Froot (1987), who studied exchange rate expectations using MMS and Economist surveys. Frankel and Froot propose a model where expectations are formed as a combination of the three processes; extrapolative, adaptive and regressive. Incorporating all three mechanisms, the model can be tested as follows:

$$\Delta s^{e}_{t,t+1} = \omega + \mu(s_t - s_{t-1}) + \vartheta(s^{e}_{t-1,t} - s_t) + \nu(s_t - \tilde{s}_t) \qquad (1)$$

where s^e, is the expected rate, s_t is the actual rate and $\tilde{s}_t$ defines the fundamental value of the exchange rate. The parameters μ, υ, ν measure the extrapolative, adaptive and regressive expectations, respectively. First, μ is positively significant when agents extrapolate the past movement of exchange rate into their expectations in the same direction – the process is defined as extrapolative. Second, expectations are adaptive, when υ is significantly negative and agents focus on correcting their past errors. Last, when agents expect the exchange rate to revert to their fundamental value, ν is significantly negative. Such a process is said to be regressive. MacDonald (2000) suggests that the null hypothesis to these processes is when agents expect the exchange rates to follow random walks, in which case the expectations can be defined as static. Hence, the evidence of static expectations is present, when the null hypothesis of $\mu=\upsilon=\nu=0$ is not rejected.

Frankel and Froot's model is suited to identify different behavior patterns for agents, and their effect on the market. One class of market behavior is defined as rational optimization. If agents are rational optimizers (or fundamentalists), they estimate the fundamental price and take advantage of temporary deviations from the equilibrium. The rational agents expect a mean reversion to the fundamentals, and therefore have a stabilizing role for the price determination of the exchange rate. The mean reversion is a prevalent force under regressive expectations. The other type of participants can be described as noise traders (chartists) who employ simple methods, such as extrapolating the current depreciation trend into the future. These types of agents have destabilizing effect on the exchange rate, as they expect the deviation from the equilibrium to continue in the future. A number of studies, including MacDonald and Torrance (1988), Cavaglia *et al.* (1993), Bénassy-Quéré et al. (2003), followed Frankel and Froot in testing expectation mechanisms using different publications of survey expectations and range of currency pairs. The general consensus is that at longer horizons (above 3 months) the expectations are stabilizing, while at shorter horizons (3 months and less) they are destabilizing.

The majority of the earlier studies typically relied on the representative agent's paradigm, which allowed for employing a consensus measure of expectations. The consensus measure is generally computed as a cross sectional mean, which summarizes the answers of all respondents of a given survey. Increasingly, the focus is being shifted towards the view that the foreign exchange rate determination is a result of the existence and interaction of different types of agents. The availability of disaggregated survey data provides an opportunity to measure heterogeneity of individual survey participants. The heterogeneity can be detected when individual exchange rate forecasts differ from the consensus value. Ito (1990) proposed a simple model to indentify expectation heterogeneity. To illustrate Ito's model, we can define the individual's *i* expectations as a function of the public information set:

$$\Delta s^e_{i,t,t+1} = f(\Omega_t) + g_i + \varepsilon_{i,t} \tag{2}$$

where $f(\Omega_t)$ is the information set commonly held by all forecasters and g_i is the individual effect. Note that equation (2) rests on the assumption that agents apply the same weights to the set $f(\Omega_t)$, meaning that they practice common interpretation of information. We can summarize the individual effect for all forecasters of the dataset by taking the cross sectional average of the exchange rate expectations $\Delta s^e_{i,t,t+1}$ as follows,

$$\Delta \bar{s}^e_{t,t+1} = f(\Omega_t) + \bar{g} + \bar{\varepsilon}_t \tag{3}$$

If we assume that $\bar{g}$ can be normalized to be zero, then subtracting equation (3) from (2) yields:

$$\Delta s^e_{i,t,t+1} - \Delta \bar{s}^e_{t,t+1} = g_i + \varepsilon_{i,t} - \bar{\varepsilon}_t \tag{4}$$

In equation (4), the individual deviations from the cross sectional average are regressed on a constant. This procedure allows for detecting individual biases. Thus, heterogeneity can be tested in an effective way, without the need to know the structure of the common information set $f(\Omega_t)$. (Jongen, 2007)

Ito estimated regression (4) using the disaggregated expectations on JPY/USD rate over the period 1985-1987. Upon distributing the analysts into different industry groups, the author showed that forecasters held biased expectation across industries. Exporters tended to expect Yen appreciation, while trading companies suffered from a depreciation bias. Ito interpreted these results as an evidence of wishful expectations. The test on individual effect was also implemented among others by MacDonald and Marsh (1996), Bénassy-Quéré et al.(2003) and Jongen et al. (2009). The general finding is that exchange rate beliefs are dispersed, and the dispersion increases as the forecast horizon lengths.

Equation (4) provides a robust tool for measuring heterogeneity, but helps little to detect its potential source. There are two competing views that offer an explanation for heterogeneity. At one end is the rational beliefs theory, which relies on the assumption that private beliefs may arise because agents do not know the structural relations of the economy (Jongen, 2007). Even though agents possess large quantity of information and economic indicators, they form exchange rate expectations merely from past prices movements. The second view follows that agents hold asymmetric information. The information asymmetries are argued to arise if information is costly to collect or process and agents are forced to optimize with regard to their investments in obtaining information (Hommes, 2006). As a result, different agents may hold different fractions of the complete information set.

It is possible to test the existence of dispersed beliefs by extending equation (4) as follows:

$$s^{e}_{i,t,t+k} - \bar{s}^{e}_{t,t+k} = (g_i - \bar{g}) + (\beta_i - \bar{\beta})x_t + \varepsilon_{i,t} - \bar{\varepsilon}_t \qquad (5)$$

which allows agents to attach different weights to the specific element of their information set. In this equation, if an agent attaches more than the average weight to the variable x_t, the coefficient $(\beta_i - \bar{\beta})$ will be significantly positive. The evidence of different use of public information is referred to as idiosyncratic effect. Ito finds that much of the heterogeneity arises mainly due to the existence of private biases and the evidence of idiosyncratic effects is somewhat lower.

Jongen et al. (2009) employ equation (5) to study whether analysts attach different weight to three models; regressive, extrapolative and uncovered interest rate parity. They find evidence of both individual and idiosyncratic effect. The results further confirm that chartist behavior is more prevalent in the short term, while fundamentalist rules are applied mainly at the longer horizon.

A natural question arises, whether the concept of dispersed beliefs can explain the large volatility of the exchange rate market. A number of studies, including Frankel and Froot (1990), MacDonald and Marsh (1996), Chionis and MacDonald (1997) and Jongen et al. (2009), have tested Granger causality between heterogeneity and volatility. These studies present general support for the relation between market volatility and analyst heterogeneity, and in some cases the dispersion of beliefs is found causing the trade volume.

Frankel and Froot's model is the dominant framework of analysis in much of the survey-based literature on heterogeneity. This model is typically based on PPP and assumes that agent expectations are derived only from past price levels. Yet, under the theory of asset pricing, the currency is treated as an asset, which follows that the agents derive their expectations from future expected fundamental rates. In the section below, we discuss these differences as we introduce the forward looking model from asset pricing theory. To do so, we need to first briefly review the basic PPP model.

2.2 Purchasing Power Parity

Most macro exchange rate models have their roots in the theory of purchasing power parity (PPP). The theory of PPP asserts that the exchange rate is a function of relative price levels in the home and foreign country. In the absolute version of PPP, the exchange rate is determined only by the price levels in the home and foreign country and thus can be defined as follows:

$$\tilde{s}_t = p_t - p_t^* \tag{6}$$

where $\tilde{s}$ is defined as domestic currency per unit of foreign currency and p_t and p_t^* are the home and foreign price levels in natural logarithms. The difficulty in applying the absolute PPP model is that the price levels which are reported by statistical agencies are defined in relative indexes and not in absolute prices (Jongen, 2007). Therefore, the empirical version of equation (6) can only be formulated using price changes from the previous period:

$$\tilde{s}_t = \tilde{s}_{t-1} + \Delta p_t - \Delta p_{t-1}^* \tag{7}$$

The initial value of $\tilde{s}_0$ is unobservable, and therefore it has to be estimated (Jongen, 2007). The PPP theory has been tested extensively over the past decades using a range of methods by a large number of researchers. The general consensus is that PPP works well over the long horizon, while in the short run it fails to explain the price determination (Hallwood and MacDonald, 2000).

2.3 The Forward Looking Exchange Rate Model

Let us consider again the regressive model tested by Frankel and Froot (1987), which we can single out from equation (1):

$$\Delta s^{e}_{t,t+k} = -\nu(s_t - \tilde{s}_t) \tag{8}$$

The regressive model allows for deviations from this fundamental rate $\tilde{s}_t$. If deviations from $\tilde{s}_t$ occur at time *t*, the rational agents should expect them to be corrected in the future. The coefficient $-\nu$ measures the speed of adjustment back to equilibrium. In the survey-based literature the fundamental rate is $\tilde{s}_t$, most often modeled using the PPP model from equation (7).

Note that in the equations (7) and (8) the spot rate expectations are defined only as a function of observed prices at time *t*. This is in contrast with the modern monetary model, which treats the exchange rate as an asset price. As such, the expectations about the future fundamentals become important. The asset pricing model is derived from the following representation:

$$s_t = \frac{1}{1+\alpha}\tilde{s}_t + \frac{\alpha}{1+\alpha} s^{e}_{t+1} \tag{9}$$

which states that the current spot rate is given by a weighted average between the current fundamental and the expected future spot rate. Upon series of iterative substitutions, it can be shown that the current exchange rate depends mainly on expectations. The following definition holds:

$$s_t = \frac{1}{1+\alpha}\sum_{j=0}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^{k} E^{k}_{t}\tilde{s}_{t+k} \tag{10}$$

Note that in (7), the spot rate is a function of the expected fundamental rate in all future periods. The future fundamental rates are discounted by a discounting factor α. We can describe this model as forward looking, because the exchange rate depends not only on the past prices but also on all information that is relevant for determining the prospects on future prices.

Testing equation (10) presents an empirical challenge because the expected fundamental rate $E^{k}_{t}\tilde{s}_{t+k}$ has to be modeled under the strict assumption that the market is homogeneous and agents have uniform expectations about future fundamentals. When agents have dispersed expectations about the future fundamentals, the representative agent assumption may not be valid. Due to the lack of suitable disaggregated data, no study in the survey-based literature so far attempted to test whether currency analysts employ expectations about future fundamentals.

Thanks to the recent availability of disaggregated data on parallel survey of expected inflation and exchange rates, we can model the forward looking model under heterogeneity. This motivates our first hypothesis, whereby we test whether currency analysts employ their personal expectations of home and foreign inflation rates. However, before we introduce our model, we will briefly discuss the potential effects of dispersed fundamental expectations.

2.4 Dispersion in Fundamental Signals

Our approach uses survey data and links the model of agent heterogeneity to the macroeconomic fundamentals. This investigation can also be motivated from the prospective of the literature on the rational noisy expectations. One study in particular, Bachetta and Wincoop (2003), is worth mentioning. Bachetta and Wincoop present a forward looking monetary model, which incorporates the heterogeneous agents. Using simulation, authors show that dispersed fundamental signals may cause large magnification of exchange rate volatility which is a product of higher order expectations.

Bachetta and Wincoop motivate their hypothesis by defining the monetary model and allowing for dispersed fundamental signals:

$$s_t = \frac{1}{1+\alpha}\sum_{j=0}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^k \overline{E}_t^k(\tilde{s}_{t+k}) \tag{11}$$

where authors define the fundamental rate $\tilde{s}_{t+j}$ using a risk adjusted uncovered interest rate parity condition. Note that the expectations sign in (11) is denoted as $\overline{E}_t^k$ and the bar indicates that the expectations are summarized across all heterogeneous market participants. The superscript k in $\overline{E}_t^k$ refers to the horizon of expectations. Note that we can write $\overline{E}_t^0(\tilde{s}_t)=\tilde{s}_t$, $\overline{E}_t^1(\tilde{s}_{t+1})=\overline{E}_t\ (\tilde{s}_{t+1})$, and so on. The higher order expectations can be expressed as:

$$\overline{E}_t^k(\tilde{s}_{t+k})=\overline{E}_t\overline{E}_{t+1}...\overline{E}_{t+k-1}(\tilde{s}_{t+k}) \tag{12}$$

Hence the exchange rate at time *t* depends on the fundamental value at time *t,* average expected fundamental value at time *t+1,* the average expectations of the average expectation of the fundamental value at time *t+2,* and so on. In other words, the expected exchange is result of higher order expectations.

Bachetta and Wincoop show that in the heterogeneous system with information dispersion the law of iterated expectation breaks down[3], such that:

$$\overline{E}_t \overline{E}_{t+1}(\tilde{s}_{t+2}) \neq \overline{E}_t(\tilde{s}_{t+2}) \qquad (13)$$

This inequality was originally shown by Townsend (1983), who solved the asset pricing model under the dynamic setting with perpetual learning. It is the basic problem of the asset pricing approach to exchange rate determination, as it deteriorates under asymmetric information. This is because when fundamental signals are dispersed, the expectations of other investors become important. Maynard Keynes (1936) described the nature of the higher order expectations using a famous metaphor, as he compared the market price determination to a beauty contest:

> ‘‘… professional investment may be likened to those newspaper competitions in which the competitors have to pick out the six prettiest faces from a hundred photographs, the prize being awarded to the competitor whose choice most nearly corresponds to the average preferences of the competitors as a whole; so that each competitor has to pick, not those faces which he himself finds prettiest, but those which he thinks likeliest to catch the fancy of the other competitors, all of whom are looking at the problem from the same point of view. It is not a case of choosing those which, to the best of one’s judgment, are really the prettiest, nor even those which average opinion genuinely thinks the prettiest. We have reached the third degree where we devote our intelligences to anticipating what average opinion expects the average opinion to be. And there are some, I believe, who practice the fourth, fifth and higher degrees.’’ Keynes (1936), page 156.

Bachetta and Wincoop (2003) show that higher order expectations in the presence of the idiosyncratic fundamental signals lead to considerable magnification effect and persistence of the effect of the non-fundamental trade on the exchange rate. Hence, this type of heterogeneity is by one suggestion an approach to explain the large volume of trade on exchange rate market and the respective close empirical relation to order flow. This is also the motivation behind our second hypothesis, which is to explore the effect of asymmetric fundamental expectations in the survey of exchange rate expectations.

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[3] For a more detailed discussion and the proof, please refer to Allen, Morris and Shin (2003).

3. THE TEST MODELS AND DATA:

Given the fact that agents engage in costly investments by forecasting future fundamentals, one may suppose they use this information in forming exchange rate expectations. For our first hypothesis, we test whether agents are forward looking, as suggested by the asset pricing view of the exchange rate. To obtain a testable proposition, we exploit the recent availability of the parallel surveys on individual financial and fundamental expectations, whereby disaggregated expectations are available for individual respondents. We define our model using relative PPP relation, and test whether individual expectations about inflation can explain his or her expectations of the expected exchange rate. This allows for individual heterogeneity of both the independent and the explanatory variable. In this method, the individual beliefs about the home and foreign inflation, as well as exchange rates, are allowed to differ across individuals. If expectations are forward looking, the inflation beliefs should include information beyond past prices or price changes. Conversely, we can also define agents as backward looking, if they form beliefs using only past prices. These questions can be tested directly using survey.

3.1 The Forward Looking Model

To test the forward looking model empirically, we need to specify the forecast horizon of the expectations. Under the assumption of a single forecast horizon, the simplified version of the forward looking model becomes:

$$s^{e}_{i,t,t+h} = E(\tilde{s}_{i,t,t+h}) \tag{14}$$

where *h* equals the forecast horizon of the expectations and $\tilde{s}$ is the fundamental value of the exchange rate at time $t+h$. Note that the subscript *i* denotes that agents may receive individual specific signals about the future fundamental rate, which allows for agent heterogeneity. For the purpose of our analysis, it is sufficient to define the fundamental value using the relative PPP model as follows:

$$\Delta\tilde{s}_{t} = \Delta p_{t} - \Delta p^{*}_{t} \tag{15}$$

where p_t and p_t^* represent the natural logarithm of the home and foreign price levels, respectively. We assume that PPP is the true model of exchange rate determination and that all relevant information is ultimately reflected in prices. We further assume that expected inflation is produced on the basis of a broad range of information from the individual's information set. The individual's set may include a range of other variables such as expected money balances, but also any qualitative information.

After taking differences in (14) and substituting for $\tilde{s}_t$, we may rewrite:

$$\Delta s^{e}_{i,t,t+h} = E(\Delta p_{i,t,t+h} - \Delta p^{*}_{i,t,t+h}) \tag{16}$$

We define the empirical version of the model using open formulation in order to achieve a more flexible setting and allowing for unrestricted coefficients at both sides:

$$\Delta s^{e}_{i,t,t+h} = g_i + \beta_i \Delta p^{e}_{i,t,t+h} + \beta_i \Delta p^{e*}_{i,t,t+h} + \varepsilon_{i,t} \tag{17}$$

where $\Delta p^{e}_{i,t,t+h}$ and $\Delta p^{e*}_{i,t,t+h}$ are expected changes in the home and foreign price levels, respectively. This representation is nothing more than the forward looking version of the PPP model. Under the strong version of the PPP hypothesis, it is assumed that $\beta_i=1$, $\beta_i^{*}= -1$ and the constant is zero. In this case, the forecaster i would expect exchange rate depreciation to exactly correspond to his expectation of the inflation differential.

If the coefficients β, β^{*} are significant and appear with a correct sign, it is possible that agents are forward looking. However, this is not a sufficient condition for an existence of forward looking expectations, particularly if forecasters merely interpolate past inflation into their expectations. If so, we can define analyst expectations as backward looking. Such a model can be specified as follows:

$$s^{e}_{i,t,t+h} = E(\tilde{s}_t\ ) \tag{18}$$

By defining $\tilde{s}_t$ using relative PPP, we can formulate the empirical version of the model as follows:

$$\Delta s^{e}_{i,t,t+h} = g_i + \gamma_i \Delta p_t + \gamma_i^{*} \Delta p^{*}_t + \varepsilon_{i,t} \tag{19}$$

The equation (19) specifies a backward looking model, where agents are assumed to interpolate the current inflation trends into their expectations of the future spot rate change. The combination of the two models can be tested as follows:

$$\Delta s^{e}_{i,t,t+h} = g_i + \beta_i \Delta p^{e}_{i,t,t+h} + \beta_i^{*} \Delta p^{e*}_{i,t,t+h} + \gamma_i \Delta p_t + \gamma_i^{*} \Delta p^{*}_t + \varepsilon_{i,t} \tag{20}$$

If agents merely rely on the past price trends, the forward looking component of the model has no explanatory power and β_i and β_i^{*} are not significant. Alternatively, if β_i and β_i^{*} are significant, agents form beliefs about future inflation on the basis of the broader set of information, which in turn influences the spot rate expectations.

The limitation of our approach is the difficulty of empirical implementation, because it requires data on individual forecasts of inflation and exchange rates produced simultaneously. However, such data has recently become available from *Consensus Forecast* survey publications. With minor adjustment in the dataset, the above propositions are empirically testable.

3.2 Consensus Survey Data

Every month, the London based organization Consensus Economics conducts surveys on financial and macroeconomic forecasts. The respondents of these surveys are multinational organizations, forecasting services agencies and banks. The survey responses are summarized in two separate publications. The first publication, known as *A Digest of Financial Forecast*, reports around 30 disaggregated survey responses of exchange rate forecasts for the main currency pairs. The second, titled simply *Consensus Forecast*, presents disaggregated forecast data on a broad range of macroeconomic fundamentals for a number of industrialized economies, which includes the inflation expectations.

The two surveys are always conducted simultaneously, typically on the second Monday of the month. As a result, many of the companies participate in both surveys. This allows for merging the datasets of inflation and exchange rate expectations and obtaining a common sample for each individual respondent.

Before our model can be estimated, two data issues come to attention. First, our approach sets a high demands on the data consistency. It is required that an individual respondent frequently forecasts the exchange rate along with both the home and foreign inflation, without many missing entries. Although the majority of the exchange rate forecasters also report the home inflation, only a minority of them do so for the foreign inflation.

Second, for any data point, the financial and fundamental forecasts need to share the common forecast date and the forecast horizon. Although the forecast date is always identical, the forecast horizon is not, requiring a minor transformation of the data. These issues and the proposed methods are discussed in the two subsequent sections.

3.3 Dataset Merger and Missing Observations

Our model, introduced in Section 3.1, is highly dependent on the quality of the individual data. The major limitation of this approach is that all forecasters included in the panel are required to simultaneously cover foreign exchange rate along with home and foreign inflation rates. If an observation is missing for any of the three series, one period must be excluded. Hence, frequent missing observation in any series leads to a very inconsistent dataset.

Table 1: Individual observations on USD/EUR (12/2002:07/2007)

		Merged Dataset		
Respondent	$\Delta s^{e}_{i,t,t+h}$	$\Delta s^{e}_{i,t,t+h}$, $\Delta p^{e}_{i,t,t+h}$	$\Delta s^{e}_{i,t,t+h}$, $\Delta p^{e*}_{i,t,t+h}$	all
	1	2	3	4
ABN	39	23	-	-
BC	31	8	-	-
BNP	48	46	-	-
BOA	45	44	43	42
BTM	54	-	-	-
CM	56	54	-	-
CS	54	-	16	-
CT	40	29	-	-
DB	48	43	-	-
DK	39	37	-	-
GI	49	49	42	42
GM	53	-	49	-
HSBC	56	47	-	-
ING	55	53	-	-
JP	50	47	50	47
ML	55	50	47	44
MS	50	40	46	37
NOM	35	-	-	-
OEF	50	50	46	46
RBC	55	-	-	-
SCB	32	-	-	-
SG	47	41	-	-
UBS	52	51	-	-
WLB	55	54	-	-
Total	1148	766	339	258
Respondent count	24	18	8	6
Observation loss %	100%	67%	30%	22%

Notes: The table displays summary of individual observations for each forecaster, upon matching the exchange rate and inflation expectations of each respondent.

The fundamental forecasts are available for most of the major economies. However, the sufficient common sample of individual exchange rate and inflation expectations are only available for the Euro. The survey on the Euro-zone fundamentals was first included in *Consensus Forecast* in December 2002. This limits the length of our dataset despite the fact that exchange rates forecasts are available for a much longer period. Our merged dataset runs from 12/2002 to 07/2007, which given the monthly frequency yields the maximum of 56 observations for each forecaster.

Table 1 shows a summary of observations after the data merger for the Euro expectations and the respective home and foreign inflation series. The first column displays the observation count for the exchange rate forecasts $\Delta s^{e}_{i,t,t+h}$, with the details on 24 forecasters which are reported during this period. The total of the observation count is considered to be 100% of the original sample.

Note that upon merging the expected exchange rate with home inflation $\Delta p^{e}_{i,t,t+h}$, we can maintain 18 out of 24 forecasters and 67% of all original observations. Column 2 shows that a fairly consistent number of observations is preserved for each respondent - mostly around 40 to 50 observations. Most cross sections are lost upon merging the currency forecasts with $\Delta p^{e*}_{i,t,t+h}$. This suggests that most of the forecasters only invest into the home currency fundamentals for this pair. When both sides of the differential are merged in one dataset, only 6 respondents and 22% of the original observations remain. This is not a very representative sample, especially if the goal is to capture much of the dynamics in the heterogeneity.

To prevent observation loss, we estimate two variants of our model. First, we focus on the home side fundamental. As such, we substitute for the missing observations for US inflation by the mean consensus value. In total 508 (out of 766) observations is substituted for 12 forecasters. Second, we estimate fully heterogeneous model with individual entries on both side of the differential. Under this specification, only 258 observations and 6 forecasters are available.

3.4 Forecast Horizon Adjustment

All exchange rates forecasts are defined in dollars and the forecasts are available in three horizons; 1, 3 and 12 months. The inflation forecasts are issued at the horizons of 1 and 2 years. To formulate our hypothesis correctly, the key idea is to match the forecast dates t to the forecast horizon h for exchange rates and inflation forecasts. The forecast dates are always identical, while the forecast horizons overlap but they are not identical. Hence, a minor adjustment in the forecast dataset is needed.

To illustrate the problem, we briefly discuss how the *Consensus Forecast* panel is prepared. The forecast of each variable is always issued on two different target horizons. The two forecast horizons are referred to as *current year* and *next year*[4]. The *Current year* forecast is prepared at time t and targets the average inflation rate over the current year T. The *next year* is issued at the same time and targets the average inflation rate over the following year $T+1$. It is declared in the publication that the inflation forecasts

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[4] The *current year* and *next year* forecast are almost always reported simultaneously, and are not subject to further loss of observations.

target is the 12 month average of the annual inflation. We assume that all survey respondents adhere to this rule. Hence, the forecast target can be defined as follows:

$$\Delta P_{t,T}^{tg} = \frac{1}{12} \sum_{n=Jan,T}^{Dec,T} \left(\frac{CPI_n}{CPI_{n-12}} - 1 \right) \tag{21}$$

where t is the forecast date, T is the target year and n is a calendar month of the given target year. Note that the forecast target refers to the average inflation over the whole calendar year. The inflation value for each month is computed on an annual basis against the index level twelve months ago, CPI_{n-12}.

It is clear from equation (21) that each of the twelve publications issued within a single calendar year have the fixed forecast target. Although the time t changes from month to month, the target year T and the target value on the right-hand side stays the same over one calendar year. Hence, the forecast issues for the months February to December contain only revisions of the first forecasts made in January. To summarize, we have a forecast with a yearly target, which is revised on monthly basis. It is easy to see that without any adjustment, this dataset is not very useful, as it can only be employed at yearly frequency, and the limited length of the dataset does not allow for that.

However, we can use this data to approximately calculate the 12-month moving average of the expected inflation at monthly frequency. This is done using combinations of the realized inflation, the *current year* forecast and the *next year* forecast. As such, the average expected inflation over the next 12 months can be defined as[5]:

$$\Delta P_{i,t,t+h}^{e} = \Delta P_{i,t,T}^{e} - w_t \Delta P_{t,T}^{a} + w_t \Delta P_{i,t,T+1}^{e} \tag{22}$$

where $\Delta P_{i,t,T}^{e}$ is the current year forecast and $\Delta P_{i,t,T+1}^{e}$ is the next year forecast. The term $\Delta P_{t,T}^{a}$ refers to the average of all known monthly realization from the current calendar year. There are twelve inflation realizations in any calendar year - one for each month. We define w_t as a simple weighting variable, which at time t signals how many realizations out of the twelve are already known. The known part of the twelve month average includes realizations of all previous months excluding the most recent one. This is because the realized inflation is typically announced with some delays, which means that January inflation is available when the March issue of *Consensus* expectations is prepared. Thus, in March, w is 1/12, as only

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[5] The equation (22) only suggests the intuition behind this approach. To take into account the delays in reports by statistical agencies the adjustment is precisely made using following equation:

$$\Delta P_{i,t,t+h}^{e} = (\Delta P_{i,t,T}^{e} - w_t \Delta P_{t,T}^{a}) \frac{1-v}{1-w} + v_t \Delta P_{i,t,T+1}^{e}$$

where v records the fraction of the calendar year at the time t; v is 1/12 in January and 12/12 in December.

one of the twelve realizations is known. Equation (22) simply states that the average expected inflation over next twelve months is the combination the *current year* and the *next year* forecast, given by the *w* ratio, less the known proportion of the inflation average from the current calendar year. Finally, we convert the expected inflation into continuously compounded series using (22):

$$\Delta p^e_{i,t,t+h} = \ln(1 + \frac{\Delta P^e_{i,t,t+h}}{100}) \tag{23}$$

The resulting $\Delta p^e_{i,t,t+h}$ is an inflation forecast issued at time *t*, with the target *t+h*, where *h* is 12 months. Thus, the adjusted forecast can be directly matched with the expected exchange rate depreciation $\Delta s^e_{i,t,t+h}$. Hence, this transformation allows for testing at monthly frequency.

4. THE ESTIMATION METHODS

We use methods to estimate the model specified in Section 3.1. First, we employ the fixed effect model to capture any common effects in the interpretation of the expected inflation. The key advantage of the panel methods is that the pooled dataset increases the level of the test robustness. The limitation is that the forecasters are assumed to be homogenous with respect to the interpretation of the information. Several studies found evidence of individual beliefs, whereby the forecasters fundamentally disagree on the implications of given information on the course of the exchange rate. Hence, to allow for individual beliefs, we also employ individual regression analysis, where coefficients are allowed to differ across forecasters.

4.1 The Fixed Effect Model

We follow Bénassy-Quéré et al. (2003) and employ the fixed effect model as our base line estimation method. The general representation of the fixed effect model is:

$$\Delta s^e_{i,t} = g_i + \beta X_{i,t} + \varepsilon_{i,t}; \quad i = 1,...,N; t = 1,...,T \tag{24}$$

where the $X_{i,t}$ is a set of individual regressors and the constant g_i varies across individual *i*. This model relies on the assumption that all individuals practice common interpretation of the information included in the information set $X_{i,t}$, meaning there is no idiosyncratic effect. At the same time, the individual effects are allowed via the individual constant g_i. The information set $X_{i,t}$ includes individual specific signals. The fixed effect specification of our model equation (17) is defined as:

$$\Delta s^{e}_{i,t,t+h} = g_{i} + \beta \Delta p^{e}_{i,t,t+h} + \beta \Delta p^{e*}_{i,t,t+h} + \varepsilon_{i,t} \tag{25}$$

Note that this model allows for individual fundamental expectations but assumes common interpretation of the rule.

Initially, we estimate the model without any lags. Subsequently, we include a distributed lag structure as suggested by Bénassy-Quéré et al. (2003). This is to allow for a more detailed analysis of the relationships. Folliwing Bénassy-Quéré et al. (2003) we set the maximum lag length to 3. Subsequently, we specify the optimal lag level of the model by minimizing the Akaike's Information Criterion (AIC). We find that for all the tested models, the AIC is minimized for specification of 3 lags, particularly at longer horizons. For the 1 month horizon, less than 3 lags is typically optimal. However, to preserve some degree of consistency, we maintain a general specification of three lags for all estimates. The summary of the AIC for all estimates is reported in Appendix A.

4.2 Overlapping Horizons

Hansen and Hodrick (1980) have suggested a presence of a moving average process in the error term when the horizon length is longer than the observational frequency. They show that overlapping horizons in the data lead to a moving average process of order *h-1* in residuals, where *h* is the forecast horizon. This creates an econometric problem, which causes the standard errors to be biased downwards.

Consider again equation (25). The exchange rate forecasts $\Delta s^{e}_{i,t,t+h}$ follow *MA(h-1)* and overlap most notably for the 12 month forecast horizon. The expected price changes $\Delta p_{i,t,t+m}$ and $\Delta p_{i,t,t+m}*$ on the right hand side, which have a forecast horizon of 12 moths, also follow moving average processes of *h-1*. Hence, moving average processes are present on the both sides of the equation, especially under the 12 month horizon of $\Delta s^{e}_{i,t,t+h}$. Thus, under certain circumstances when PPP holds, the common moving average processes might be offset. Hence, we avoid directly assuming any specific type of the residual process. Instead, we conduct the diagnostic testing, and find a general support for an AR(1) residual process for our model.

4.3 Autocorrelation and Heteroskedasticity in Panel Estimates

Aside from the temporal issues with the residual process, the panel data might also suffer from potential contemporaneous autocorrelation and heteroskedasticity. If we assume that residuals follow an AR(1) process, such that:

$$u_{it} = \rho u_{i,t-1} + \varepsilon_{i,t} \tag{26}$$

where,

$$\varepsilon_{i,t} \to N(0, \sigma_i^2) \tag{27}$$

then the residuals may further have the following properties:

$$E(u_{it}, u_{jt} | X_i) = \begin{cases} \sigma_i^2 & if \quad i = j \\ \sigma_{i,j} & if \quad i \neq j \end{cases} \tag{28}$$

meaning that the residuals can be both contemporaneously correlated and panel heteroskedastic. In our context, the errors might be contemporaneously correlated because the forecasts of each individual are perhaps driven by similar sets of information. Part of the common information set may be explicitly included in the model, like expected PPP is included in equation (17). However, there may be other relevant information which is not specifically included in the model. If the set of regressors does not include the complete set of common information which determines the exchange rate forecasts, the errors can be spatially correlated.

The panel heteroskedasticity arises because the error variances may have a tendency to vary across individuals. This may be the case when forecasts have either heterogeneous beliefs or possess idiosyncratic information. For instance, the scaling of the forecast might depend on the set of information available. Alternatively, individuals may hold different beliefs about the impact of given information on the exchange rate, which again may result in special heteroskedasticity.

The traditional approach to dealing with the contemporaneous correlation in panels is often referred to as Parks method, originally proposed by Parks (1967). The Parks method is based on Feasible Generalized Least Squares (FGLS), which relies on the assumption that the specific form of serial correlation is either known, or can be feasibly estimated. Assuming the residuals are AR(1), we have a model with somewhat more complex variance-covariance matrix of residuals, with a presence of both the period and special autocorrelation.

The estimation of the residual matrix in fact works in two steps. First, an AR(1) model is estimated in a traditional way. The method relies on estimating the residual structure of the OLS estimator and then correcting for autocorrelation using the standard Cochrane-Orcutt or Prais-Winsten approach. Second, residuals from the AR(1) model are then used to estimate special correlation, and the GLS model is estimated again, using the weights from the AR(1) residual matrix.

Equation (26) represents the assumption that the temporal correlation can be captured by a common AR(1) process for all individuals. This assumption restricts the order and the degree of serial correlation to be constant across the individuals. Alternatively, we may allow each cross section to be dominated by different processes. The disadvantage of the latter approach is that the number of parameters which need to be estimated is inflated.

4.4 Panel-Corrected Standard Errors PCSE

Our model, specified in Section 3.1, can be described as Time series cross section model. This term TSCS has been coined by Stimson (1985), who used it to describe models where relatively few units are pooled together, for a relatively long time period. The assumption behind this type of models is that one regression can accurately specify the behaviour of all units for each time period.

Beck and Katz (1995) have studied the accuracy of the Parks method on a particular set of modes which are referred to as temporally dominated Time series cross section data (TSCS). They show that the main limitation of the Parks approach is that it can only be applied in cases when N is larger then T. Beck and Katz hypothesize that even when T is sufficiently larger then N, the standard errors are underestimated. This is because each element of the contemporaneous correlation is estimated using 2T/N observation on average. Therefore, when the N to T ratio is 3 (as is approximately the case for our dataset), there are only 6 observations to estimate each element, which, as Beck and Katz argue, is the source of inaccuracy in standard errors. Using Monte Carlo simulations, they show that Parks estimation method leads to 600% overconfidence for standard errors.

The authors propose an alternative method. The process of the analysis should start with the temporal properties of the data to correct for autocorrelation, for instance by including AR terms. Beck and Katz then suggest estimating the model parameters using OLS, arguing that OLS parameter estimates are unbiased and efficient. Last, a correct estimates of standard errors can be derived, by using the so-called PCSE (Panel-Corrected standard errors).

The procedure involves organizing the vectors of residuals from each cross section, and grouping them into a T x N matrix E:

$$E = [\hat{\varepsilon}_1 \ \hat{\varepsilon}_2 \ \dots \ \hat{\varepsilon}_{N-1} \ \hat{\varepsilon}_N] \tag{29}$$

PCSE robust errors are then computed by taking the square root of the diagonal elements of

$$Cov(\hat{\beta}) = (X'X)^{-1} X'(\frac{E'E}{T} \otimes I_T) X (X'X)^{-1} \tag{30}$$

where $\otimes$ is the Kronecker product. In the absence of the contemporaneous correlation, the formula is simplified to the OLS standard errors which are computed using the square roots of the diagonal terms of

$$Cov(\hat{\beta}) = \hat{\sigma}^2 (X'X)^{-1} \tag{31}$$

where $\hat{\sigma}^2$ is the OLS error variance.

Besides a likely contemporaneous correlation, there is another reason to implement PCSE for our dataset. Due to frequent missing observations, the model can only be estimated as an unbalanced dataset. This would cause additional complexity, and even fewer observations per parameter. We follow Beck and Kats, applying OLS to estimate the parameters and using the PCSE method to correct for standard errors. To account for temporal autocorrelation, we assume an AR(1) residual structure and employ the Prais-Winsten correction.

4.5 Multiple regression approach

The fixed effect model described above assumes a common interpretation of all information across all forecasters. To facilitate for additional degree of heterogeneity, for each individual we estimate the model as specified in equation (17) - where all coefficients g_i, β_i and β_i^* can vary across individuals. This allows for idiosyncratic effects. The equation is estimated using OLS independently for each individual *i*. The temporal serial correlation and heteroskedasticity still remain to be an issue for the individual regressions. To account for both, we employ the Newey–West Heteroskedasticity and Autocorrelation consistent errors.

The Newey-West method is preferred in the context of individual regressions as they allow for preserving the degrees of freedom, unlike the autoregressive model. Preserving degrees of freedom becomes particularly important because the average number of observations for each individual is only around 40. Due to unbalanced nature of the dataset, the addition of AR terms in the regression causes considerable observation losses in nearly each cross section. Therefore, the model without AR terms is the preferred method of estimation. For the consistency, we nevertheless estimate the OLS model including the AR(1) term for each individual, and these results are summarized in Appendix B. The next chapter is devoted to results and interpretation.

5. THE EMPIRICAL ANALYSIS AND INTERPRETATION

5.1 Unit Root Test and Data Analysis

A number of authors have shown evidence that price levels are I(2) processes, and inflation is an I(1) process. Evans and Lewis (1995), Crowder and Wohar (1999), Crowder and Hoffman (1996), and Ng and Perron (2001) have suggested a possibility that US inflation contains unit root. Others presented alternative evidence. Rose (1988), for instance, rejects unit root for US inflation and Peng (1995) finds German inflation stationary. (Henry and Shields 2004)

Granger and Newbold (1974) show that the standard asymptotic properties of OLS do not apply in the presence of non-stationary variables. When two unrelated non-stationary variables with a common trend are regressed on each other, the results tend to exhibit the so-called spurious relationship. To rule out such possibility, we conduct a unit root analysis of our dataset.

Two different tests are commonly used for this purpose, the Augmented Dickey Fuller test and the KPSS test. The Augmented Dickey Fuller test (ADF) takes a unit root as the null hypothesis. This leads to some criticism, because, as some argue, this test suffers from poor precision when variables are near unit root processes. Kwaitkowski et. al. (1992) have developed an alternative test (KPSS), which assumes stationarity under the null hypothesis, the so-called stationarity test. Applying the combination of the stationarity and unit root tests allows for confirmatory analysis and higher robustness of the test results (Brooks, 2002). We follow this approach and conduct unit root analysis on the series of exchange rate, home and foreign inflation and inflation differential.

We focus on the first two columns in *Table 2* that present ADF and KPSS tests on expected values of inflation. The tests are conducted on consensus expectations of both variables. As discussed above, the expected exchange rate depreciation is available in three horizons - 12, 3 and 1 month. The unit root tests on the three horizons are displayed in the fist three rows. Recall that inflation forecasts are only available at the 12-month horizon. The test results on the expected home and foreign inflation and inflation differential are respectively reported in the last three rows of the table.

Table 2: Unit Root Tests

Diagram 1: Expected values: USD/EUR					Diagram 2: Realized values		
	ADF	KPSS	IPS	IPS test obs./ cross. size		ADF	KPSS
column	1	2	3	4		5	6
$\Delta s^{e}_{t,t+12}$	-3.8^{***}	0.13	-3.19^{***}	770	$\Delta s_{t,t+12}$	-2.08	0.16
Critical value/(P-value)	-2.91	0.46	(0.00)	17		-2.91	0.46
$\Delta s^{e}_{t,t+3}$	-6.26^{***}	0.10	-12.09^{***}	797	$\Delta s_{t,t+3}$	-3.28^{**}	0.15
	-2.91	0.46	(0.00)	17		-2.91	0.46
$\Delta s^{e}_{t,t+1}$	-6.82^{***}	0.11	-14.99^{***}	808	$\Delta s_{t,t+1}$	-5.41^{**}	0.16
	-2.91	0.46	(0.00)	17		-2.91	0.46
$\Delta p^{e}_{t,t+h}$	-2.84	0.07	-3.46^{***}	534	$\Delta p_{t,t+h}$	-3.46^{***}	0.10
	-3.49	0.15	(0.00)	11		-2.91	0.46
$\Delta p^{e*}_{t,t+h}$	-3.12^{**}	0.22	-2.14^{**}	367	$\Delta p^{*}_{t,t+h}$	-2.56	0.32
	-2.9	0.46	(0.02)	6		-2.92	0.46
$\Delta p^{e}_{t,t+h} - \Delta p^{e*}_{t,t+h}$	-2.27	0.15	-2.19***	541	$\Delta p_{t,t+h} - \Delta p^{*}_{t,t+h}$	-2.55	0.24
	-2.92	0.46	(0.01)	11		-2.91	0.46

Notes: The remarks *,**,*** indicate the rejection of the null hypothesis at 10,5, and 1% level respectively. The null hypothesis of ADF and IPS is unit root, the null hypothesis of KPSS test is stationarity. For the ADF and KPSS, the table displays test values with the critical value below. For the IPS test, the P-value reported in the brackets.

The results of both tests and all horizons show reconfirming evidence of stationary expected exchange rate changes. We note that the ADF test null is rejected at the 1% level for all horizons, while the KPSS test null is never rejected. Less convincing evidence of stationarity is found for inflation. The ADF test for the Euro-zone expected inflation and the inflation differential does not reject the null hypothesis of unit root. The fact that the KPSS null hypothesis of stationary is not rejected, leads to conflicting evidence.

One possible reason why the conflicting evidence is found for expected inflation is that the series are near unit root. The high tests statistics of the ADF test may also be a consequence of a low number of observations. To resolve the conflicting evidence, we may further analyze the properties of the full panel dataset of individual expectations. This is possible by employing the panel unit root test.

Table 3: Descriptive Statistics for Expected EUR depreciation and the Home and Foreign Inflation Rates: (pooled sample: 2002:12-2007:7)

	$\Delta s^{e}_{i,t,t+12}$	$\Delta s^{e}_{i,t,t+3}$	$\Delta s^{e}_{i,t,t+1}$	$\Delta p^{e}_{i,t,t+h}$	$\Delta p^{e*}_{i,t,t+h}$	$\Delta p^{e}_{i,t,t+h}$ - $\Delta p^{e*}_{i,t,t+h}$
Mean	-0.026	-0.011	-0.005	0.018	0.023	-0.004
Median	-0.028	-0.013	-0.004	0.018	0.024	-0.004
Maximum	0.147	0.115	0.077	0.024	0.036	0.008
Minimum	-0.189	-0.147	-0.088	0.012	0.009	-0.018
Std. Dev.	0.064	0.034	0.022	0.002	0.005	0.004
Skewness	0.159	0.161	-0.115	-0.055	-0.210	0.251
Kurtosis	2.418	3.153	3.977	2.637	2.399	2.903
Jarque-Bera	21.011^{***}	6.099^{**}	48.028^{***}	5.183^{*}	8.473^{**}	3.147
Observations	1148	1147	1145	866	378	288
Cross sections	24	24	24	18	8	6

Notes: The descriptive statistics are pooled across all individual forecasters.

One such test has been proposed by Im, Pesaran, and Shin (1997). The procedure involves specifying a separate ADF regression for each cross section of panel dataset and then transforming the individual test values into a common test statistics. This so-called IPS test has two advantages. First, the test allows for an individual unit root process for each forecaster. This is in contrast with the ADF and KPSS test approach described above, where only the consensus mean was considered. As such, we have implicitly assumed that individual forecast data shares a common root process. Secondly, the test is much more powerful. Because there are 18 forecasters in the cross section, the number of observation can increase by up to a factor of 18. Note that the ADF and KPSS test results are based on only 56 observations available for the consensus mean.

The IPS test results are reported in the third column of Table 3. The column presents the number of observations on which the test statistics is based on. The exclusion of some observations is caused by the automatic selection of the lag length. The IPS test provides strong evidence of stationarity for both variables. The null hypothesis of unit root is in nearly all cases rejected at 1% level.

Diagram 2 of *Table 2* presents unit root tests on actual realized values of the two variables. In general, these results confirm the conclusion above. As noted before, slightly conflicting evidence of stationarity is found for inflation. We assume that this result is influenced by the limited number of observations available for individual series. In summary, we define expected exchange rate depreciation and inflation as stationary series.

Before estimate the model, we briefly consider the descriptive statistics for the expected Euro appreciation, and the bilateral expectations on the inflation rates. These are reported in *Table 3*. Note that the Euro is defined as the home currency and $\Delta s^{e}_{i,t,t+h}$ represents the price of Euro per unit of dollars in natural logarithm. We record that over the specified period, the analysts expected average Euro appreciation of 2.6% over the 12 month horizon. At the same time, analysts expected negative inflation differential of less than a half percent, which means that the Euro Area prices were expected to accelerate at a slower pace than the US prices. The table also shows that the Jarque-Bera test of normality is rejected for all series with the exception of the expected inflation differential.

5.2 The Forward looking PPP model

We estimate the fixed effect model for equation (25). The model is estimated under the following specifications. The first specification is a fully heterogeneous model, where the exchange rate and both home and foreign inflation are all produced by one individual. Recall from Section 3.2 that this specification allows up to 258 observations[6]. Under the second specification, the missing individual observations for the expected US inflation are substituted for, by using the consensus forecast. As such, the number of observations is increased to 766.

The fixed effect model results are reported in *Table 4*, *Diagram 1*. The table displays three horizons for each specification, 12, 3 and 1 month, respectively. First, we focus on the 12-month horizon. For *specification 1*, the β and β^* coefficients are estimated with correct signs: 4.281 and -0.327, respectively. Note that only the home inflation coefficient β is significant. The estimate of β is also much above the hypothesized value of 1. Under specification 2, estimates of β and β^* are 2.769 and -0.433. Only the home inflation enters as significant and we also record that β is larger than the PPP theory would suggest. We record that the results from the two specifications are qualitatively similar.

For the shorter horizons, we can not reject the statistical insignificance of β coefficients. It is worth mentioning however, that coefficient signs are correct for the home inflation, and are always larger than expected. Consider, for instance, that we should expect a β coefficient of approximately 0.25 for the three-month horizon. Recall that our model uses 12-month expected inflation under all three horizons. If we assume a time consistency in inflation expectations, then one percentage point increase in the inflation should trigger about ¼ percentage point increase in the 3-month exchange rate change. However, the β coefficients estimates are 2.229 and 1.642 for specifications 1 and 2, respectively, which is nearly 9 and 7 times more than the hypothesized values.

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[6] This number is further reduced, due to inclusion of an AR(1) term.

Table 4: Forward looking PPP model

	Specification 1			Specification 2		
Forecast Horizon	12 m	3 m	1 m	12 m	3 m	1 m
			Diagram 1: Fixed effect model			
$\overline{g}_i$	-0.097**	-0.058**	-0.036*	-0.081**	-0.038	-0.027*
	(2.23)	(1.95)	(1.65)	(2.32)	(1.58)	(1.67)
β	4.281**	2.229	0.701	2.769**	1.642	0.788
	(2.07)	(1.36)	(0.53)	(1.95)	(1.33)	(0.86)
β^*	-0.327	0.035	0.625	-0.433	-0.286	0.275
	(0.31)	(0.05)	(1.08)	(0.42)	(0.42)	(0.56)
AR(1)	0.823***	0.529***	0.246***	0.76***	0.516***	0.347***
	(17.70)	(7.63)	(3.14)	(19.05)	(10.52)	(6.61)
Adjusted R^2	0.784	0.427	0.171	0.747	0.353	0.179
DW stat.	2.225	2.018	1.999	2.173	2.029	1.992
Forecasters (cross-sections)	6	6	6	18	18	18
Observations	214	214	214	645	645	641
			Individual Regression method			
$\overline{\beta}_i$	5.761	0.893	0.381	7.727	1.341	0.712
$\hat{\beta}_i > 0$	100.0%	66.7%	66.7%	94.1%	64.7%	52.9%
$\beta_i > 0$ *(5% level)*	16.7%	16.7%	16.7%	29.4%	17.6%	11.8%
$\beta_i \neq \hat{\beta}$ *(5% level)*	16.7%	0.0%	16.7%	17.7%	17.7%	17.7%
$\overline{\beta}_i^*$	-2.370	-0.065	0.487	-4.235	-0.632	0.152
$\hat{\beta}_i^* < 0$	66.7%	50.0%	33.3%	82.4%	64.7%	58.8%
$\beta_i^* < 0$ *(5% level)*	33.3%	16.7%	16.7%	47.1%	11.8%	0.0%
$\beta_i^* \neq \hat{\beta}$ *(5% level)*	33.3%	16.7%	16.7%	47.1%	17.7%	5.9%
Mean R^2	0.225	0.076	0.075	0.233	0.102	0.078
Mean Adjusted R^2	0.186	0.029	0.028	0.194	0.057	0.031
Forecasters (cross-sections)	6	6	6	17	17	17
Sum of Obs.	258	258	258	758	758	756

Notes: The remarks *,**,*** indicate the rejection of the null hypothesis at 10,5, and 1% level respectively. Under specification 1, all expectations of both the home and foreign inflation are unique for each individual. Under specification 2, we substitute for missing values in foreign inflation using consensus mean. The t-test statistics are reported in the parentheses. The F-test test statistics on the joint hypothesis of lag significance are reported in the square brackets. The remark $\hat{\beta}_i > 0$ indicates the percentage of individual β_i with positive signs. The remark $\beta_i > 0$ *(5% level)* indicates percentage of individual β_i positive sign, which are significant. The remark $\beta_i^* \neq \hat{\beta}$ indicates percentage individual β_i, which are significantly different from the fixed effect model of the β.

The result suggests that the expected PPP does explain the EUR/USD expectations. However, the forecasters seem to focus only on the Euro zone inflation. One explanation may be that most of our respondents are in fact Euro-zone based organizations. As such, the large majority of respondents only publish the forecasts on the home inflation and only few of them do so for the US inflation.

Alternatively, we may ask whether forecasters are more heterogeneous with respect to the interpretation of the foreign inflation. If so, then the fixed effect model might not describe the relationship optimally, because the estimates of β are common for all individuals. To gain more insight, we estimate individual regressions for each respondent, so that coefficients β are allowed to vary across forecasters. Summary of the results is provided in *Diagram 2, Table 3.*

Let us first focus on the 12-month horizon and specification 2, which allows for 17 individual regressions[7]. We record that the individual coefficients estimates have much more extreme values than seen under the fixed effect model. For the 12-month horizon, the mean values of β and β* coefficients are 7.727 and -4.235. It should be noted however, that the values are less extreme when AR(1) is included (see Appendix B). Second, we find that forecasters generally agree on the sign of the coefficient. In line with the PPP theory, the home inflation coefficient β is positive for 94% of the forecasters and β* is negative for 82% of the forecasters. For nearly 30% of the forecasters, β is significant and has a correct sign. Surprisingly, this proportion is even higher for β^*, where the coefficient is significantly negative for almost 50% of the forecasters. Therefore, in contrast with the fixed effect model, this approach suggests that exchange rate forecasts can be explained by both sides of the expected PPP.

The fourth line of the first two rows reports the fractions of the forecasters with β coefficients significantly different from the fixed effect estimates. We use this measure to capture the amount of heterogeneity in the coefficients β and β^*. If individual's β are significantly different from the fixed effect estimates, it shows that he or she attaches different weight to the PPP. We find only 3 out of 17 (17.7%) forecasters apply significantly different weight on the expected home inflation. However, nearly half of them (8/17) do so for the foreign inflation, which suggests a substantial idiosyncratic effect. We may argue that the idiosyncratic effect is the explanation behind insignificant estimates of β^* from fixed effect model. This result suggests that forecasters have very dispersed beliefs about the interpretation of the foreign inflation.

At the shorter horizons, estimates generally confirm the evidence obtained from the fixed effect model. The lower the horizon, the less evidence there is in favor of the forward looking PPP model. This pattern

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[7] One forecaster with fewer then 25 observations is removed form the sample.

also emerges out of R^2 comparison. The average adjusted R^2 for the 12-month horizons is nearly 0.20, which is in contrast with 0.057 and 0.031 for the 3 and 1 month horizon, respectively.

To summarize, this section presents an evidence of forward looking expectations, for the USD/EUR rate at the 12-month horizon. We also find a considerable magnification effect, whereby PPP fundamental rate is magnified up to a factor of 7 in the exchange rate expectations. Next, to put the model under more scrutiny, we estimate an extended specification which allows for both forward and backward looking expectations.

5.3 Forward versus Backward looking expectations.

The above section suggests a relationship between expected PPP signals and expected exchange rates. As discussed above however, the significance of β and β^* in specification (25) is not the sufficient condition for forward looking expectations. This is because forecasters may be merely interpolating past trends of inflation into their currency expectations, rather then estimating inflation on the basis of broader information sets.

Before we proceed with extending the model, we first estimate the distributed lag on the forward looking model. The distributed lag provides more information about the expectation mechanism. It also allows accounting for simultaneity in the preparation of expectations. To illustrate the point, let us assume there are two analysts working for the same firm, one of whom forecasts fundamentals (i.e. inflation) and the other focuses on the exchange rate forecasts. If we assume that both forecasts are prepared simultaneously and independently at time *t*, then the exchange rate analyst can view the point estimate of inflation forecast only after time *t*, after his exchange rate forecasts was prepared.

Alternatively, we can assume that both analysts work as one, having the same information set and they perfectly communicate their beliefs. If both analysts believe in PPP, the information which signals inflation pressures will also likely signal the exchange rate depreciation. Hence, even if exchange rate forecasts are prepared simultaneously, the exchange rate forecaster would need to make no revisions after seeing the inflation forecast of his colleague. Therefore, the lagged fundamentals should have no explanatory power. The distributed lag model is specified adding lagged regressors as follows:

$$\Delta s^e_{i,t,t+h} = g_i + \beta_0 \Delta p^e_{i,t,t+h} + \beta^*_0 \Delta p^{e*}_{i,t,t+h} + \sum_{k=1}^{j} \beta_k \Delta p^e_{i,t-k,t+h-k} + \sum_{k=1}^{j} \beta^*_k \Delta p^{e*}_{i,t-k,t+h-k} + \phi + \varepsilon_{i,t} \qquad (32)$$

where *j* is the maximum lag. We estimate the model with three lags so that *j=3*, as the AIC is minimized under this specification (see Appendix A).

The results on the distributed lag model are reported in the first diagram of *Table 5*. Note that for the 12-month horizon, β_1 which specifies the first lag on home inflation is significantly positive at one percent level. This suggests that there is some degree of inefficiency, as forecasters react to some of the information with delay. Beyond the second lag, the effect disappears on the home side and the third lag is only significant at 10% level. On the foreign inflation side, the coefficients are generally not significant, although the coefficient signs are correct for both the current and lagged values of inflation. Only the third lag is significantly negative, which possibly suggests that agents react to some of their own information with delay.

Next, we include the backward looking component in the model adding the distributed lag on recent observed inflation, for the home and foreign country:

$$\Delta s^{e}_{i,t,t+h} = g_i + \beta_0 \Delta p^{e}_{i,t,t+h} + \beta^{*}_0 \Delta p^{e*}_{i,t,t+h} + \sum_{k=1}^{j} \beta_k \Delta p^{e}_{i,t-k,t+h-k} + \sum_{k=1}^{j} \beta^{*}_k \Delta p^{e*}_{i,t-k,t+h-k} + \sum_{k=1}^{j} \gamma_k \Delta p_{t-k-1} \sum_{k=1}^{j} \gamma^{*}_k \Delta p^{*}_{t-k-1} + \phi + \varepsilon_{i,t} \tag{33}$$

where Δp_t is the annual price level change at time *t*. Note that at time *t* agents have access to the observed values of Δp_{t-2} , due to delays in the releases of statistical agencies. We estimate the model by setting *j* to 3 lags as suggested by AIC (see Appendix A).

Diagram 2 displays the results for the extended model. We find that β coefficient estimates are nearly the same as in the forward looking model. The expected inflation is still highly significant on the home side, suggesting that there is little co-linearity between the current and expected inflation. As for the backward looking component, the coefficient γ_1 in only marginally significant for the home side realized inflation. Interestingly, γ_1* is highly significant and negative at every horizon. This suggests that the trend interpolation using past values of foreign inflation, is the dominant practice among the forecasters. In summary, agents are forward looking with respect to home inflation, while on the foreign side, they merely interpolate the past price trends. There is also evidence that analysts react to the foreign information with some delay.

Table 5: Forward vs. Backward looking content

	Diagram 1: Distributed lag model			Diagram 2: Extended model: Forward vs. backward looking expectations		
	12m	3m	1m	12m	3m	1m
$\overline{g}_i$	-0.160***	-0.047	-0.024	-0.208	-0.034	-0.008
	(2.86)	(1.61)	(1.17)	(2.82)	(0.74)	(0.26)
β_0	3.889***	2.444*	1.600	3.411**	2.100	1.233
	(2.55)	(1.80)	(1.44)	(2.36)	(1.59)	(1.14)
β_1	3.780***	0.988	0.074	3.829***	0.830	0.002
	(2.65)	(0.78)	(0.07)	(2.84)	(0.67)	(0.00)
β_2	2.371*	-0.045	-0.783	2.638**	0.282	-0.508
	(1.67)	(0.04)	(0.75)	(1.96)	(0.23)	(0.49)
β_3	1.054	-0.585	-0.333	1.247	-0.292	-0.130
	(0.73)	(0.48)	(0.32)	(0.91)	(0.24)	(0.13)
β_0*	-0.465	0.106	0.006	0.871	0.845	0.567
	(0.48)	(0.14)	(0.01)	(0.91)	(1.13)	(0.86)
β_1*	-0.394	0.269	1.098	0.402	0.945	1.287*
	(0.39)	(0.33)	(1.47)	(0.37)	(1.11)	(1.65)
β_2*	-1.764*	-0.338	-0.494	-0.897	0.228	-0.349
	(1.78)	(0.43)	(0.68)	(0.83)	(0.27)	(0.46)
β_3*	-1.390	-1.026	-0.390	-1.752*	-1.089	-0.640
	(1.38)	(1.23)	(0.57)	(1.68)	(1.36)	(0.91)
γ_1				3.498*	1.097	1.590
				(1.68)	(0.65)	(1.16)
γ_2				0.968	0.751	-0.078
				(0.43)	(0.43)	(0.05)
γ_3				-2.020	-3.249*	-2.676*
				(0.92)	(1.85)	(1.89)
$*\gamma_1$				-2.428***	-1.786***	-1.394***
				(2.80)	(2.63)	(2.55)
$*\gamma_2$				-1.120	-0.035	0.235
				(1.30)	(0.05)	(0.40)
$*\gamma_3$				1.222	0.771	0.953*
				(1.42)	(1.14)	(1.70)
ϕ	0.702***	0.441***	0.327***	0.699***	0.426***	0.310***
	(16.05)	(8.54)	(5.85)	(16.96)	(8.40)	(5.61)
$\sum\beta$	11.095***	2.801	0.557	11.125***	2.920	0.597
$H_0=\beta_0=\beta_1=\beta_2=\beta_3=0$	[3.259]	[1.184]	[0.608]	[3.647]	[1.138]	[0.365]
$\sum *\beta$	-4.013	-0.989	0.219	-1.376	0.929	0.865
$H_0=*\beta_0=*\beta_1=*\beta_2=*\beta_3=0$	[1.799]	[0.645]	[0.674]	[0.929]	[1.011]	[1.259]
$\sum \gamma$				2.446	-1.401	-1.164
$H_0=\gamma_1=\gamma_2=\gamma_3=0$				[1.191]	[1.166]	[1.356]
$\sum * \gamma$				-2.326***	-1.05**	-0.206**
$H_0=*\gamma_1=*\gamma_2=*\gamma_3=0$				[4.624]	[2.932]	[3.267]
Adjusted R-squared	0.735	0.334	0.187	0.756	0.364	0.219
Durbin-Watson stat	2.150	2.086	2.060	2.244	2.156	2.113
cross-section	18	18	18	18	18	18
Observations	501	501	497	501	501	497

Notes: The remarks *,**,*** indicate the rejection of the null hypothesis at 10,5, and 1% level respectively. The t-test statistics are reported in parentheses. The results of the F-test statistics on the joint significance of lags are reported in square brackets.

5.4 Frankel and Froot Model with Forward Looking Component

We also examine how the forward looking model performs as a component of the traditional Frankel and Froot expectation model. Accordingly, we re-specify the model from equation (33) by including extrapolative, adaptive and regressive components.

To begin with, we analyze the potential loss of observation, due to the inclusion of the additional terms. To illustrate the problem, consider again the Frankel and Froot model, which is specified for heterogeneous agents as follows:

$$\Delta s^{e}_{i,t,t+h} = \omega + \mu(s_t - s_{t-1}) + \vartheta(s^{e}_{i,t-h,t} - s_t) + \nu(\tilde{s}_t - s_t) \qquad (34)$$

The fundamental rate $\tilde{s}_t$ is computed using the PPP relation, as follows:

$$\tilde{s}_t = s_0 P_t / P^{*}_t \qquad (35)$$

where P_t and P^{*}_t are the price level indexes of the Euro Area and United States, respectively, and s_0 is the exchange rate at time 0. Multiplication by s_0 is necessary, because the price indexes are defined in relative rather than absolute terms. Therefore, the initial level of exchange rate has to be imposed. We follow Jognen et.al. (2009) and set the value of s_0 equal to the spot exchange rate on the date when CPI series were first issued. CPI series are collected from International Financial Statistics.

Note that the adaptive term in (34) can also be described as the most recent forecast error. As the forecast error is individually specific under the adaptive model, it varies across individuals. Hence, the missing individual values can further inflate the observation losses. The extrapolative and regressive models do not vary across individuals on the right hand side, and therefore there are no observation losses from these terms. To assess the potential observation losses, we first pretest the equation (34) without the forward looking term.

We find that the ϑ coefficient on the adaptive model is only significant for the 1-month horizon but not for longer ones. The reason is perhaps that under the 12-month horizon, the forecast error is 12 months old. The target rate from time *t* is used to evaluate the forecast from time *t-12*. It is easy to see why the adaptive model has little explanatory power for longer horizons. In addition, there are considerable observation losses resulting from the inclusion of the adaptive term. Therefore, to avoid unnecessary observation losses, we do not include the adaptive model in further analysis.

Table 6: Regressive, Extrapolative and Forward looking models:

	12m	3m	1m
$\bar{g}_i$	-0.155***	-0.045*	-0.025
	(4.04)	(1.77)	(1.39)
β_0	2.987***	1.915	1.089
	(2.66)	(1.60)	(1.09)
β_1	1.712	0.166	-0.393
	(1.60)	(0.15)	(0.40)
β_2	0.955	0.062	-0.572
	(0.88)	(0.06)	(0.59)
β_3	0.681	-0.004	0.414
	(0.63)	(0.00)	(0.44)
$*\beta_0$	0.106	0.531	0.449
	(0.17)	(0.89)	(0.80)
$*\beta_1$	-0.059	0.417	1.211*
	(0.09)	(0.64)	(1.88)
$*\beta_2$	-0.667	0.178	-0.155
	(1.02)	(0.28)	(0.25)
$*\beta_3$	-1.520**	-1.700***	-1.072*
	(2.25)	(2.62)	(1.79)
μ_0	-0.600***	-0.353***	-0.253***
	(13.27)	(7.25)	(5.94)
μ_1	-0.294***	-0.098**	-0.050
	(6.65)	(2.05)	(1.18)
ν	-0.265***	0.008	0.034
	(3.43)	(0.14)	(0.84)
ϕ	0.770***	0.511***	0.380***
	(22.54)	(10.83)	(7.16)
$\sum\beta$	6.335**	2.140	0.539
$H_0=\beta_0=\beta_1=\beta_2=\beta_3=0$	(2.41)	(0.74)	(0.41)
$\sum*\beta$	-2.140	-0.574	0.433
$H_0=*\beta_0=*\beta_1=*\beta_2=*\beta_3=0$	(1.75)	(1.85)	(1.98)
Adjusted R-Squared	0.834	0.457	0.345
Durbin-Watson stat	2.053	2.084	2.083
cross-section	18	18	18
observations	501	501	497

Notes: The remarks *,**,*** indicate the rejection of the null hypothesis at 10,5, and 1% level respectively. The results of the F-test statistics on the joint significance of lags are reported in square brackets.

The final specification is formulated as follows:

$$\Delta s^{e}_{i,t,t+h} = g_i + \beta_0 \Delta p^{e}_{i,t,t+h} + \beta^{*}_{0} \Delta p^{e*}_{i,t,t+h} + \sum_{k=1}^{j} \beta_k \Delta p^{e}_{i,t-k,t+h-k} + \sum_{k=1}^{j} \beta^{*}_{k} \Delta p^{e*}_{i,t-k,t+h-k} + \mu_0 (s_t - s_{t-1}) + \mu_1 (s_{t-1} - s_{t-2}) + \nu (s_t - \bar{s}_t) + \phi + \varepsilon_{i,t} \qquad (36)$$

We initially tested (36), allowing for up to 3 lags for the extrapolative model. However, the experiments showed that AIC is minimized under the specification of one lag for the extrapolative model and three lags of the forward looking model. The results on this specification are displayed in *Table 6*.

Focusing first on the extrapolative term, we notice that μ_0 is significantly negative for all horizons. We see that agents expect a reversal of the past changes. As such, they have a stabilizing effect on the exchange rate. This finding is in line with much of the empirical literature on surveys of expectations, which suggests stabilizing effect for longer horizon. Slightly surprising is that respondents have stabilizing expectations also for the 1-month horizon. A number of studies have shown that expectations may be destabilizing under the shorter horizons. Frankel and Froot (1987) and Torrance (1988) using MMS survey data show evidence of destabilizing expectations for the 3-month horizon and less. On the other hand, this result is in line with the findings of Cavaglia et al. (1993) who, using EMS rates, found general support for stabilizing expectations for the 3-month horizon.

The evidence of regressive expectations is only found for the 12-month horizon. The speed of adjustment coefficient is -0.265, which means that the deviations from the fundamental PPP rate are expected to revert at the annual rate of 26.5%. This implies that the half-life of disturbances from the long run PPP rate is expected to be approximately 2.5 years. This result is consistent with the findings of Frankel and Froot (1987). Somewhat faster mean reversion was shown by Benassy-Quere et al (2003).

Even after including the regressive and explorative terms, β_0 which specifies the home side forward looking term, remains highly significant for the 12-month horizon. For the 3-month horizon, the t-statistics is slightly below the 10% significance level. It is worth noting that the distributed lag structure on the home expected inflation is no longer significant after including the additional terms. In contrast to Section 4.3, this result suggests that forecasters make full use of their current fundamental expectations, and there are no delays in processing the information. On the foreign side, the forecasters react with delays. This may be also due to the fact that their approach is simply backward looking, and they focus on past inflation releases.

5.5 The effect of Dispersed Fundamental Expectations

Above we find that currency analysts make use of expectations about future fundamentals. This raises the question, whether the fundamental beliefs are dispersed, and what is the effect of such dispersion. This leads to our second hypothesis, which we formulate as a question on whether heterogeneity is caused by dispersion effect in expected fundamentals.

The empirical test can be modeled as an extension of Ito’s model. To obtain a testable proposition, we formulate private signals about fundamentals as a difference between individual expected inflation and the cross sectional average, as follows:

$$s^e_{i,t,t+h} - \overline{s}^e_{t,t+h} = g_i + \beta(p^e_{i,t,t+h} - \overline{p}^e_{t,t+h}) + \beta^*(p^{e*}_{i,t,t+h} - \overline{p}^{e*}_{t,t+h}) + \varepsilon_{i,t} - \overline{\varepsilon}_{i,t} \tag{37}$$

where the term $p^e_{i,t,t+h} - \overline{p}^e_{t,t+h}$, measures effect of the private fundamental signals. Significant values of β and β^* would suggest that individual differences in the fundamental expectations can explain the dispersion in expectations of currency analysts.

Due to inconsistencies in the datasets, we test the proposition separately for the foreign and home fundamental signals, to allow for the full use of our dataset. We also allow for the distributed lag on the signals up to a maximum of three lags, which is supported by AIC (see Appendix A). The test equations can be specified as follows:

$$s^e_{i,t,t+h} - \overline{s}^e_{t,t+h} = g_i + \lambda_0(p^e_{i,t,t+12} - \overline{p}^e_{t,t+12}) + \sum_{k=1}^{j} \lambda_k(p^e_{i,t-k,t+12-k} - \overline{p}^e_{t-k,t+12-k}) + \phi + \varepsilon_{i,t} \tag{38}$$

$$s^e_{i,t,t+h} - \overline{s}^e_{t,t+h} = g_i + \lambda^*_0(p^{e*}_{i,t,t+12} - \overline{p}^{e*}_{t,t+12}) + \sum_{k=1}^{j} \lambda^*_k(p^{e*}_{i,t-k,t+12-k} - \overline{p}^{e*}_{t-k,t+12-k}) + \phi + \varepsilon_{i,t} \tag{39}$$

whereby (38) tests the effect of individual signals in the home inflation and equation (39) measures the same effect for foreign inflation. When the coefficients λ are significant, we can infer that the private signals on inflation do matter.

We estimate the model using two methods. First, we apply the fixed effect estimator. This test relies on the assumption that there is some degree of homogenous interpretation of the fundamental information and forecasters generally believe in the PPP model. Second, we estimate individual OLS regressions for each forecaster. In this model, the standard errors are corrected using Newey West. We also tested the

Table 7: Effect of Dispersed Fundamental Expectations

Diagram 1: Home Fundamentals				Diagram 2: Foreign Fundamentals			
	12m	3m	1m		12m	3m	1m
Fixed Effect model							
$\bar{g}_i$	-0.028***	-0.009***	-0.004***	$\bar{g}_i$	-0.006	-0.005	-0.004**
	(7.05)	(4.32)	(3.27)		(0.79)	(1.47)	(2.21)
λ_0	3.267***	1.961*	0.679	λ_0^*	0.666	-0.444	0.392
	(2.98)	(1.79)	(0.74)		(0.79)	(0.52)	(0.57)
λ_1	1.787*	1.421	1.012	λ_1^*	0.522	1.087	-0.290
	(1.71)	(1.35)	(1.16)		(0.59)	(1.22)	(0.42)
λ_2	2.267**	2.088**	0.387	λ_2^*	0.725	0.099	0.541
	(2.21)	(2.02)	(0.45)		(0.81)	(0.19)	(0.80)
λ_3	1.272	1.419	0.083	λ_3^*	0.829	0.686	0.396
	(1.26)	(1.35)	(0.09)		(0.97)	(0.86)	(0.59)
ϕ	0.759***	0.517***	0.411***	ϕ	0.799***	0.462***	0.432***
	(22.68)	(11.40)	(8.20)		(21.28)	(6.94)	(6.81)
	0	0	0		0	0	0
$\sum \lambda$	8.593***	6.889***	2.161	$\sum \lambda^*$	2.742	1.429	1.039
$H_0 = \lambda_0 = \lambda_1 = \lambda_2 = \lambda_3 = 0$	[3.388]	[3.118]	[0.684]	$H_0 = \lambda_0^* = \lambda_1^* = \lambda_2^* = \lambda_3^* = 0$	[0.412]	[0.662]	[0.403]
Adjusted R-squared	0.800	0.430	0.250	Adjusted R-squared	0.790	0.446	0.221
Durbin-Watson stat	2.090	2.067	2.044	Durbin-Watson stat	2.203	2.005	2.093
cross-section	18	18	18	cross-section	8	8	8
observations	501	501	497	observations	285	230	285
Individual Regressions (OLS)							
$\overline{\lambda_i}$	5.449	4.198	1.897	$\overline{\lambda_i^*}$	-0.068	-0.101	0.267
$\hat{\lambda}_i > 0$	68.8%	75.0%	68.8%	$\hat{\lambda}_i^* < 0$	42.9%	57.1%	42.9%
$\lambda_i > 0$ *(5% level)*	31.3%	37.5%	18.8%	$\lambda_i^* < 0$ *(5% level)*	0.0%	0.0%	0.0%
Mean R^2	0.095	0.085	0.049	Mean R^2	0.092	0.043	0.037
Mean Adjusted R^2	0.074	0.063	0.027	Mean Adjusted R^2	0.071	0.021	0.016
Forecaster count	16	16	16	Forecaster count	7	7	7
Sum of all Obs.	735	735	733	Sum of all Obs.	323	323	323

Notes: The remarks *,**,*** indicate the rejection of the null hypothesis at 10,5, and 1% level respectively. The t-test statistics are reported in parentheses. The F-test test statistics on the joint hypothesis of lag significance are reported in square brackets. The remark $\hat{\lambda}_i > 0$ indicates the percentage of individual λ_i with positive signs. The remark $\lambda_i > 0$ *(5% level)* indicates percentage of individual λ_i positive sign, which are significant.

model including AR(1), however, this led to large observation losses. The results from AR(1) model are reported in Appendix B.

We focus first on the fixed effect model results, reported in first part of *Table 7*. *Diagram 1* of the table displays the results on home fundamentals, equation (38). For the 12-month horizon, we find the λ_0 coefficient significantly positive at 1% level. This means that when forecasters hold higher than average expectations about inflation, they also expect a faster then average depreciation of the home currency. This indicates that individual fundamental signals help explain the agent heterogeneity. The magnitude of the coefficient is also similar to the one found under the forward looking PPP model. The coefficient estimate is much larger than the hypothetical value of 1, indicating that the effect of dispersed fundamental signals is magnified in the exchange rate expectations.

The coefficient λ_0 is also significant at the 3-month horizon (at 10% level), but not so for the 1-month horizon. This finding is consistent with the results from the previous section, where we found that expected fundamentals only matter for the long horizons. We also find that the lagged terms of the home signals are also significantly positive up to the second lag, for the 12 and 3-month horizons. Hence, not only the current but also the past difference in fundamental signals contribute to the agent heterogeneity.

In the second diagram, the differences in the foreign signals are not significant for any of the horizons. One interpretation may be that there is no significant dispersion in fundamental signals. Alternatively, this result may be affected by the much lower number of observations and cross sections. Note also that this test has little power when agents have very dispersed beliefs and as shown above in Section 3.2, beliefs about the foreign fundamentals are significantly dispersed.

Last, we consider the individual estimates OLS estimation. For the home fundamental signals, the average mean estimate $\overline{\lambda_i}$ is displayed in the first row of the section. The magnitude of the coefficients is similar, but slightly higher compared to the fixed effect model, which is perhaps the result of an absent AR(1) in the OLS model[8]. In the second row, we report the fraction of the estimates λ_i which are positive. For all horizons, around 70% of the individual estimates have a positive sign. The third row shows that for long horizons, more than 30% of the λ_i are significantly positive at 5% level, and this fraction decreases for the 1 month horizon. The result for the foreign fundamentals, confirm the findings above, as no λ_i are always found insignificant at all horizons.

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[8] When an AR(1) process is included in the individual OLS regression, the estimates are larger in absolute values (see Appendix B).

In summary, the results of this section suggest that the dispersion in the home fundamentals can help in explaining the agent heterogeneity. We find that dispersion in inflation expectations at longer horizons significantly affects heterogeneity for more than one third of the participants. Our results show that heterogeneity can arise even when agents are fully rational, because differences in fundamental expectations reinforce the dispersion in the exchange rate beliefs.

6. CONCLUDING REMARKS

In this paper, we tested for the forward looking content in survey of exchange rate expectations. Our findings can be summarized in three key points.

First, we find that forecasters employ information contained in their home fundamental forecasts to form exchange rate expectations. This implies that agents are forward looking and rational to the extent that they employ their private expectations of future home fundamentals.

Second, agents expect a considerable magnification effect, which may be as large as 1 to 7, when the distributed lag model is considered. Generally, we find that one percentage point change to the expected fundamental rate translates to 3 percentage point shock in the expected spot rate. There are at least two ways we can look at the effect of the expected magnification. On one hand, if agents expect magnification, it may be a potential source of volatility, particularly if analysts trade on their beliefs. Another way is to view the expected magnification as a result of past excess volatility. If agents observe large volatility in the past, they may incorporate these observations into their expectations of future spot rates.

Last, we test whether heterogeneity in analyst expectations results from dispersion of fundamentals expectations. As individual beliefs or information agents are not observable, this raises a question about the impact of the private fundamental expectations. We show that individual differences in inflation expectations reinforce agent heterogeneity. This result suggests that a significant degree of dispersion arises even among rational, forward looking agents.

This is only a first step in the direction of a potentially new line of research. Further studies may be extended in scale, by focusing on a broader range of surveys and currency pairs, and also in scope, by examining other fundamental models and variables. An alternative approach would be to link fundamental expectations directly to spot rates. One suggestion would be to examine whether the dispersion in fundamental expectations can be in any way linked to the exchange rate volatility or order flow.

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APPENDIX A:

Summary of AIC Criteria:

Table 4

Lag levels of inflation	*Diagram 1: Distributed lag model*			*Diagram 2: Forward vs. Backward Looking Expectations*		
	12 m	3 m	1 m	12m	3m	1m
3	-4.434*	-4.434*	-4.821	-4.238*	-4.469*	-4.850*
2	-4.405	-4.405	-4.824	-4.205	-4.421	-4.836
1	-4.387	-4.387	-4.815	-4.174	-4.407	-4.837
0	-4.390	-4.390	-4.841*	-4.146	-4.390	-4.841

Table 5: Mixed Model

	12 m	3 m	1 m
3	-4.633*	-4.668*	-5.011
2	-4.587	-4.629	-5.010
1	-4.580	-4.613	-5.015*
0	-4.468	-4.583	-4.997

Table 6: Idiosyncratic information

	Diagram 1: Home Fundamentals			*Diagram 2: Foreign fundamentals*		
3	-4.756*	-4.819*	-5.163	-4.648*	-4.859*	-5.163
2	-4.722	-4.793	-5.173	-4.614	-4.823	-5.141
1	-4.722	-4.765	-5.193*	-4.603	-4.849	-5.158
0	-4.749	-4.753	-5.189	-4.620	-4.792	-5.167*

Notes: The asterisk indicates the minimum AIC for a given model.

APPENDIX B:

Individual Regression Estimates with AR(1) for Forward Looking Model (Table 3)

	Individual Regression method					
	Specification 1			Specification 2		
$\overline{\beta}_i$	3.659	1.041	-0.034	2.534	1.901	1.045
$\hat{\beta}_i > 0$	66.7%	66.7%	50.0%	66.7%	66.7%	53.3%
$\beta_i > 0$ *(5% level)*	16.7%	16.7%	33.3%	13.3%	13.3%	20.0%
$\overline{\beta}_i^*$	-0.152	-0.038	0.774	-0.313	-0.284	0.016
$\hat{\beta}_i^* < 0$	50.0%	50.0%	16.7%	73.3%	60.0%	46.7%
$\beta_i^* < 0$ *(5% level)*	33.3%	0.0%	0.0%	20.0%	6.7%	13.3%
$\overline{\phi}_i$	0.697	0.371	0.135	0.687	0.397	0.271
$\overline{\phi}_i \neq 0$ *(5% level)*	100.0%	66.7%	16.7%	93.3%	66.7%	46.7%
Mean R^2	0.670	0.281	0.172	0.589	0.289	0.201
Mean Adjusted R^2	0.640	0.210	0.094	0.553	0.227	0.133
Forecasters (cross-sections)	6	6	6	15	15	15
Sum of Obs.	214	214	214	610	610	608

Notes: Under the specification 1 all expectations of both the home and foreign inflation are unique for each individual. Under the specification 2 we substitute for missing values in foreign inflation using consensus mean. The remark $\hat{\beta}_i > 0$ indicates the percentage of individual β_i with positive signs. The remark $\beta_i > 0$ *(5% level)* indicates percentage of individual β_i positive sign, which are significant.

Individual Regression Estimates with AR(1) for Table 6:

	Individual Regressions						
Home Fundamentals				Foreign Fundamentals			
$\overline{\lambda}_i$	1.920	2.223	0.724	$\overline{\lambda}_i^*$	0.895	0.096	0.438
$\hat{\lambda}_i > 0$	73.3%	86.7%	46.7%	$\hat{\lambda}_i^* < 0$	42.9%	42.9%	42.9%
$\lambda_i > 0$ *(5% level)*	0.0%	6.7%	6.7%	$\lambda_i^* < 0$ *(5% level)*	0.0%	0.0%	0.0%
$\overline{\phi}_i^*$	0.756	0.479	0.418	$\overline{\phi}_i^*$	0.735	0.444	0.297
$\overline{\phi}_i^* \neq 0$ *(5% level)*	100.0%	80.0%	73.3%	$\overline{\phi}_i^* \neq 0$ *(5% level)*	100.0%	71.4%	42.9%
Mean R^2	0.596	0.320	0.214	Mean R^2	0.646	0.258	0.136
Mean Adjusted R^2	0.572	0.281	0.171	Mean Adjusted R^2	0.627	0.218	0.089
Forecasters (cross-sections)	15	15	15	Forecasters (cross-sections)	7	7	7
Sum of Obs.	610	610	608	Sum of Obs.	280	280	280

Notes: The remark $\hat{\lambda}_i > 0$ indicates the percentage of individual λ_i with positive signs. The remark $\lambda_i > 0$ *(5% level)* indicates percentage of individual λ_i positive sign, which are significant.