
Heterogeneity in Macroeconomic News Expectations: A disaggregate level analysis

Document de Travail
Working Paper
2015-17

Imane El Ouadghiri



UMR 7235

Université de Paris Ouest Nanterre La Défense
(bâtiment G)
200, Avenue de la République
92001 NANTERRE CEDEX

Tél et Fax : 33.(0)1.40.97.59.07
Email : nasam.zaroualete@u-paris10.fr

université
Paris Ovest

Nanterre La Défense

Heterogeneity in Macroeconomic News Expectations: A disaggregate level analysis *

Imane El Ouadghiri[†]

July 16, 2015

Abstract

The aim of this paper is to investigate heterogeneity in macroeconomic news forecasts using disaggregate data of monthly expectation surveys conducted by Bloomberg on macroeconomic indicators from January 1999 to February 2013. We find three major results. First, we show that macroeconomic indicator forecasters are mostly heterogeneous and their expectations are found to violate the rational expectation hypothesis. Second, the use of the expectation mixed model –combining extrapolative, regressive and adaptive components– reveals a large dominance of the chartist profile among forecasters with a systematical persistence over time despite all the structural breaks determined endogenously by the Bai-Perron estimation method. Third, we find that forecasters whose forecasting models combine at least two or three anticipatory components (extrapolative, and regressive or/and adaptive) and display high temporal flexibility, thus adapting to different structural breaks, are those which provide the most accurate forecasts.

JEL Classification: G14, G12, E44, C22.

Keywords: announcements, heterogeneity, survey data, expectation formation.

*We are especially grateful to Remzi Uctum for helpful discussions. We also thank Pr.Valérie Mignon for providing constructive remarks and suggestions that improved this work.

[†]EconomiX-CNRS, University of Paris Ouest, 200 av. de la République, 92001 Nanterre Cedex, France.
Tel: +33 (0)1 40 97 59 63, E-mail: imane.elouadghiri@u-paris10.fr.

There is a little incentive for those paid to forecast the future to confess that it cannot be done, so they are unlikely to put much weight on the random walk view.

Goodhart (1988)

1 Introduction

There exists an extensive literature devoted to the market impact of macroeconomic announcement releases that highlights the substantial effects that data surprises have on asset prices (stock prices, bond prices, exchange rates...). In other words, this literature puts forward the existence of a strong relationship between surprises in macroeconomic data and financial market volatility.¹

The crucial component characterizing the scheduled macroeconomic news announcements is the expectation made regarding the upcoming release. Insofar as traders take positions based on their expectations of future events, it is not the published value in itself which determines the response of the market to the new information but rather its deviation from its expected value. This deviation is generally referred to as “unexpected” component of scheduled news or “surprise”. Hence, as notably argued by Lefevre (2011), the reaction of market participants to macroeconomic figures is not made in absolute terms but rather in relative terms.

A number of studies have considered the impact of these surprises on individual markets² as the equity market (see inter alia Fama et al. (1969), Pearce and Roley (1983), French and Roll (1986), Sun and Tong (2000), Nikkinen and Sahlstrom (2001), Birz and Lott Jr. (2011)), the bond market (see inter alia Becker et al. (1996), Jones et al. (1998), Fleming and Remolona (1999), Bollerslev et al. (2000), Balduzzi et al. (2001)) and the FX market (see inter alia Ito and Roley (1987), Ederington and Lee (1993), Almeida et al. (1998), Lobo et al. (2006)). More recently, a literature has emerged which considers the impact of such macroeconomic announcements across multiple markets rather than a single one (Graham et al. (2005) and Rigobon and Sack (2006)).³

In light of this, understanding the expectation building process is of crucial importance for both investors, who aim to maximize their gains, and regulators in their optimal choice of future economic policies. Individual expectation behavior becomes hence, an essential part of this process.⁴

Expectations in the market place have been a central problem in economic theory. The rational expectations hypothesis forms by itself a building block of the traditional macroeconomic theory. However, the new behavioral approach based on heterogeneous

¹See Andersen et al. (2007) among others.

²For each of these markets, the impact of macroeconomic news announcements on returns and volatility is most frequently examined.

³This literature highlights the existence of simultaneous jumps in multiple markets (i.e. cojumps). See among others, Lahaye et al. (2011), Gilder et al. (2014).

⁴Keynes (1936) argued that investors’ sentiment and market psychology play an important role in financial markets.

agents beliefs challenges the traditional representative rational agent framework in so far as it admits that in the real world markets, individuals have heterogeneous beliefs and use more than one forecasting model.

In the late eighties and early nineties, a number of authors have turned to investigate the properties of survey based expectations, developing heterogeneous agent models. These works differ from others with respect to the type of the survey data used (aggregated or disaggregate data), the time-horizon of expectations (short or long term), the data structure (panel or time series) and finally, the expectation model used (single of mixed model).

Frankel and Froot (1987) in their pioneering paper considered the three standard models for expectations, namely extrapolative, regressive (or mean reverting) and adaptive expectations, describing respectively three profiles/classes of agents: technical analysis⁵ (chartists), fundamental analysis⁶(fundamentalists) and the learning process (errors and self-correction behavior). Prat and Uctum (1994, 2000, 2007) showed that the best model to describe aggregated (average) predictions is a model mixing extrapolative, regressive and adaptive behavior. These expectation models are generally used on summary measurements of expectations (aggregate data), mainly standard deviations, medians or means –commonly referred to as consensus market survey – (see Takagi (1991), Benassy-Quere (1997), MacDonald (2000) to name a few). Some of these authors have also analyzed individual survey data using panel procedures (see among others, Ito (1990), Benassy-Quere et al. (1999)) and traditional chronological series’ statistical procedures (see MacDonald (1992)). For the vast majority of cases, this previous literature deals with stock prices and foreign exchange rates.

In this paper we aim at investigating heterogeneity in macroeconomic news forecasts by estimating the expectation models on a unique disaggregated macroeconomic survey database of around 15 leading macroeconomic news forecasters. Theses database include forecasts of three different real economic variables, the consumer confidence index, the new home sales and the unemployment rate, all provided by Bloomberg. To the best of our knowledge such a prospective study has not been previously undertaken and should therefore provide useful information about a key aspect of expectations behavior in this area.

As any economist knows, macroeconomic forecasting is really difficult. Predicting the evolution of an economic indicator is an arduous task for various reasons; the most important being that economies are in perpetual change, therefore one cannot always extrapolate behavior and relationships from past business cycles to predict the future. Consequently, on the one hand, assuming that agent’s behavior remain constant over large periods would be erroneous and so estimating such models regardless of the numerous structural breaks inherent to the environment in which professional forecasters carry out their expectations

⁵Technical analysts (or chartists) construct their expectations about future values by scrutinizing observed historical patterns in past prices (e.g the moving average technical analysis) without taking into account market fundamentals.

⁶Fundamentalists construct their expectations about their trading strategies by analyzing market fundamentals and economic indicators, such as macroeconomic reports, dividends, earnings, etc.

–may be due to various shocks which hit the economy as a whole or even to some personal shocks to which the forecasters were exposed during their career– could lead to large bias and a misapprehension of the heterogeneity modeling results. On the other hand, as the evolution of economic indicators is the consequence of the decisions of all market participants, the use of disaggregate survey data becomes very relevant in the extent that it aims at capturing the behavior of each actor in the market, allowing hence a much better comprehension of the marketplace.

This study draws on the works of MacDonald (1992) and Benassy-Quere et al. (2003) who both investigated the heterogeneous anticipation formation by estimating the same mixed models using survey data of foreign exchange rates. However, our approach differs from theirs in many ways: *(i)* the type of survey data used and the sampling period, *(ii)* the nature of forecasts data selected, *(iii)* the methodology used to estimate the mixed model. Regarding the first point, using individual expectations allows us to evaluate the degree of heterogeneity among market forecasters and throughout different crisis periods. Turning to the second point, we consider forecasts of three macroeconomic indicators associated with different economic sectors (employment, housing and consumption), which allow to compare forecasts made by each forecaster on each of these figures. Regarding the methodology, while these previous studies used panel data by estimating fixed-effects models or random effects models, assuming that slope coefficients are identical for all the individual, we state that *(i)* heterogeneity can stem from agents’ sensitivity to some components and *(ii)* this sensitivity can change over time. So, we estimate our mixed model using the Bai-Perron procedure on time series, which allows us to model the expectations’ formation whilst taking into account behaviors’ evolution throughout economic structural breaks. We find that there is a strong evidence of heterogeneity which, in addition, varies across periods and news, horizons and groups of forecasters.

The paper is organized as follows. In section 2, we present the survey data used in this paper and test whether or not these expectations are unbiased and heterogeneous. In section 3 we discuss the specification of the mixed model. Section 4 contains our results concerning heterogeneity based on the estimation of the mixed model by the Bai-Perron method. In section 5 we compare the forecasts accuracy of our practitioners. Section 6 concludes.

2 Data

2.1 Data description

Macroeconomic announcements are often used as a measure of public information to test the efficient market hypothesis⁷ and the rational expectations theory⁸ by confronting announcements with their survey forecasts. The main contribution of our paper is to examine expectation heterogeneity using disaggregated macroeconomic forecasts.

The macroeconomic news are released at scheduled times, which allows Bloomberg to perform a survey of analysts – various well-known forecasters – before each publication. In fact, as reported in Chen et al. (2013), the Bloomberg survey procedure is conducted as follows: one month prior to the news release, a Bloomberg employee sends out surveys to a list of analysts (academicians and financial institutions’ forecasters) to provide their forecasts of the upcoming announcements. The number of subjects varies across news and can reach – for important news announcements – more than 80 analysts.

We collect monthly data for three major macroeconomic indicators:⁹ consumer confidence index, new home sales and unemployment rate. For each announcement, we obtain the actual announcement value, the consensus market forecast – which is the median of all submitted forecasts – and the disaggregated dataset of individual analyst’s forecasts from Bloomberg terminal which is the main source of information for market professionals.

Our sample consists of 170 observations covering the report period from January 1999 to February 2013. During these 14 years, the list of those who replied to any of the Bloomberg surveys includes hundreds of forecasters. However the majority of forecasters have been listed as missing once or few times, only two of them provided a total of 170 predictions for at least one macroeconomic news. Others stalled off during one or two sub-periods (maybe because of staff restructuring). So the selection of the forecasters panel (number of participants) has been conditioned by the number of missing values. Since we limited our selection to those who provide at least 40% of submissions (i.e. for which missing values do not exceed $1/3^{rd}$ of the whole number of observations (170)),¹⁰ we end up with fifteen individuals in our sample.¹¹

⁷According to this hypothesis introduced by Fama (1965), asset prices should reflect all the available information.

⁸Introduced by Muth(1961), this theory assumes that economic agents are rational optimizers in making forecasts and take actions based on such forecasts, implying that prices react only to the unexpected component of announcements.

⁹We use initially announced, i.e. unrevised, figures for macroeconomic series because Bloomberg typically allows analysts to update their forecasts until one week prior to the announcement.

¹⁰Note that an exception was made for two forecasters (from Nomura Securities Intl. and PNC Bank) for their consumer confidence predictions which do not exceed 30 observations. This exception was made in order to keep a homogeneous sample.

¹¹The fifteen individuals are from the following companies: Briefing.com, Wrightson ICAP, Deutsche Bank Sec, IDEA global, Credit Suisse, BMO Capital Markets, Morgan Stanley & Co., BofA Merrill Lynch, Citigroup NY, High Frequency Economics, CIBC World Markets, Nomura Securities Intl., PNC Bank, First Trust Advisors and Daiwa Securities America.

2.2 Data properties

Figures 1 to 3 present the real value of each macroeconomic news for each of the fifteen selected individual forecasters.¹²

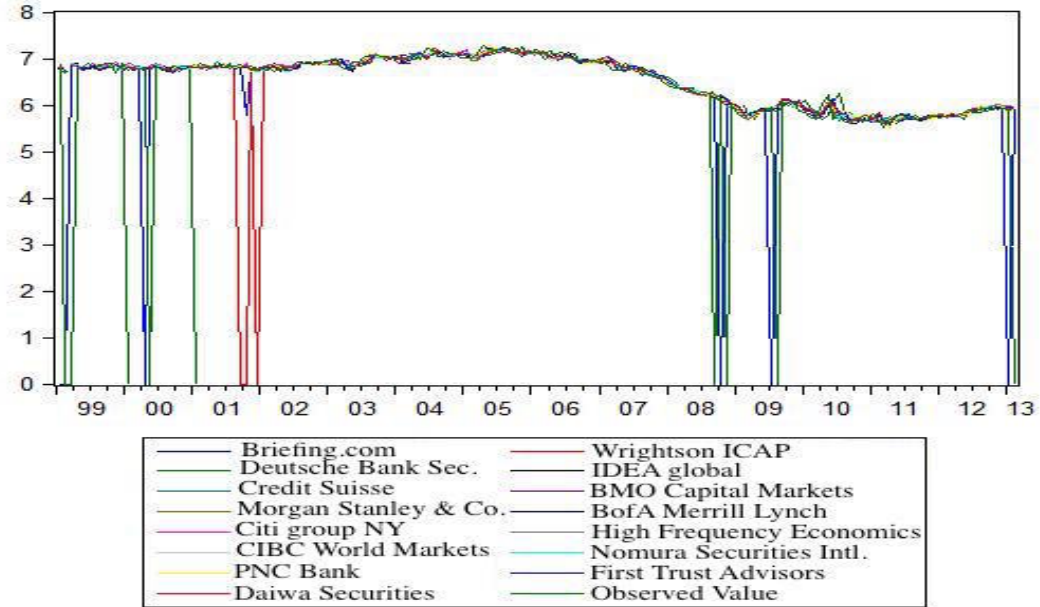


Figure 1: Comparing New Home Sales Forecasts

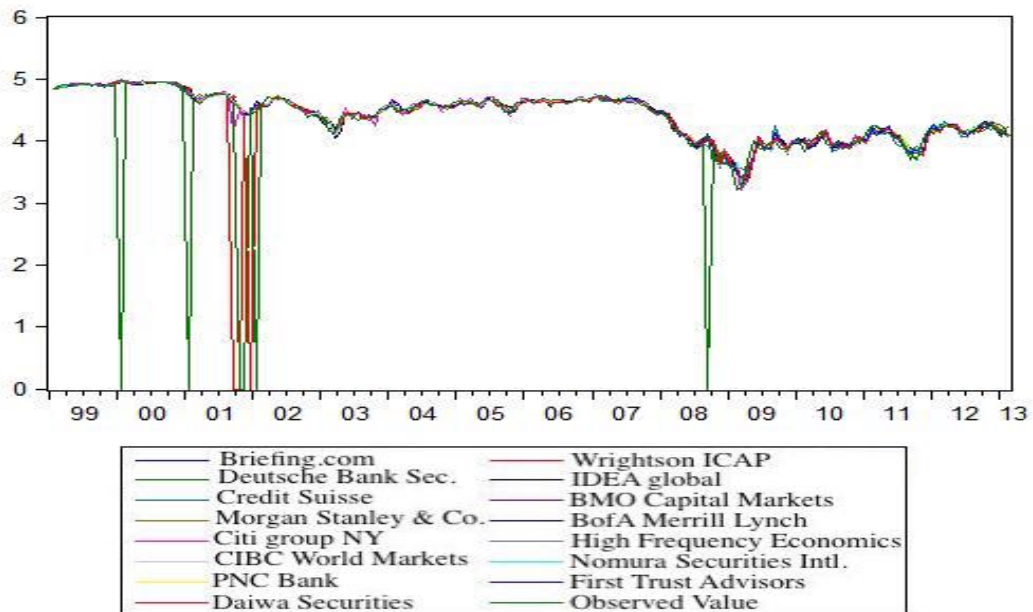


Figure 2: Comparing Consumer Confidence Index Forecasts

¹²The graphs are presented in logarithmic scale.

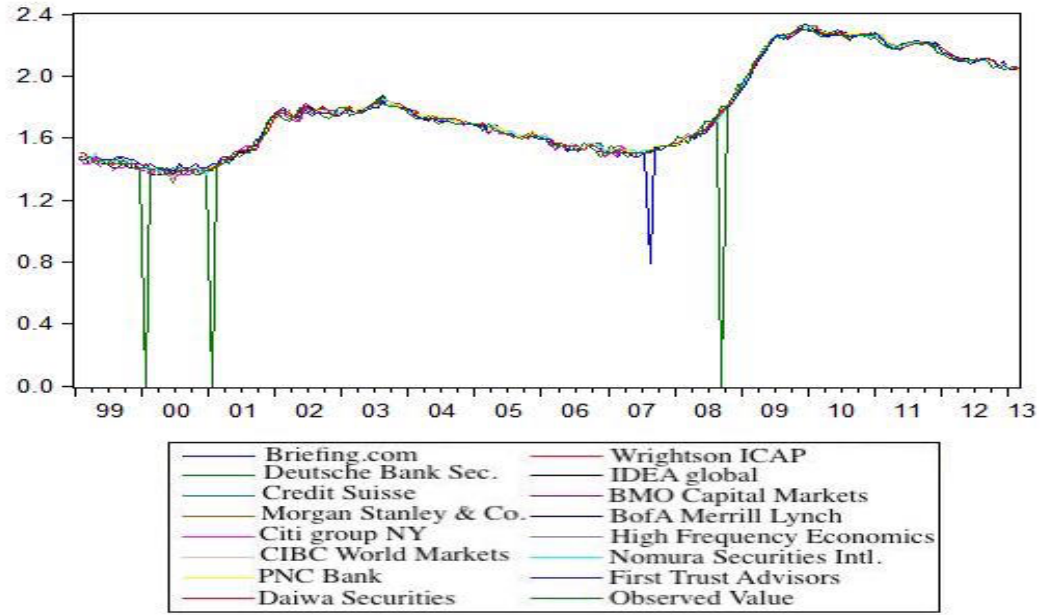


Figure 3: Comparing Unemployment Rate Forecasts

These figures, especially Figures 1 and 2, highlight the impact of the global crisis and other major events on the forecasting behavior of financial analysts. Indeed, events as the Internet bubble, the September 11 attacks and the recent financial crisis induce a large change in the behavior of some forecasters that may result from a change in their forecasting process. We can see a deterioration of forecasts around these events proving that financial analysts have faced important difficulties to maintain the accuracy of their forecasts over the whole period. This finding justifies the importance to investigate expectations' heterogeneity into sub-periods and not on the entire period as has been done in a large number of previous studies.

To further illustrate the differences in forecasts between the individuals surveyed, we report in Table 1 the descriptive statistics for each company to which they belong.

Forecasters	Briefing.com			Wrightson ICAP			Deutsche Bank Sec		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
Mean	784.98	88.57	6.20	779.50	88.61	6.18	778.22	87.97	6.19
Std. Dev.	339.04	28.65	1.99	332.41	28.88	1.92	334.20	28.72	1.92
Skewness	-0.24	0.07	0.72	-0.22	0.08	0.74	-0.21	0.09	0.72
Kurtosis	1.63	2.10	2.16	1.62	2.07	2.09	1.63	2.19	2.03
Jarque-Bera	14.54 (0.00)	5.71 (0.06)	19.26 (0.00)	14.72 (0.00)	6.23 (0.04)	21.40 (0.00)	13.80 (0.00)	4.77 (0.09)	20.86 (0.00)
Observations	164	165	167	169	167	170	162	165	167
Forecasters	BMO Capital Markets			Morgan Stanley & Co.			BofA Merrill Lynch		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
Mean	773.65	85.93	6.32	773.74	88.16	6.26	805.59	90.52	6.12
Std. Dev.	339.22	28.17	1.97	340.46	29.64	1.99	332.01	27.30	1.93
Skewness	-0.15	0.10	0.64	-0.14	0.06	0.67	-0.32	0.16	0.86
Kurtosis	1.59	2.29	1.93	1.61	2.05	1.92	1.76	2.09	2.29
Jarque-Bera	13.75 (0.00)	3.65 (0.16)	18.12 (0.00)	12.63 (0.00)	5.82 (0.05)	19.51 (0.00)	12.47 (0.00)	6.00 (0.05)	22.05 (0.00)
Observations	159	158	157	151	152	158	153	154	153
Forecasters	CIBC World Markets			Nomura Securities Intl.			PNC Bank		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
Mean	761.31	90.89	6.25	784.13	57.74	6.18	762.39	62.12	6.60
Std. Dev.	351.90	20.51	1.95	332.12	20.24	1.95	363.47	8.65	1.90
Skewness	-0.06	-0.70	0.72	-0.24	1.87	0.78	0.02	-0.72	0.58
Kurtosis	1.45	3.14	2.05	1.64	8.74	2.10	1.49	2.68	1.79
Jarque-Bera	14.05 (0.00)	7.92 (0.02)	20.53 (0.00)	13.75 (0.00)	46.97 (0.00)	21.41 (0.00)	13.60 (0.00)	1.73 (0.42)	16.62 (0.00)
Observations	140	96	165	159	24	160	143	19	142
Forecasters	IDEA global			Credit Suisse			Citigroup NY		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
Mean	793.32	88.53	6.19	769.49	85.04	6.31	798.82	88.26	6.17
Std. Dev.	335.08	29.18	1.95	347.54	28.29	1.98	338.83	30.08	1.97
Skewness	-0.25	0.08	0.71	-0.13	0.14	0.65	-0.25	0.14	0.72
Kurtosis	1.67	2.10	2.05	1.50	2.20	1.89	1.64	2.11	2.06
Jarque-Bera	14.04 (0.00)	5.89 (0.05)	20.35 (0.00)	15.11 (0.00)	4.69 (0.10)	18.53 (0.00)	14.08 (0.00)	5.64 (0.06)	19.49 (0.00)
Observations	166	170	167	156	155	154	161	154	157
Forecasters	High Frequency Economics			First Trust Advisors			Daiwa Securities America		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
Mean	793.10	87.98	6.14	758.73	64.75	6.26	763.61	78.80	6.08
Std. Dev.	331.14	28.03	1.85	330.84	20.77	1.92	331.08	24.82	1.89
Skewness	-0.34	0.10	0.81	-0.12	0.87	0.69	-0.14	0.12	0.90
Kurtosis	1.65	2.29	2.28	1.59	2.98	1.98	1.59	2.31	2.39
Jarque-Bera	14.35 (0.00)	3.43 (0.18)	20.27 (0.00)	13.40 (0.00)	9.52 (0.01)	19.69 (0.00)	12.51 (0.00)	2.56 (0.28)	20.16 (0.00)
Observations	150	153	156	157	75	160	145	114	135
Observed Values									
News	New Home Sales			Consumer Confidence Index			Unemployment Rate		
Mean	789.28			88.13			6.16		
Std. Dev.	344.25			1.92			29.63		
Skewness	-0.18			0.07			0.75		
Kurtosis	1.67			2.11			2.11		
Jarque-Bera	13.34 (0.00)			5.89 (0.05)			21.61 (0.00)		
Observations	170			170			170		

Note: NHS: New Home Sales, CCF: Consumer Confidence index, UP: Unemployment Rate. For the Jarque-Bera test, P-values are given in parentheses.

Table 1: Preliminary results: Descriptive statistics

First, by comparing the observed average value of the new home sales indicator (789.28) with the averages of the forecasts, we find that over the entire period, 73% of forecasters are below the actual average while only 27% of them are above this value. This results means that forecasters tend to underestimate this figure. Note that, and this also applies to the consumer confidence index, a tightened expectation on this figure (i.e. when the released value is greater than its expectation) is a good news for markets,¹³ indicating hence that forecasters who expressed these forecasts are primarily optimistic. In the same way, regarding the real average of unemployment rate (6.16) we see that 80% of the forecasters overestimate the value of this indicator. As it is well known, an excessive anticipation in unemployment rate is a good news (i.e. the unemployment rate is lower than expected), reflecting the forecasters' pessimism also for this indicator too. For the consumer confidence

¹³It is important to distinguish the negative figures (unemployment rate, inflation...) from the positive ones (new home sales, consumer confidence, activity and trade indicators...). Unemployment rate is called negative figure because an increase in its value is interpreted by market participants as a bad news, insofar as it reflects a downturn in the economy. On the contrary an increase in a positive figure contributes to the growth of the economy and is therefore considered as a good news for markets. This definition is important when examining market pessimism and optimism.

index, we note (as for the previous indicators) a deviation from the real average (88.13), but the number of overestimation is very close to the number of underestimation.

These results are confirmed by the skewness values which are systematically (99%) negative. The excess kurtosis is positive only in 4% of cases reflecting a fat tails distribution of these forecasts. Regarding the Jarque and Bera test, we globally note a large number of rejections of the null hypothesis of a Gaussian distribution.

Finally, most standard deviation values seem homogeneous, except for two forecasts of the consumer confidence index, those with a large number of missing values (Nomura Securities Intl. and PNC Bank).

3 Unbiasedness and heterogeneity tests

3.1 Unbiasedness test

According to the rational expectations hypothesis (REH), the expected value should be an unbiased predictor of the considered variable. We investigate whether the Bloomberg surveys are consistent with this hypothesis by performing an unbiasedness test.¹⁴ The test is conducted on a sequence of monthly data for n macroeconomic news and m forecasters indexed by j . More specifically, we have:

$$E_t^j a_{t+\tau} - a_t = \alpha_t^j + \beta_t^j (a_{t+\tau} - a_t) + \nu_{t+\tau}^j \quad j = 1, \dots, 15 \quad (1)$$

In this formulation, $E_t^j a_{t+\tau}$ is the log value of the expectation for each macroeconomic news made by the forecaster j at the horizon τ (submitted to Bloomberg) and a_t denotes the actual value of this macroeconomic news.

Within this framework, the unbiasedness hypothesis can be stated as follows:

$$H_0 : \quad \alpha_t^j = 0, \quad \beta_t^j = 1$$

Market efficiency requires that $\alpha = 0$ and $\beta = 1$. Rejection of the restrictions imposed to the parameters α and β means that expectations are not rational.

We estimate this system of $m \times n$ regressions by ordinary least squares (OLS) using the Newey-West methodology, which is robust to autocorrelation and heteroskedasticity in residuals. The regression results are reported in Table 2.

¹⁴Initially developed by Muth (1961).

Forecasters	Briefing.com			Wrightson ICAP			Deutsche Bank Sec		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
α	-0.0065 (0.448)	0.0078 (0.145)	0.0011 (0.831)	-0.0029 (0.635)	0.0129 (0.045)	0.0033 (0.107)	-0.0047 (0.513)	0.0018 (0.735)	-0.0003 (0.925)
β	0.2888 (0.000)	0.1626 (0.000)	0.1253 (0.103)	0.2787 (0.000)	0.1022 (0.071)	0.1952 (0.006)	0.2462 (0.001)	0.1767 (0.018)	0.1948 (0.014)
R^2_{adj}	0.05	0.04	0.00	0.11	0.01	0.05	0.05	0.04	0.04
DW	1.83	2.06	1.97	1.46	1.93	1.79	1.64	2.01	1.724
Wald Test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Forecasters	IDEA global			Credit Suisse			BMO Capital Markets		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
α	0.0042 (0.441)	0.0088 (0.125)	-0.0006 (0.831)	-0.0015 (0.776)	0.0017 (0.721)	0.0044 (0.062)	-0.0027 (0.681)	0.0043 (0.448)	0.0047 (0.051)
β	0.2266 (0.001)	0.0845 (0.236)	0.1434 (0.085)	0.2494 (0.001)	0.2453 (0.001)	0.1734 (0.034)	0.2311 (0.001)	0.0901 (0.245)	0.1507 (0.049)
R^2_{adj}	0.06	0.01	0.02	0.09	0.09	0.03	0.06	0.01	0.02
DW	1.73	1.98	1.58	1.86	2.33	1.56	1.70	2.13	1.70
Wald Test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Forecasters	Morgan Stanley & Co.			BofA Merrill Lynch			Citigroup NY		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
α	0.0009 (0.881)	0.0050 (0.436)	0.0031 (0.217)	-0.0022 (0.735)	0.0034 (0.468)	0.0052 (0.034)	0.0137 (0.027)	0.0057 (0.346)	-0.0016 (0.536)
β	0.2451 (0.001)	0.0520 (0.539)	0.1584 (0.069)	0.2495 (0.000)	0.0913 (0.039)	0.1936 (0.005)	0.2379 (0.000)	0.0609 (0.536)	0.3124 (0.000)
R^2_{adj}	0.08	0.00	0.03	0.08	0.01	0.04	0.07	0.00	0.10
DW	1.81	1.92	1.62	1.59	2.13	1.54	1.64	2.14	1.45
Wald Test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Forecasters	High Frequency Economics			CIBC World Markets			Nomura Securities Intl.		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
α	-0.0050 (0.391)	0.0064 (0.286)	0.0055 (0.018)	0.0038 (0.526)	0.0052 (0.428)	0.0056 (0.031)	-0.0005 (0.095)	-0.0057 (0.851)	0.0034 (0.103)
β	0.3268 (0.000)	0.1090 (0.092)	0.1573 (0.059)	0.2143 (0.001)	0.1478 (0.324)	0.1349 (0.116)	0.2399 (0.000)	0.0584 (0.691)	0.1700 (0.037)
R^2_{adj}	0.17	0.02	0.03	0.05	0.02	0.02	0.07	0.00	0.03
DW	1.43	2.00	1.56	1.94	2.01	1.60	1.59	1.64	1.58
Wald Test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Forecasters	PNC Bank			First Trust Advisors			Daiwa Securities America		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
α	0.0051 (0.407)	0.0142 (0.617)	0.0080 (0.000)	0.0015 (0.838)	0.0119 (0.216)	0.0006 (0.842)	-0.0041 (0.551)	0.0071 (0.377)	0.0034 (0.149)
β	0.1942 (0.000)	0.2011 (0.061)	0.1469 (0.037)	0.2712 (0.000)	0.1037 (0.148)	0.1806 (0.065)	0.2303 (0.000)	0.0747 (0.298)	0.1732 (0.033)
R^2_{adj}	0.04	0.01	0.03	0.07	0.01	0.03	0.06	0.01	0.03
DW	1.69	1.91	1.75	1.57	2.14	1.37	1.52	2.17	1.74
Wald Test	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: NHS: New Home Sales, CCF: Consumer Confidence index, UP: Unemployment Rate.
For each estimated coefficient, the corresponding P-value is given in parentheses. For the Wald test, the P-value reported corresponds to the null hypothesis $\alpha = 0, \beta = 1$.

Table 2: Preliminary results: Unbiasedness test

The results report a very clear rejection of unbiasedness in the sense that β^j is statistically less than unity, invalidating hence the rational expectations hypothesis for all forecasters and all news. The form of the bias is nonetheless similar for all forecasts, as the estimated coefficient (β) is characterized by a positive sign and a low amplitude, ranging between 0.05 and 0.32. This result reflects a correct global prediction regarding the direction of the future variations of the three macroeconomic indicators.

3.2 Heterogeneity test

Before modeling the expectation process, we proceed to a preliminary estimate often used in the literature (MacDonald and Marsh (1996), Elliott and Ito (1999), Benassy-Quere et al. (2003)), in which we regress the difference between the individual and the median anticipation on a constant coefficient δ^j_τ . The regression is defined as follows:

$$E^j_t a_\tau - m_t = \delta^j_\tau + \varepsilon^j_\tau \quad (2)$$

Where $E^j_t a_\tau$ is the log value of the individual expectation and m_t is the log value of the median forecast, better known as “the consensus value”. The intuition behind this estimation is straightforward: if δ^j_τ is significantly different from zero, the forecaster’ expectation

differs from that of the consensus, which implies the existence of individual heterogeneity. The results are reported in Table 3.

Forecasters	Briefing.com			Wrightson ICAP			Deutsche Bank Sec		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
$\delta_{t,\tau}$	-0.0091 (0.187)	0.0027 (0.139)	-0.0022 (0.608)	-0.0034 (0.107)	0.0088 (0.000)	-0.0002 (0.801)	-0.0051 (0.056)	-0.0019 (0.421)	-0.0041 (0.003)
Forecasters	BMO Capital Markets			Morgan Stanley & Co.			BofA Merrill Lynch		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
$\delta_{t,\tau}$	-0.0043 (0.028)	-0.0002 (0.889)	0.0015 (0.048)	-0.0031 (0.203)	-0.0005 (0.794)	0.0006 (0.521)	-0.0029 (0.151)	-0.0004 (0.854)	0.0004 (0.675)
Forecasters	CIBC World Markets			Nomura Securities Intl.			PNC Bank		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
$\delta_{t,\tau}$	0.0005 (0.813)	6.4e07 (0.999)	0.0022 (0.008)	-0.0011 (0.587)	0.0061 (0.338)	0.0002 (0.805)	0.0015 (0.627)	0.0114 (0.185)	0.0035 (0.000)
Forecasters	IDEA global			Credit Suisse			Citigroup NY		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
$\delta_{t,\tau}$	0.0043 (0.031)	0.0041 (0.026)	-0.0041 (0.000)	-0.0029 (0.272)	-0.0034 (0.361)	0.0007 (0.333)	0.0107 (0.000)	0.0011 (0.813)	-0.0048 (0.000)
Forecasters	High Frequency Economics			First Trust Advisors			Daiwa Securities America		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
$\delta_{t,\tau}$	-0.0038 (0.192)	0.0025 (0.228)	0.0026 (0.002)	0.0002 (0.917)	0.0021 (0.573)	-0.0028 (0.032)	-0.0047 (0.029)	-0.0004 (0.821)	0.0010 (0.147)

Note: NHS: New Home Sales, CCF: Consumer Confidence index, UP: Unemployment Rate
For each estimated coefficient the corresponding P-value is given in parentheses.

Table 3: Preliminary results: Heterogeneity test

The unemployment rate is the indicator that generates the most heterogeneous forecasts (53%), probably because it is the most followed indicator of growth (highly related to the U.S. monetary policy, especially the Quantitative easing) and whose prediction is formed with the utmost precision. Exploiting various sources of information (public as private) to reach this accuracy may explain the prevailing heterogeneity associated with this macroeconomic news. The other two announcements' expectations (consumer confidence index and new home sales) are fairly homogeneous (only 13% and 26% of heterogeneity raised respectively), suggesting that agents limit themselves to public information and/or adopt a mimetic behavior. The number of heterogeneous forecasts remains rather weak which is quite surprising at a first sight. However, this can be viewed as a strategic choice for forecasters to remain closer to the consensus forecast. We must remember that every year, Bloomberg conducts a ranking of top forecasters (also called "qualified economists") for many macroeconomic news, their names and affiliations are then publicly listed in the Bloomberg terminal and consulted by all market participants including their clients. So, the more their forecasts are accurate, the more profit opportunities they create for their firms. It is a sufficient incentive to make predictions far from the forecasts distribution tails and submit forecasts in accordance with the conventional value expected to be set by the market,¹⁵ in a way that Keynes dubs « the beauty contest».¹⁶

Another interpretation could be related to the publication date of these macroeconomic news. We know that employment data (as the non-farm payrolls and unemployment rate) are released at the beginning of the month – on the first Friday of each month – and so, before many other macroeconomic figures. Due to the lagged nature of this indicator and

¹⁵Details on the forecast bias are discussed by Laster et al. (1999), Elliott and Ito (1999), Lamont (1995), Batchelor (2007), Frankel (2011a) and Frankel (2011b) who found evidence of an upward bias in economic forecasts using a sample of 33 countries.

¹⁶"It is not a case of choosing those [faces] 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..." J.M.Keynes 1936, General Theory of Employment Interest and Money, Chap 12.

its early release relative to other macroeconomic data, there is a truly limited number of predictors available to model and predict the value of the unemployment rate. In contrast, consumer confidence index (CCF) and new home sales (NHS) are released at the end of the month (typically during the last week of every month, respectively the 27th and 25th of every month). It is likely that by the end of the month, forecasters have already received updated data on a huge number of macroeconomic variables that can be used as predictors to model consumer confidence, new home sales and all other indicators released during this period of the month. Thus, forecasting these latter may be considered easier and safer than predicting employment. To sum up, the release timing of a target variable is very important in the forecasting process. Excess homogeneity in forecasts can be explained by (i) the fact that many practitioners try to match their expectations as much as possible to the optimal prediction in order to minimize the risk of being too far from the actual value, and (ii) the publication date of the indicators, because it is easier to make predictions while we have access to a large set of information, which contributes to the convergence of the forecasted values.

4 Heterogeneous beliefs: The mixed model

We now proceed to the estimation of the expectations' model by accounting for the heterogeneity previously highlighted. To this end, we use a model wherein macroeconomic indicators forecasts are formulated via a mix of three expectation processes (extrapolative, regressive and adaptive components). For simplicity, we assume (i) that the extrapolative model is associated to chartist analysts that have static expectations because they believe that the actual value will not vary, and (ii) that the regressive model is used by fundamentalists (see also Prat and Uctum (2007) and Prat and Uctum (2015)). If analysts combine the extrapolative (regressive) with the adaptive process, we consider then that they have a chartist(fundamentalist) behavior with a learning process. If they use the three specifications, they are chartists and fundamentalists with a learning process.

4.1 Expectation model

The extrapolative component (EXT)

The extrapolative expectation component involves the prediction of future values from an analysis of past variations. The standard extrapolative component for a variable a_t is defined as:

$$EXT : \alpha_\tau(a_t - a_{t-1}), \quad \tau = t + 1 \quad (3)$$

If $\alpha_\tau > 0$, it means that a projection into the future of a trend observed in the past (i.e an extrapolative expectation), whatever the shape it takes (upward or downward) is conceptually destabilizing because a persistence in this behavior will lead to divergent forecasts (far from the true value). However, if the coefficient α_τ is negative, when the past observation increases (decreases) then the future value will decrease (increase), so the anticipated move

in this case is mean reverting and the forecast is stabilizing.

The regressive component (REG)

Also called the mean reverting expectation model, the regressive component is a weighted average between the current log value and the log long-run equilibrium value. If the equilibrium variable is defined as a moving average or Hodrick-Prescott filter of the actual value, the regressive model could be associated with the chartist behavior. If the equilibrium variable is a fundamental such as NAIRU for the unemployment rate or the inflation target for the consumer price index then this component will be associated with a fundamentalist behavior. Denoting by \bar{a}_t the long-run equilibrium value, the regressive component is given by:

$$REG : \beta_\tau(\bar{a}_t - a_t), \quad \tau = t + 1 \quad 0 < \beta_\tau < 1 \quad (4)$$

If the regressive component coefficient β_τ is positive, the generated forecast will be stabilizing (mean reverting expectation), describing an upward (downward) forecast if the observed value is lower (higher) than the equilibrium value. However, if the coefficient β_τ is negative, each observed value that is lower (higher) than the equilibrium value will generate a downward (upward) forecast, reflecting a cumulative effect that describes a destabilizing process.

The adaptive component (ADA)

The adaptive component is a form of learning process where forecasters revise their expectations in light with their recent experience. The adaptive component implies that expectations formed at time t for one period ahead is a weighted average of the expectation of the same variable formed one period earlier for the present time t and its actual value.

$$ADA : \gamma_\tau(E_t^j a_{\tau-1} - a_t) \quad \tau = t + 1 \quad 0 < \gamma_\tau < 1 \quad (5)$$

A positive coefficient of the adaptive component means that the actual forecast is adjusted because of the past forecast error, which can be assimilated to a stabilizing process. However, a negative coefficient has no economic sense other than to say that the uncertainty of shady periods (troubling times) makes forecasts more erratic.

Weighting the three basic specifications in equations (3) to (5), we obtain the following mixed expectation model:

$$E_t^j a_{t+\tau} - a_t = \omega_\tau^j + \rho_\tau^j(a_t - a_{t-1}) + \theta_\tau^j(\bar{a}_t - a_t) + \varphi_\tau^j(E_t^j a_{\tau-1} - a_t) + u_\tau^j \quad (6)$$

The endogenous variable is the expected rate of change in the macroeconomic indicator made by forecaster j and is explained by the three components (extrapolative / regressive / adaptive). This model thus allows us to account for heterogeneity across forecasters and across time. All variables are expressed in logarithmic terms and the constant term represents the measurement errors or other idiosyncratic effects. This model is estimated

by the Bai-Perron method.¹⁷

4.2 Switching between chartists, fundamentalists and learning process : The Bai-Perron estimation

In previous studies, the heterogeneity tests are performed on coefficients estimated over the whole period, which probably tends to skew the test results if there are some ignored breaks. By estimating the model with endogenous structural breaks, we represent more accurately the behavior of each forecaster by accounting for their reactions to the various potential shocks. Tables 4a to 4e present the estimation results of the mixed expectation model for the different sub-periods identified, depending on the detected break dates.

Firms	Briefing.com			Wrightson ICAP			Deutsche Bank Sec		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
	99/01 - 13/02	99/01 - 13/02	99/01 - 13/02	99/04 - 07/11	99/02 - 03/02	99/02 - 09/08	99/05 - 06/04	99/02 - 09/01	99/02 - 03/09
C	-0.0124 (0.093)	0.0043 (0.147)	0.0035 (0.449)	-0.0107 (0.000)	-0.0019 (0.729)	0.0101 (0.000)	-0.0104 (0.004)	-0.0099 (0.012)	0.0102 (0.000)
EXT	-0.6098 (0.000)	-0.6934 (0.000)	-0.8361 (0.000)	-0.4267 (0.000)	-0.7605 (0.000)	-0.5938 (0.000)	-0.4866 (0.000)	-0.7365 (0.000)	-0.7169 (0.000)
REG	0.1037 (0.355)	0.0851 (0.008)	-0.0279 (0.118)	0.1971 (0.005)	0.0604 (0.462)	-0.0261 (0.001)	0.1959 (0.028)	0.1029 (0.055)	-0.0426 (0.001)
ADA	0.1056 (0.125)	-0.0725 (0.092)	-0.0062 (0.931)	0.3546 (0.000)	0.0697 (0.515)	0.0991 (0.061)	0.2822 (0.000)	-0.1351 (0.052)	0.1743 (0.008)
	-	-	-	07/12 - 10/02	03/03 - 07/08	09/09 - 13/02	06/05 - 09/02	09/02 - 13/02	03/10 - 07/08
C	-	-	-	-0.0051 (0.412)	-0.0019 (0.668)	0.0008 (0.945)	-0.0343 (0.000)	0.0211 (0.000)	-0.0123 (0.000)
EXT	-	-	-	-0.8026 (0.000)	-0.4989 (0.000)	-0.7963 (0.000)	-0.8835 (0.000)	-0.7368 (0.000)	-0.7875 (0.000)
REG	-	-	-	-0.0664 (0.266)	0.2539 (0.000)	0.0064 (0.821)	-0.1761 (0.164)	0.0991 (0.026)	0.0862 (0.000)
ADA	-	-	-	0.1178 (0.138)	-0.2326 (0.036)	0.0248 (0.845)	0.2366 (0.001)	-0.0226 (0.678)	0.2891 (0.000)
	-	-	-	10/03 - 13/02	07/09 - 13/02	-	09/03 - 11/01	-	07/09 - 09/06
C	-	-	-	0.0071 (0.144)	0.0278 (0.000)	-	0.0219 (0.000)	-	0.0292 (0.000)
EXT	-	-	-	-0.3804 (0.000)	-0.6975 (0.000)	-	-0.9612 (0.000)	-	-0.8157 (0.000)
REG	-	-	-	0.6333 (0.000)	0.1518 (0.000)	-	-0.1091 (0.025)	-	-0.0709 (0.000)
ADA	-	-	-	-0.1905 (0.072)	-0.0934 (0.034)	-	0.1002 (0.014)	-	0.2681 (0.053)
	-	-	-	-	-	-	11/02 - 13/02	-	09/07 - 13/02
C	-	-	-	-	-	-	-0.0073 (0.264)	-	0.0025 (0.827)
EXT	-	-	-	-	-	-	-0.4548 (0.000)	-	-0.6441 (0.000)
REG	-	-	-	-	-	-	0.7019 (0.001)	-	0.0177 (0.542)
ADA	-	-	-	-	-	-	-0.0384 (0.803)	-	0.1998 (0.099)
R^2 adj	0.37	0.77	0.15	0.87	0.84	0.63	0.91	0.79	0.73
DW	2.08	1.68	1.99	1.88	2.03	1.71	2.41	1.70	1.71
AIC	-1.91	-3.74	-2.82	-4.19	-3.95	-5.54	-4.28	-3.50	-5.52
BIC	-1.83	-3.66	-2.74	-3.97	-3.72	-5.39	-3.96	-3.34	-5.21
L	155.70	177.54	237.79	361.91	335.95	476.31	345.28	285.85	465.63

Note: NHS: New Home Sales, CCF: Consumer Confidence index, UP: Unemployment Rate
For each estimated coefficient, the corresponding P-value is given in parentheses
DW: Durbin Watson test, AIC: Akaike information criterion and BIC: Bayesian information criterion.

Table 4a: Estimation results: Bai-Perron method

¹⁷A brief presentation of this method is given in the appendix.

Firms	IDEA global			Credit Suisse			BMO Capital Markets		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
	99/04 - 08/12	99/02 - 08/10	99/02 - 01/01	99/08 - 08/12	99/01 - 13/02	99/08 - 03/06	99/11 - 09/03	99/12 - 09/02	99/11 - 02/02
C	-0.0069 (0.017)	0.0015 (0.569)	-0.0516 (0.054)	-0.0132 (0.001)	-0.0017 (0.742)	0.0183 (0.000)	-0.0165 (0.000)	-0.0014 (0.582)	0.0583 (0.000)
EXT	-0.6693 (0.000)	-0.6145 (0.000)	-0.4891 (0.000)	-0.5103 (0.000)	-0.6017 (0.000)	-0.6045 (0.000)	-0.6824 (0.000)	-0.7835 (0.000)	-0.5933 (0.000)
REG	0.2702 (0.000)	0.0811 (0.024)	0.1544 (0.113)	0.2357 (0.011)	0.1391 (0.005)	-0.0449 (0.003)	0.0096 (0.855)	0.0789 (0.011)	-0.20990 (0.000)
ADA	-0.1351 (0.052)	0.0684 (0.169)	0.0291 (0.572)	0.4883 (0.000)	0.2124 (0.003)	0.2712 (0.000)	0.2373 (0.000)	-0.1348 (0.002)	0.3135 (0.000)
	09/01 - 13/02	08/11 - 11/01	01/02 - 13/02	09/01 - 13/02	-	03/07 - 06/10	09/04 - 13/01	09/03 - 12/11	02/03 - 09/08
C	0.0123 (0.007)	0.0319 (0.000)	0.0062 (0.000)	0.0059 (0.281)	-	-0.0014 (0.529)	0.0125 (0.004)	0.0135 (0.001)	0.0104 (0.000)
EXT	-0.6358 (0.000)	-0.9243 (0.000)	-0.6643 (0.000)	-0.6228 (0.000)	-	-0.8587 (0.000)	-0.6302 (0.000)	-0.8618 (0.000)	-0.6923 (0.000)
REG	-0.0475 (0.416)	0.0736 (0.044)	0.0078 (0.134)	0.0181 (0.775)	-	0.0081 (0.696)	0.0690 (0.238)	0.0318 (0.326)	-0.0340 (0.000)
ADA	0.2071 (0.000)	-0.0975 (0.017)	0.0929 (0.051)	-0.0032 (0.964)	-	0.0859 (0.361)	0.1213 (0.022)	-0.0274 (0.449)	0.0892 (0.105)
	-	11/02 - 13/02	-	-	-	06/11 - 09/06	-	-	09/09 - 13/02
C	-	0.0017 (0.751)	-	-	-	0.0294 (0.000)	-	-	-0.0011 (0.914)
EXT	-	-0.6904 (0.000)	-	-	-	-0.7746 (0.000)	-	-	-0.7194 (0.000)
REG	-	0.1713 (0.001)	-	-	-	-0.0905 (0.000)	-	-	-0.0089 (0.717)
ADA	-	-0.0296 (0.674)	-	-	-	0.4079 (0.000)	-	-	0.2368 (0.018)
	-	-	-	-	-	09/07 - 13/02	-	-	-
C	-	-	-	-	-	-0.0053 (0.552)	-	-	-
EXT	-	-	-	-	-	-0.7036 (0.000)	-	-	-
REG	-	-	-	-	-	-0.0175 (0.414)	-	-	-
ADA	-	-	-	-	-	0.2499 (0.004)	-	-	-
R^2 adj	0.87	0.90	0.72	0.76	0.55	0.80	0.88	0.91	0.74
DW	2.06	1.81	1.50	1.67	1.77	1.56	1.62	1.95	1.38
AIC	-4.11	-4.28	-5.54	-3.61	-2.70	-6.02	-4.17	-4.31	-5.78
BIC	-3.96	-4.06	-5.39	-3.45	-2.61	-5.69	-4.01	-4.16	-5.54
L	338.77	373.53	459.68	275.00	199.45	452.26	334.98	340.10	451.35

Note: NHS: New Home Sales, CCF: Consumer Confidence index, UP: Unemployment Rate
For each estimated coefficient, the corresponding P-value is given in parentheses
DW: Durbin Watson test, AIC: Akaike information criterion and BIC: Bayesian information criterion.

Table 4b: Estimation results: Bai-Perron method

Firms	Morgan Stanley & Co.			BofA Merrill Lynch			Citigroup NY		
	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
	99/04 - 09/04	99/03 - 08/11	99/01 - 13/02	99/05 - 10/05	99/04 - 03/07	99/05 - 02/07	99/04 - 08/11	99/02 - 01/10	99/02 - 02/02
C	-0.0166 (0.000)	-0.0048 (0.200)	0.0053 (0.000)	-0.0101 (0.000)	-0.0068 (0.195)	0.0246 (0.000)	0.0002 (0.951)	-0.0092 (0.400)	0.0565 (0.000)
EXT	-0.6731 (0.000)	-0.4856 (0.000)	-0.5665 (0.000)	-0.6866 (0.000)	-1.0761 (0.000)	-0.7793 (0.000)	-0.5905 (0.000)	0.3526 (0.204)	-0.5344 (0.000)
REG	-0.0074 (0.916)	0.0242 (0.624)	-0.0045 (0.336)	-0.0369 (0.457)	-0.0288 (0.656)	-0.0937 (0.000)	0.2405 (0.000)	-0.5162 (0.032)	-0.2229 (0.000)
ADA	0.2579 (0.000)	0.032296 (0.640)	0.1315 (0.008)	0.2291 (0.000)	-0.2763 (0.000)	0.0007 (0.993)	0.2064 (0.000)	-0.7627 (0.000)	0.5542 (0.000)
	09/05 - 13/02	08/12 - 12/12	-	10/06 - 13/02	03/08 - 13/02	02/08 - 13/02	08/12 - 13/02	01/11 - 13/02	02/03 - 13/02
C	0.0199 (0.000)	0.013667 (0.015)	-	0.0011 (0.832)	0.0041 (0.259)	0.0027 (0.029)	0.0116 (0.046)	0.0038 (0.419)	0.0016 (0.423)
EXT	-0.5918 (0.000)	-0.7821 (0.000)	-	-0.3449 (0.000)	-0.5995 (0.000)	-0.5934 (0.000)	-0.5169 (0.000)	-0.7614 (0.000)	-0.5569 (0.000)
REG	0.1712 (0.017)	0.0721 (0.073)	-	0.3895 (0.000)	0.1026 (0.019)	-0.0043 (0.366)	-0.0044 (0.953)	0.0117 (0.769)	-0.0133 (0.085)
ADA	-0.0195 (0.789)	-0.0677 (0.194)	-	0.2267 (0.004)	0.0095 (0.867)	0.2737 (0.000)	0.2329 (0.000)	-0.0888 (0.106)	0.1502 (0.049)
C	-	-	-	-	-	-	-	-	-
EXT	-	-	-	-	-	-	-	-	-
REG	-	-	-	-	-	-	-	-	-
ADA	-	-	-	-	-	-	-	-	-
C	-	-	-	-	-	-	-	-	-
EXT	-	-	-	-	-	-	-	-	-
REG	-	-	-	-	-	-	-	-	-
ADA	-	-	-	-	-	-	-	-	-
R^2 adj	0.84	0.80	0.64	0.88	0.74	0.78	0.82	0.70	0.52
DW	1.82	2.08	1.15	1.81	1.95	1.81	1.91	1.81	1.49
AIC	-3.91	-3.76	-5.49	-4.20	-3.79	-5.90	-3.75	-3.18	-4.97
BIC	-3.74	-3.59	-5.41	-4.04	-3.63	-5.73	-3.59	-3.01	-4.80
L	277.90	267.47	410.10	319.03	290.57	444.27	292.91	229.04	365.53

Note: NHS: New Home Sales, CCF: Consumer Confidence index, UP: Unemployment Rate
For each estimated coefficient, the corresponding P-value is given in parentheses
DW: Durbin Watson test, AIC: Akaike information criterion and BIC: Bayesian information criterion.

Table 4c: Estimation results: Bai-Perron method

Firms	High Frequency Economics			CIBC World Markets			Nomura Securities Intl.		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
	99/08 - 10/05	99/01 - 13/02	99/08 - 01/12	00/01 - 07/04	00/06 - 07/08	99/02 - 01/08	99/04 - 09/04	99/01 - 13/02	99/01 - 13/02
C	-0.0095 (0.000)	0.0053 (0.119)	0.0546 (0.000)	-0.0118 (0.000)	-0.0032 (0.401)	0.1112 (0.000)	-0.0144 (0.000)	0.0121 (0.381)	0.0059 (0.000)
EXT	-0.4006 (0.000)	-0.5835 (0.000)	-0.3768 (0.000)	-0.5555 (0.000)	-0.6810 (0.000)	-1.0933 (0.000)	-0.5518 (0.000)	-0.6991 (0.000)	-0.5566 (0.000)
REG	0.1475 (0.022)	0.1054 (0.000)	-0.1966 (0.000)	0.2213 (0.031)	0.1263 (0.016)	-0.4355 (0.000)	0.0435 (0.419)	0.0421 (0.268)	0.0055 (0.209)
ADA	0.3318 (0.000)	-0.0421 (0.401)	0.5976 (0.000)	0.2300 (0.000)	-0.1510 (0.056)	0.1410 (0.171)	0.3256 (0.000)	0.0630 (0.205)	0.1719 (0.000)
	10/06 - 13/02	-	02/01 - 06/10	07/05 - 10/05	07/09 - 13/02	01/09 - 06/09	09/05 - 12/10	-	-
C	-0.0058 (0.351)	-	0.0053 (0.006)	-0.0102 (0.050)	0.0403 (0.000)	0.0089 (0.000)	0.0193 (0.000)	-	-
EXT	-0.0213 (0.764)	-	-0.6270 (0.000)	-1.0937 (0.000)	-1.1434 (0.000)	-0.7242 (0.000)	-0.5647 (0.000)	-	-
REG	0.6083 (0.000)	-	-0.0507 (0.005)	-0.0393 (0.458)	0.2736 (0.027)	-0.0188 (0.262)	0.1849 (0.000)	-	-
ADA	0.2633 (0.036)	-	0.3089 (0.000)	-0.1457 (0.248)	-0.4563 (0.000)	0.1170 (0.036)	0.0781 (0.171)	-	-
	-	-	06/11 - 09/07	10/06 - 13/02	-	06/10 - 09/04	-	-	-
C	-	-	0.0240 (0.000)	0.0040 (0.485)	-	0.0316 (0.000)	-	-	-
EXT	-	-	-0.5306 (0.000)	-0.4778 (0.000)	-	-0.6474 (0.000)	-	-	-
REG	-	-	-0.0533 (0.000)	0.5051 (0.000)	-	-0.1111 (0.000)	-	-	-
ADA	-	-	0.4328 (0.000)	0.0175 (0.832)	-	0.4831 (0.000)	-	-	-
	-	-	09/08 - 13/02	-	-	09/05 - 13/02	-	-	-
C	-	-	-0.0072 (0.517)	-	-	-0.0099 (0.258)	-	-	-
EXT	-	-	-0.8560 (0.000)	-	-	-0.6126 (0.000)	-	-	-
REG	-	-	-0.0109 (0.697)	-	-	-0.0353 (0.099)	-	-	-
ADA	-	-	0.2908 (0.008)	-	-	0.1904 (0.038)	-	-	-
R^2 adj	0.82	0.71	0.76	0.88	0.77	0.82	0.89	-	0.69
DW	1.58	1.80	1.73	1.80	1.95	1.62	2.15	-	1.47
AIC	-4.02	-3.62	-5.80	-4.14	-4.01	-5.98	-4.27	-	-5.64
BIC	-3.85	-3.54	-5.47	-3.87	-3.77	-5.68	-4.12	-	-5.56
L	287.25	259.25	444.88	266.77	168.30	497.56	335.01	-	441.09

Note: NHS: New Home Sales, CCF: Consumer Confidence index, UP: Unemployment Rate
For each estimated coefficient, the corresponding P-value is given in parentheses
DW: Durbin Watson test, AIC: Akaike information criterion and BIC: Bayesian information criterion.

Table 4d: Estimation results: Bai-Perron method

Firms	PNC Bank			First Trust Advisors			Daiwa Securities America		
News	NHS	CCF	UP	NHS	CCF	UP	NHS	CCF	UP
	01/07 - 09/04	99/01 - 13/02	01/04 - 03/07	99/05 - 09/02	99/01 - 13/02	99/05 - 02/03	99/08 - 09/01	2000/07 - 09/03	99/10 - 01/08
C	-0.0118 (0.000)	0.0056 (0.000)	0.02174 (0.000)	-0.0138 (0.000)	0.0093 (0.109)	0.0382 (0.000)	-0.0154 (0.000)	-0.0047 (0.261)	0.0903 (0.000)
EXT	-0.6152 (0.000)	-0.5411 (0.000)	-0.7853 (0.000)	-0.6469 (0.000)	-0.6877 (0.000)	-0.7211 (0.000)	-0.4275 (0.000)	-0.6624 (0.000)	-0.7891 (0.000)
REG	0.0613 (0.422)	0.0841 (0.147)	0.0584 (0.005)	0.0613 (0.211)	0.1096 (0.016)	-0.0564 (0.013)	0.3102 (0.000)	0.1923 (0.000)	-0.3125 (0.000)
ADA	0.1773 (0.012)	0.1563 (0.011)	0.0807 (0.258)	0.2558 (0.000)	-0.1171 (0.067)	0.0984 (0.257)	0.2546 (0.000)	-0.0361 (0.537)	0.1993 (0.225)
	09/05 - 13/02	-	03/08 - 09/08	09/03 - 13/02	-	02/04 - 13/02	09/02 - 13/02	09/04 - 13/02	01/09 - 09/08
C	0.0158 (0.015)	-	0.0112 (0.000)	0.0181 (0.000)	-	-0.0026 (0.067)	0.0177 (0.000)	0.0151 (0.021)	0.0119 (0.000)
EXT	-0.4307 (0.000)	-	-0.6081 (0.000)	-0.7331 (0.000)	-	-0.5655 (0.000)	-0.6041 (0.000)	-0.8945 (0.000)	-0.6682 (0.000)
REG	0.0785 (0.367)	-	-0.0331 (0.000)	0.0684 (0.132)	-	-0.0034 (0.503)	-0.0824 (0.091)	-0.0109 (0.882)	-0.0405 (0.000)
ADA	0.2499 (0.000)	-	0.0635 (0.328)	0.1349 (0.000)	-	0.1239 (0.018)	0.1937 (0.000)	-0.0419 (0.391)	0.1497 (0.004)
	-	-	09/09 - 13/02	-	-	-	-	-	09/09 - 12/11
C	-	-	-0.0110 (0.223)	-	-	-	-	-	-0.0005 (0.979)
EXT	-	-	-0.6597 (0.000)	-	-	-	-	-	-0.7901 (0.000)
REG	-	-	-0.0326 (0.137)	-	-	-	-	-	-0.0041 (0.916)
ADA	-	-	0.3541 (0.000)	-	-	-	-	-	0.1647 (0.223)
	-	-	-	-	-	-	-	-	-
C	-	-	-	-	-	-	-	-	-
EXT	-	-	-	-	-	-	-	-	-
REG	-	-	-	-	-	-	-	-	-
ADA	-	-	-	-	-	-	-	-	-
R^2 adj	0.75	-	0.78	0.92	0.78	0.76	0.88	0.91	0.80
DW	1.82	-	1.62	2.12	2.14	1.54	2.31	1.69	1.64
AIC	-3.44	-	-5.99	-4.58	-3.17	-5.76	-4.23	-4.02	-5.95
BIC	-3.28	-	-5.73	-4.41	-3.04	-5.60	-4.05	-3.80	-5.66
L	249.14	-	422.34	344.45	119.58	448.47	278.87	192.91	345.44

Note: NHS: New Home Sales, CCF: Consumer Confidence index, UP: Unemployment Rate
For each estimated coefficient, the corresponding P-value is given in parentheses
DW: Durbin Watson test, AIC: Akaike information criterion and BIC: Bayesian information criterion.

Table 4e: Estimation results: Bai-Perron method

The completeness and temporal flexibility of the expectation model

Results in Tables 4a to 4e reveal instability in both the coefficients and the functional form of the forecasting model. Indeed, only 10 forecasts out of 45 (which is equivalent to about 22% of the total forecasts) show a time consistency in the use of predictive models, indicating that most forecasters have flexible anticipative behavior over time, i.e. the model changes at least partially and the feedback coefficients change from one sub-period to the next. The model shift is partial, in the way that over two contiguous sub-periods, one mixed model component persists while the other changes (only 24% of cases where the whole mixed model remains constant over two successive sub-periods), indicating that changes in expectation processes occur while exhibiting some internal inertia. This finding on individual expectations is in line with Prat and Uctum (2007) on consensus expectations data, although the estimation method used is very different. Results also suggest that forecasters' behavior changes over time. Indeed, estimating our mixed model with the Bai-Perron approach allow us to find multiple breaks. These breakpoints are unknown, i.e. they are not imposed according to some *a priori* information. So, the break dates are determined endogenously which is interesting insofar as they are often located around the bursting of the subprime crisis (2008-2009) and / or the global crisis (2010-2012), but also around some idiosyncratic shocks (such as those related to the corporation or the forecaster...). On the whole, the completeness of the model and temporal flexibility are the dominant features of macroeconomic indicators' forecasts.¹⁸ In contrast to Ito (1994) who suggested a stability in the expectation process over time for the yen/dollar exchange rate, our results are in line with those of Prat and Uctum (2007) who confirm both the relevance of the mixed expectation model and the time-varying process by using a switching-regime probabilistic model on exchange rate consensus expectations. These findings on both disaggregated macroeconomic forecasts and aggregated exchange rate expectations highlight that previous studies that ignored these endogenous structural breaks have estimated expectation models with some kind of bias.

Mixed expectation process with a large dominance of chartists

All agents typically generate their forecasts using a mixed model combining at least two or three components (87%). This result invalidates the findings of previous studies that are based on the assumption of a single type of anticipation process.

The chartist profile is the dominant fraction in macroeconomic forecasting universe since the extrapolative model is almost systematically involved (99%) in predicting all news by all agents in each period of time.

This result was also pointed out by Taylor and Allen (1992), Lui and Mole (1998) and Gehrig and Menkhoff (2004) to name a few, who found that at least 90% of exchange rates' forecasters place more weight on the technical analysis relatively to other forms of trading analysis and are therefore –at least in the short term– first and foremost chartists before

¹⁸These two hypotheses were initially addressed by Frankel and Froot (1987) without having resulted in any empirical evidence.

being fundamentalists or both. This position is summarized in the first stylized fact introduced in the Menkhoff and Taylor (2007)’s survey of the literature on technical analysis in the foreign exchange market, which states that “*almost all foreign exchange professionals use technical analysis as a tool in decision making at least at some degree*”.¹⁹

Subsequently, in a roughly balanced way, the fundamentalist behavior (regression model) and the error correction behavior (adaptive model). Our findings therefore give a minor weight to the “chartist-fundamentalist” behavior (only 20%) which has become popular since the seminal work of Frankel and Froot (1987), and reported in the second stylized fact of Menkhoff and Taylor (2007) as “*most foreign exchange professionals use some combination of technical and fundamental analysis*”. This finding leads us to believe that this popular profile is thus simply the consequence of the aggregation of heterogeneous individual expectations or that it stems from the asset price dynamics.

In the absence of fundamentalist activity, the chartist behavior rarely occurs in isolation (13%). Results show that very often, forecasters use some combination of technical analysis and a learning process (28%) trying to learn the “true” level of the variable rather than its underlying process (Benassy-Quere et al. (1999)).²⁰ This finding is all the more important as we perceive this complementarity around crisis periods, which means that market practitioners no longer build their forecasts on a completely subjective analysis based primarily on intuition but incorporate an error correction process (learning process) in turmoil periods.²¹ However, this profile comes second after the full mixed model (chartist-fundamentalist-learning process) which appears in 36% of cases, with 19% manifested in the first sub-period (post subprime crisis).

Stabilizing and destabilizing moves in the three expectation components

Results highlight stabilizing and destabilizing moves in the three expectation components which is in line with previous studies such as Reitz et al. (2012) who reported the same stylized facts on oil price expectations, and with Benassy-Quere et al. (1999) who identified these characteristics on exchange rate expectations. The stabilizing effect concerns the extrapolative component, which is systematically affected by a negative coefficient, indicating that any pattern observed in the past led to make anticipations in the opposite direction. This behavior is stabilizing as it reflects a systematic turnaround in the trend. It stands out from the standard extrapolative model with a positive parameter which describes a projection of the past trend toward the future and which leads to destabilizing expectations.

The regressive component parameter is mainly positive (60%) –which is the expected sign– or negative following individuals and sub-periods, indicating that any deviation from the equilibrium value is interpreted by forecasters either as a temporary misalignment that

¹⁹Menkhoff and Taylor (2007) provide a critical overview of studies based on surveys where market practitioners in Forex are asked directly what forecasting method they use. These studies were summarized by authors in Tables 1 to 3.

²⁰The inductive analysis of past movements (trends-technical analysis) is usually combined with a correction of past forecast errors

²¹Defeating Malkiel (1999) who compared technical analysis to some kind of “astrology”.

will subside by market reaction (mean reversion reaction) or as a persistent imbalance doomed to widen further. Hence, expectations based on the first perception are stabilizing while those based on the second are destabilizing.

The adaptive component parameter is also mostly positive (80%) according to the standard adaptive model, i.e adjusting the actual forecast by taking into account the past forecast error led to formulate a stabilizing forecast. However, it takes a negative value in 20% of cases. Since we observe that coefficients become negative around the subprime crisis and the global financial crisis, it appears likely that they reflect the difficulty forecasters have to self-correct in an environment characterized by unrest and uncertainty.

These results confirm the dominance of the mixing behavior found in exchange rates expectations at both the disaggregate level (Benassy-Quere et al. (1999)) and the aggregate one using consensus forecasts as in Uctum and Prat (2000).

5 How good are the forecasters?

In this section we compute the root mean square error (RMSE) of each forecast submitted by each forecaster. Comparison of RMSE enabled us to classify agents according to their anticipative performance in predicting each news allowing hence to complete the heterogeneity analysis. By combining forecasters performance with the expectation models results used to predict macroeconomic indicators, we draw an interesting conclusion about the best forecasting model for the studied period and the profile of forecasters associated with the highest rate of good predictions (chartist profile, fundamentalist profile, a learning process user or a mix of two or three of these components).

Forecasters	NHS	CCF	UP
Briefing.com	0.1277	0.1169	0.0682
Wrightson ICAP	0.0995	0.1244	0.0338
Deutsche Bank Sec	0.1143	0.1197	0.0359
IDEA global	0.1101	0.1304	0.0375
Credit Suisse	0.1028	0.1201	0.0352
BMO Capital Markets	0.1102	0.1330	0.0358
Morgan Stanley & Co.	0.1079	0.1280	0.0360
BofA Merrill Lynch	0.1063	0.1090	0.0345
Citigroup NY	0.1104	0.1313	0.0341
High Frequency Economics	0.0944	0.1210	0.0355
CIBC World Markets	0.1116	0.1009	0.0373
Nomura Securities Intl.	0.1070	0.2205	0.0354
PNC Bank	0.1119	0.1515	0.0354
First Trust Advisors	0.1095	0.1617	0.0365
Daiwa Securities America	0.1065	0.1477	0.0355

*Note:*NHS: New Home Sales, CCF: Consumer Confidence index, UP: Unemployment Rate

Table 5: Forecast accuracy evaluation: RMSE

The results (see Table 5) provide three interesting findings. First, we can observe a high

concentration of the best forecasts (lowest RMSE) for the unemployment rate followed by the new home sales and finally consumer confidence index (see figure 4) .

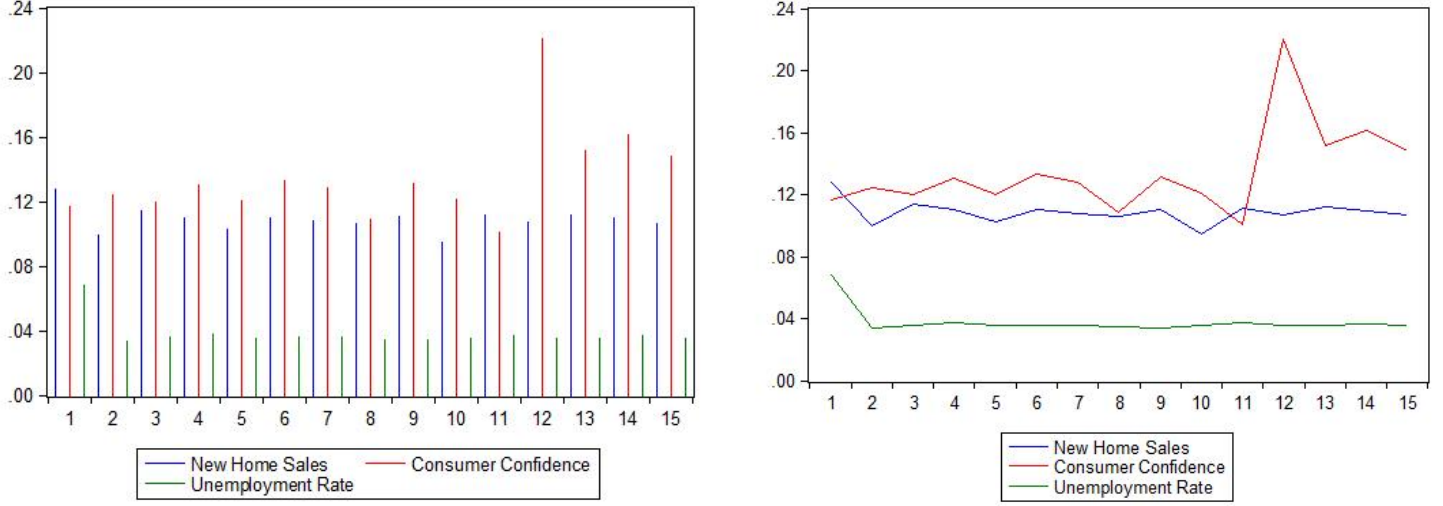


Figure 4: RMSE per forecaster / News

In the light of the previous results concerning the heterogeneity test and the forecast accuracy evaluation, one would think that there is a connection between forecasters' anticipative performance and their heterogeneity degree. Second, combining results in Tables 4a to 4e and 5, we can state that the model providing the best anticipative performance is always the one whose parameters are flexible over time, i.e. those which change over sub-periods. Recall also that the estimation results for the unemployment rate showed the highest number of structural breaks (up to 4 sub-periods), which highlights a wide temporal flexibility in forecasting this indicator.

A third result concerns the forecasters' profile associated with the best forecasts. We find that the more the model is general the lower is the RMSE value and therefore the higher is the forecast quality. However, results show that it is less the expectation component complementarity (once a minimum of 2 insured) than the flexibility of the model parameters that seems to improve the forecast accuracy. This result is interesting because it excludes any rigidity in the behavior of those rushing through the best forecasting performance *"Win those who adapt best"*.

We also note a concentration of RMSE around small variable values, essentially for the unemployment rate forecasts, which indicates that the forecasters performances are rather homogeneous for that indicator.

6 Conclusion

The aim of this paper is to investigate forecasters' heterogeneity in predicting scheduled macroeconomic indicators by using a mixed expectation model. To this end, we use a high quality disaggregated survey data based on the expected values of three macroeconomic indicators provided by Bloomberg. To the best of our knowledge such a prospective study has not been previously undertaken and should therefore provide useful information about a key aspect of expectations behavior in this area.

The estimation of the mixed expectation model, combining extrapolative, regressive and adaptive components, reveals a large dominance of the chartist profile among forecasters with a systematical persistence over time, even during turmoil periods. This highlights that technical analysis is an important and persistent tool in the decision making of macroeconomic indicator forecasters. Using the Bai-Perron method, that accounts for structural breaks, we show that the forecaster's behavior changes over time. In particular, forecasters exhibit specific profiles especially around the different crises that affected markets these last decades.

The chartist-fundamentalist-learning process and the chartist-learning process are the most present mixed profiles of forecasters found in this study, supporting Menkhoff and Taylor (2007) who argued that “*extrapolative expectations and respective technical trading rules may have a rational basis*”. While we also find evidence of a temporal instability of forecaster behaviors within sub-periods, we show that chartists and fundamentalists have typically a stabilizing behavior.

Finally, our main finding concerns the results arising from the comparison of forecasters' performance and the mixed model estimation results. We show that forecasters whose forecasting models combine at least two or three anticipatory components (extrapolative, and regressive or/and adaptive) and display high temporal flexibility, are those which provide the most accurate forecasts.

Appendix

Estimating mixed model with multiple endogenous structural breaks

The structural break model

The Bai Perron estimation procedure is the suitable method for our purposes. Insofar as our main goal is to point out the temporary flexibility of the expectation mixed models, the Bai Perron method allows us to determine endogenously multiple structural breaks at unknown dates in our series. We consider a pure structural change model with m unknown breaks where all coefficients are subject to change. The multiple linear regression is given by:

$$y_t = x_t' \beta_j^0 + \nu_t \quad j = 1, \dots, m+1 \quad t = T_{j-1}^0 + 1, \dots, T_j^0 \quad (\text{A1})$$

Where $T_0^0 = 0$, $T_{m+1}^0 = T$ and m is the number of unknown breaks. y_t is the observed dependent variable, x_t is a $k \times 1$ vector of regressors and β_j^0 is the vector of regression coefficients. A structural break occurs if at least one of these coefficients changed at a given date –the break-date– in the sample period. This break-date is defined as the last observation of a sub-period where the coefficients are stable, the change occurring at the following date. When no structural break occurs (coefficients remain stable over the entire period), the parameters are estimated over the full sample and equation (A1) shifts to a standard linear regression without any structural break.

The starting point of this procedure is that the true model is either a linear model or a structural break model (but possibly with one break), so the first choice is between $m = 0$ (linearity) and $m = 1$ (two regimes). Break location \hat{T}_i with $i = 1, \dots, m$ is then determined sequentially, starting with $m = 1$ (single break), the model is estimated over the full period so as to determine the first break location \hat{T}_1 that minimizes the sum of squared residuals (SSR) of the one break model. Once a first break date is identified, the sample is split into two sub-samples $[1, \hat{T}_1]$ and $[\hat{T}_1, T]$ and a one-break model is estimated in order to determinate two potential break dates \hat{t}_1 and \hat{t}_2 . The selected candidate will be the one with the minimum SSR between the two. This process is repeated sequentially to find further breaks.

Information criteria (IC)

The number of significant breaks in (A1) can be found via information criteria, as the idea behind consists in partitioning the sample by estimating additional break dates until the IC is minimized, so that, $\hat{m} = \arg \min_{m=0, \dots, M} IC(m)$. Following Yao (1988), Bai and Perron (1998) and Bai and Perron (2003), we use the modified Bayesian information criterion (BIC) in which a penalty factor is included to compensate for the necessary decrease in the SSR with each additional new break. For a regression model as in (A1), this penalty

component takes the form:²²

$$BIC(n) = \ln[S_T(\hat{T}_1, \dots, \hat{T}_m)] + K(m, T) \quad (\text{A2})$$

$$K(m) = [(m + 1)p + m] * \ln(T)/T$$

where $S_T(\hat{T}_1, \dots, \hat{T}_m)$ is the global minimum of the residual sum of squares for m breaks, $K(m, T)$ is the penalty term that depends on the dimension of the model and p the number of regressors supposed unstable.

²²See more details in Bai and Perron (2006).

References

- Almeida, A., Goodhart, C., and Payne, R. (1998). The effects of macroeconomic news on high frequency exchange rate behavior. *Journal of Financial and Quantitative Analysis*, 33(03):383–408.
- Andersen, T. G., Bollerslev, T., Diebold, F. X., and Vega, C. (2007). Real-time price discovery in global stock, bond and foreign exchange markets. *Journal of International Economics*, 73(2):251 – 277.
- Bai, J. and Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 66(1):47–78.
- Bai, J. and Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1):1–22.
- Bai, J. and Perron, P. (2006). Multiple structural change models: A simulation analysis. In Corbae, D., Durlauf, S. N., and Hansen, B. E., editors, *Econometric Theory and Practice*, pages 212–238. Cambridge University Press. Cambridge Books Online.
- Balduzzi, P., Elton, E. J., and Green, T. C. (2001). Economic news and bond prices: Evidence from the u.s. treasury market. *The Journal of Financial and Quantitative Analysis*, 36(4):pp. 523–543.
- Batchelor, R. (2007). Bias in macroeconomic forecasts. *International Journal of Forecasting*, 23(2):189–203.
- Becker, K. G., Finnerty, J. E., and Kopecky, K. J. (1996). Macroeconomic news and the efficiency of international bond futures markets. *Journal of Futures Markets*, 16(2):131–145.
- Benassy-Quere, A. (1997). Les anticipations de change d’après les données d’enquêtes : un bilan de la littérature.
- Benassy-Quere, A., Larribeau, S., and MacDonald, R. (1999). Models of exchange rate expectations: Heterogeneous evidence from panel data. Working Papers 1999-03, CEPII research center.
- Benassy-Quere, A., Larribeau, S., and MacDonald, R. (2003). Models of exchange rate expectations: how much heterogeneity? *Journal of International Financial Markets, Institutions and Money*, 13(2):113–136.
- Birz, G. and Lott Jr., J. R. (2011). The effect of macroeconomic news on stock returns: New evidence from newspaper coverage. *Journal of Banking & Finance*, 35(11):2791–2800.
- Bollerslev, T., Cai, J., and Song, F. M. (2000). Intraday periodicity, long memory volatility, and macroeconomic announcement effects in the U.S. treasury bond market. *Journal of Empirical Finance*, 7(1):37 – 55.

- Chen, L. H., Jiang, G. J., and Wang, Q. (2013). Market reaction to information shocks, does the bloomberg and briefing.com survey matter? *Journal of Futures Markets*, 33(10):939–964.
- Ederington, L. H. and Lee, J. H. (1993). How markets process information: News releases and volatility. *The Journal of Finance*, 48(4):1161–1191.
- Elliott, G. and Ito, T. (1999). Heterogeneous expectations and tests of efficiency in the yen/dollar forward exchange rate market. *Journal of Monetary Economics*, 43(2):435–456.
- Fama, E. F. (1965). The behavior of stock-market prices. *The Journal of Business*, 38(1):pp. 34–105.
- Fama, E. F., Fisher, L., Jensen, M. C., and Roll, R. (1969). The adjustment of stock prices to new information. *International Economic Review*, 10(1):1–21.
- Fleming, M. J. and Remolona, E. M. (1999). Price formation and liquidity in the u.s. treasury market: The response to public information. *The Journal of Finance*, 54(5):pp. 1901–1915.
- Frankel, J. (2011a). A solution to fiscal procyclicality: the structural budget institutions pioneered by chile. Working Papers Central Bank of Chile 604, Central Bank of Chile.
- Frankel, J. A. (2011b). Over-optimism in forecasts by official budget agencies and its implications. NBER Working Papers 17239, National Bureau of Economic Research, Inc.
- Frankel, J. A. and Froot, K. A. (1987). Short-term and long-term expectations of the yen/dollar exchange rate: Evidence from survey data. *Journal of the Japanese and International Economies*, 1(3):249–274.
- French, K. and Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics*, 17(1):5–26.
- Gehrig, T. and Menkhoff, L. (2004). The use of flow analysis in foreign exchange: exploratory evidence. *Journal of International Money and Finance*, 23(4):573 – 594.
- Gilder, D., Shackleton, M. B., and Taylor, S. J. (2014). Cojumps in stock prices: Empirical evidence. *Journal of Banking & Finance*, 40(C):443–459.
- Goodhart, C. (1988). The foreign exchange market: A random walk with a dragging anchor. *Economica*, 55(220):437–60.
- Graham, J. R., Harvey, C. R., and Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, 40:3 – 73.
- Ito, T. (1990). Foreign exchange rate expectations: Micro survey data. *American Economic Review*, 80(3):434–49.

- Ito, T. (1994). Short-run and long-run expectations of the yen/dollar exchange rate. *Journal of the Japanese and International Economies*, 8(2):119–143.
- Ito, T. and Roley, V. V. (1987). News from the u.s. and japan : Which moves the yen/dollar exchange rate? *Journal of Monetary Economics*, 19(2):255–277.
- Jones, C. M., Lamont, O., and Lumsdaine, R. L. (1998). Macroeconomic news and bond market volatility. *Journal of Financial Economics*, 47(3):315–337.
- Keynes, J. M. (1936). *General Theory of Employment, Interest and Money*. Cambridge University Press, Cambridge.
- Lahaye, J., Laurent, S., and Neely, C. J. (2011). Jumps, cojumps and macro announcements. *Journal of Applied Econometrics*, 26(6):893–921.
- Lamont, O. (1995). Macroeconomics forecasts and microeconomic forecasters. Working Paper 5284, National Bureau of Economic Research.
- Laster, D., Bennett, P., and Geoum, I. S. (1999). Rational bias in macroeconomic forecasts. *The Quarterly Journal of Economics*, 114(1):293–318.
- Lefevvre, E. (2011). *Marches financiers - La logique du hasard*. Eyrolles.
- Lobo, B. J., Darrat, A. F., and Ramchander, S. (2006). The asymmetric impact of monetary policy on currency markets. *Financial Review*, 41(2):289–303.
- Lui, Y.-H. and Mole, D. (1998). The use of fundamental and technical analyses by foreign exchange dealers: Hong kong evidence. *Journal of International Money and Finance*, 17(3):535–545.
- MacDonald, R. (1992). Exchange rate survey data: A disaggregated g-7 perspective. *The Manchester School of Economic & Social Studies*, 60(0):47–62.
- MacDonald, R. (2000). Expectations formation and risk in three financial markets: Surveying what the surveys say. *Journal of Economic Surveys*, 14(1):69–100.
- MacDonald, R. and Marsh, I. W. (1996). Currency forecasters are heterogeneous: confirmation and consequences. *Journal of International Money and Finance*, 15(5):665–685.
- Malkiel, B. (1999). *A Random Walk Down Wall Street: Including a Life-cycle Guide to Personal Investing*. Norton.
- Menkhoff, L. and Taylor, M. P. (2007). The obstinate passion of foreign exchange professionals: Technical analysis. *Journal of Economic Literature*, 45(4):936–972.
- Muth, J. A. (1961). Rational expectations and the theory of price movements. *Econometrica*, 29(6):315–335.

- Nikkinen, J. and Sahlstrom, P. (2001). Impact of scheduled u.s. macroeconomic news on stock market uncertainty: A multinational perspective. *Multinational Finance Journal*, 5(2):129.
- Pearce, D. K. and Roley, V. V. (1983). The reaction of stock prices to unanticipated changes in money: A note. *Journal of Finance*, 38(4):1323–33.
- Prat, G. and Uctum, R. (2007). Switching between expectation processes in the foreign exchange market: a probabilistic approach using survey data. *Review of International Economics*, 15(4):700–719.
- Prat, G. and Uctum, R. (2015). Expectation formation in the foreign exchange market: a time-varying heterogeneity approach using survey data. *Applied Economics*, 47(34-35):3673–3695.
- Reitz, S., Rülke, J.-C., and Stadtmann, G. (2012). Nonlinear expectations in speculative markets : Evidence from the ecb survey of professional forecasters. *Journal of Economic Dynamics and Control*, 36(9):1349–1363.
- Rigobon, R. and Sack, B. (2006). Noisy macroeconomic announcements, monetary policy, and asset prices. Working Paper 12420, National Bureau of Economic Research.
- Sun, Q. and Tong, W. H. (2000). The effect of u.s. trade deficit announcements on the stock prices of u.s. and japanese automakers. *Journal of Financial Research*, 23(1):15–43.
- Takagi, S. (1991). Exchange rate expectations: A survey of survey studies. *IMF Staff Papers*, 38(1):156–183.
- Taylor, M. P. and Allen, H. (1992). The use of technical analysis in the foreign exchange market. *Journal of International Money and Finance*, 11(3):304–314.
- Uctum, R. and Prat, G. (2000). The evidence of a mixed expectation generating process in the foreign exchange market. In F.Gardes and G.Prat, editors, *Price Expectations in Goods and Financial Markets: New developments in theory and empirical research*, pages 251–70. Edward Elgar.
- Yao, Y.-C. (1988). Estimating the number of change-points via schwarz criterion. *Statistics & Probability Letters*, 6(3):181 – 189.