ECONOMICS BULLETIN

Can earnings forecasts be improved by taking into account the forecast bias?

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Abstract

The recent period has highlighted a well-known phenomenon, namely the existence of a positive bias in experts' anticipations. Literature on this subject underlines optimism in the financial analyst community. In this work, our significant contributions are twofold: we provide explanatory bias prediction models which will subsequently allow the calculation of earnings adjusted forecasts, for horizons from 1 to 24 months. We explain the bias using macroeconomic as well as sector and firm specific variables. We obtain some important results. In particular, the macroeconomic variables are statistically significant and their signs are coherent with the intuition. However, we conclude that the microeconomic variables are the main explanatory variables. From the forecast evaluation statistics viewpoints, the adjusted forecasts make it possible quasi-systematically to improve the forecasts of the analysts.

Citation: DOSSOU, François, Sandrine LARDIC, and Karine MICHALON, (2008) "Can earnings forecasts be improved by taking into account the forecast bias?." *Economics Bulletin*, Vol. 7, No. 11 pp. 1-20
Submitted: September 7, 2006. **Accepted:** August 29, 2008.
URL: http://economicsbulletin.vanderbilt.edu/2008/volume7/EB-06G10031A.pdf

Introduction

Evaluating the reliability of analysts' earnings forecasts is an important aspect of research for several reasons. In order to identify the unanticipated component of earnings, many empirical studies employ analysts' consensus forecasts as a proxy for the market's expectations of future earnings. Additionally, institutional investors make considerable use of analysts' forecasts when evaluating and selecting individual shares. The performance of analysts' forecasts sheds light on the process underlying market players' expectations about key economic and financial variables, as the behaviour and use of earnings estimates have been widely studied since the 1970s (Crichfield, Dyckman and Lakonishok, 1978…).

Herding and bias are among the main statistical observations regarding earnings forecasts behaviour. Herding (the incentive to conform that increases with the number of previous adopters) leads to an unusually narrow dispersion of individual analysts' forecasts. Even when this narrow dispersion is irrational, it should not affect the accuracy of the average forecast. However, the evidence is strong that not only forecast dispersions, but also their means, are constantly biased. The recent period has highlighted a well-known phenomenon, the existence of a positive bias (in terms of earnings) in experts' anticipations. In other words, the literature underlines the optimism in the financial analyst community (Brown, 1993; Dreman and Berry, 1995; O'Brien, 1988, Brous and Kini, 1993; Clayman and Schwartz, 1994; and Olsen, 1996...) and whether or not this forecast optimism is intentional is subject to debate between Efficient Market Hypothesis supporters and behavioural researchers. Francis and Philbrick (1993) attribute a positive bias in earnings forecasts to the analyst-management relation. A followed company's management is found to be an important information source for financial analysts in predicting earnings. Analysts are anxious to accept the consequences of unfavourable forecasts imposed by a firm's management, and therefore, are eager to produce overly optimistic reports. A second, more obvious explanation for a positive bias in earnings forecasts is the existence of a direct relationship between a followed company's management and a following company's management (cf. Lin and McNichols (1993) and Dugar and Nathan (1995)). Both explanations concern financial analysts' conscious actions. Thus, the bias at issue may be labelled a reporting bias (see Francis and Philbrick (1993)). Alternative explanations relate to processing biases. If forecast errors are associated with unanticipated macro-economic information negatively affecting many firms, then, on average, financial analysts may overstate earnings (O'Brien 1988).

In this work, our aim is to respond to the following question: can earnings forecasts be improved by taking into account the forecast bias? We develop an explanatory bias prediction model to calculate earnings adjusted forecasts. Previous studies of factors influencing bias have concentrated on the effect of a single variable. We explain the bias using macroeconomic, sector and firm specific variables. The contents are as follows: in the first section, we describe the anticipation database; specifically, we calculate the earnings forecast bias, validating its descriptive statistics. The second section details the explanatory variables selected, with the third section describing the estimated models' characteristics. Study of the estimation results leads to the fourth section, which determines the adjusted earnings forecasts that we compare to analysts' earnings forecasts.

1. Data description

Analysts' forecasts are taken from the Institutional Brokers Estimate System (IBES), which collects forecasts from security analysts employed by institutional brokers and research firms. Our study is based on the consensus[1] mean estimates of 16 countries, with companies belonging to the MSCI indices,[2] [3] for the period January 1990 to December 2002.

[1] We do not avoid the measurement bias to which a consensus is susceptible (cf. Capstaff et al., 1995), but using individual forecasts inevitably means there will be an element of double counting. Capstaff, Paudyal and Rees (2001) indicate that the double counting may result in forecast accuracy and bias being overstated.

[2] The definition of forecast and reported EPS varies from country to country but in most cases they are based on the EPS as used in published financial statements. For more detail and examples, see for instance Capstaff, Paudyal and Rees (2001).

[3] It happens that 2 securities of the same firm differ only on tax arguments. In this case, the forecasts of benefit of only one were available in our sample. Since the forecasts were the same, we supplemented the base where necessary.

Table 1. Description of the sample

Country	Number of firms (%)	Country	Number of firms (%)
Austria	2.77	**UK**	10.00
Belgium	2.48	**Italy**	6.24
Switzerland	6.14	**Netherlands**	2.77
Germany	7.82	**Norway**	3.47
Denmark	2.48	**Portugal**	1.49
Spain	4.55	**Sweden**	4.75
Finland	3.07	**US**	33.76
France	8.22		

	US (%)	Europe (%)
Consumer Discretionary	16.62	15.47
Consumer Staples	3.50	6.86
Energy	5.54	3.36
Financials	17.78	18.98
Health care	6.71	4.82
Industrials	14.87	23.07
Information Technology	5.83	6.13
Materials	11.95	14.01
Telecommunication Services	4.37	3.36
Utilities	12.83	3.94

We selected all the companies followed, on average, by at least 6 analysts and for which three successive forecasts are available, so that the concept of consensus remains meaningful from both a spatial and temporal viewpoint. Only companies ending their fiscal year in December were selected for comparable horizons, and, indeed, most companies finish their fiscal year in December. The classification of the sample at country level highlights the predominant weight of the US in terms of the number of firms' earnings anticipations, with 33.76% of the firms. The UK, France and Germany follow. The classification of the sample at sector level highlights the predominant weight of the financial and consumer discretionary firms for the US and of industrial and financial firms for the European panel.

Forecast errors constitute an invaluable indicator, allowing us to judge the quality of analysts' estimates. Over several successive horizons, the forecasting errors provide information a posteriori for the way in which analysts revise their anticipations. They enable us to see whether analysts are mistaken about performance by systematically over or underestimating it. Analysts' forecasting error (AFE) is computed as the average earning per share (EPS) forecast minus the last forecast[4] (before publication) of the EPS being the subject of the forecast reported by IBES, divided by the absolute value of the last EPS forecast (before publication);[5] nonzero AFE provides an obvious bias. The statistic of the bias is defined as follows:

$$\mathrm{AFE}_{i,h,T} = \frac{(F_{i,h,T} - F_{i,T})}{\left|F_{i,T}\right|} \quad (1)$$

[4]Choosing the last forecast before publication, without taking published earnings into account, allows us to distinguish between the bias forecast and the surprise (i.e. exceptional results, mainly due to the fact that firms record provisions on acquisitions, change their dividend policy, …).

[5]Because of the delay in reporting earnings, the actual earnings are not known after the year has ended.

where $F_{i,h,T}$ corresponds to the forecast of earnings per share of company i, concerning its fiscal year T, calculated on a horizon h; and $F_{i,T}$ represents the last forecast (before the publication) of the EPS being the subject of the forecast.[6]

Outliers are evident in the upper and lower tails of the AFE distribution. In order to eliminate undue influence by extreme values, distributions are winsorized at ±1% for all subsequent analysis. However, as Collins and Hopwood (1980) point out, "there is no unique definition or value that defines an outlier."[7]

The bias was calculated by country, sector and horizon. Concerning the forecasting horizon, we selected horizons from 24 months to 1 month (before the last forecast).

2. Bias forecasting model

Explanatory variables were chosen based on existing literature (cf. Dossou, Lardic, Michalon, 2004) and on a priori results from a statistical study of the bias. The selected variables are macroeconomic and individual.

2.1. Macroeconomic variables

Some authors have underlined a link between economic growth and analysts' forecasts. When economic growth strengthens, actual earnings accelerate toward the normally optimistic forecasts, so forecasting errors decline. If economic growth is very strong, earnings rise well beyond the forecasts: analysts end up under forecasting earnings for a while. When the economy begins to slow down, earnings start declining too, yet analysts' optimism prevents a drastic downward revision in their forecasts. Therefore, forecasting errors increase in size. Emanuelli and Pearson (1994) described an approach to global asset allocation that relies on estimate revisions: recognizing that biases in earnings forecasts are linked to the business cycle and adjusting earnings forecasts to reduce the bias will improve the performance of such global asset allocation strategies. Due to the monthly availability of production data, we used industrial production growth to measure economic activity. We introduced the following other variables in the model: year-over-year inflation growth,[8] annual exchange rate growth (US dollar performance against domestic currency for the European model and CEERUS[9] for the US model) and interest rate slope curve (long interest rate – short interest rate). We expect a negative sign for industrial production growth and the slope curve and a positive one for annual inflation growth. Note that due to adoption of the Euro, European economies will integrate over time, which should eliminate the interest and inflation differences between countries in the European model. Moreover, we could have used variables of anticipation; La Porta (1996), Dechow and Sloan (1997) and Rajan and Servaes (1997) showed that analysts are all the more optimistic in their forecasts when anticipated growth is strong. However, anticipated data never appears significant in our study.

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[6]We use the last earnings forecast as a deflator. Various other deflators including price and/or the previous level of earnings, have been used in other studies. Capstaff, Paudyal and Rees (2001) indicate they have replicated their tests using different deflators and have found the results to be qualitatively similar.

[7]Fried and Givoly (1982) and Capstaff et al. (1995) truncate observations for which forecast error exceeds 100%. Elton et al. (1984) and O'Brien (1988) include in their sample only those companies for which initial earnings are above $0.20 per share. Capstaff et al. (1995) and Harris (1999) exclude companies for which forecast earnings growth or actual earnings growth exceeds 100%.

[8] Chordia and Shivakumar (2005) show that part of the drift anomaly is attributable to the inflation illusion argument of Modigliani and Cohn (1979). They explain that whereas bond market investors understand the impact of inflation on discount rates, stock market investors do not account for the impact on future earnings growth.

Basu, Markov and Shivakumar (2005) found that expected inflation proxies (such as lagged inflation) predict future earnings growth of a portfolio long in high-SUE (Standardized Unexpected Earnings) firms and short in low-SUE firms, but analysts do not fully adjust for this relation. They conclude that analysts' earnings forecasts are not fully efficient with respect to earnings information in inflation. Inflation illusion will cause firms with positive earnings sensitivities to inflation to be undervalued and stocks with negative earnings sensitivities to inflation to be overvalued.

[9]Effective exchange rate index (weighted by trades).

2.2. Microeconomic variables

Harris (1999) undertook a study of the accuracy, bias and efficiency of analysts' forecasts of long-run earnings growth for US companies over the period 1982-1992, showing that analysts' forecasts do not incorporate all information available at the time of the forecast. In addition, much of analysts' forecasting error is at the individual firm level. The inability of analysts to forecast average earnings growth in the economy does not contribute substantially to their inaccuracy. However, there is evidence that the level of aggregation at which analysts' errors are being made is changing over time, with increasing accuracy at the industry level and decreasing accuracy at the firm level. In order to take firm specific information into account, we retained the following variables:

- The coefficient of variation (called Lcv in the regressions), i.e. the dispersion between analysts'/absolute value of the average EPS (cf. for instance De Bondt and Forbes, 1999). This variable corresponds to an indicator of uncertainty, or the degree of disagreement between the estimates: the more uncertain the universe, the larger the dispersion of analysts' forecasts. In particular, it suggests that one expects this variable to be more explanatory over long horizons (where uncertainty is stronger) than over shorter horizons (increasing visibility of the company's prospects), as with small capitalizations rather than major ones. We expect a positive coefficient for this variable, the bias range proportionally increasing with analyst disagreement. The relative variation of the forecast (called Delprev) corresponds to the percentage difference between current forecast and the first forecast earnings. The more analysts revise their forecasts in a given year, the smaller the bias.
- The firm capitalization. Das et al. (1998) and others found that optimistic bias is more pronounced in firms whose earnings are relatively difficult to predict from publicly available information. Lim (2001) provides theory and evidence that analysts' earnings forecasts are more optimistically biased for firms with less predictable earnings. Similarly, Das, Levine and Sivaramakrishnan (1998) report a positive relation between optimistic bias and the unpredictability of analysts' earnings forecasts, i.e. in smaller firms. In Dossou, Lardic and Michalon (2004), we showed the importance of stock exchange capitalization as a discriminating variable: concerning the United States,[10] one observed that the mean bias is weaker for large capitalizations than for others. The spread, however, tends to decline with the forecasting horizon. In addition, the spread is essentially due to the positive mean bias: the experts tend to overestimate the benefits for moderate sized companies. One can attribute this phenomenon to the amount of public information available concerning each firm group; the less information the experts have, the more they will tend to overestimate their forecasts in order to ensure that they do not finally underestimate the benefit.
- The price variation between the last earnings announcement and the previous month (called Var-p in regressions).[11] Brown, Foster and Noreen (1985), Brown, Hagerman, Griffin and Zmijewski (1987), Lys and Sohn (1990), Abarbanell (1991) et al., and Klein and Rosenfeld (1992) documented evidence that forecasting errors can be predicted by prior period stock returns. A significant price increase corresponds to good results. The published earnings will converge towards expected earnings, thus reducing the bias. As such, we expect a negative sign for the coefficient.
- Net revisions (called Lecart) are defined as the number of downward revised estimates minus the number of upward estimates. This is an activity indicator. This variable implicitly measures the

[10] Similar behaviour for bias was observed for the United Kingdom, but for Germany and France, the spread (in terms of bias for the two sub-groups of capitalization) is weaker. Even in Germany, one observes spreads between the positive mean bias that are compensated by the spreads between the negative mean bias. This heterogeneity by country is also observed at the sector level (Figures 8.1 to 8.4): for the materials and industrial sectors. Biases associated with the largest capitalizations are weaker than those associated with moderate capitalizations. On the other hand, for the consumer, discretionary and financial sectors, sub-sample bias is indistinguishable regardless of the horizon for finance and over long horizons for the consumer discretionary sector.

[11] Prices come from the IBES MSCI database.

uncertainty of the environment. We do not capture the importance of the revisions with this variable (positive and negative).

- Number of analysts (called NA): we expect a negative relation between the bias and the number of analysts. Moreover, a priori, we expect a substantial correlation between the number of analysts and the firms' market capitalization. We will then need to take care of colinearity relationships.

3. Regression results

Given the number of countries (16) and forecasting horizons (24) we chose to retain only certain forecast horizons and group the countries in two clusters, namely the United States and Europe. This choice of two clusters was also guided by the fact that for certain European countries, the number of observations is relatively weak. Other pooling could have been carried out, particularly by sector. However, it appeared more relevant to retain a country rather than a sectorial pool: given the constitution of our sample (cf. Table 1), the significant weight of the American companies would have systematically dominated the more specific behaviours of the smaller countries. However, it is important not to neglect the existence of a sectorial effect. It was taken into account through the introduction of additive sectorial dummies to our regressions. In particular, Dossou, Lardic and Michalon (2004) found some sectors more prone to bias: information technology, materials, telecommunications and to a lesser extent, industrials and the consumer discretionary sectors. The utilities sector is characterized by the weakest mean bias regardless of the horizon. Capstaff et al. (1999, 2001) have also shown that earnings forecast accuracy differs by the industry covered.

Concerning the European sample, we also introduced additive country dummies in order to take the unique characteristics of each country in the zone into account; the behaviour of reported EPS may be influenced by accounting practices that either understate or exaggerate the underlying earnings behaviour[12] (cf. Rees, 1998; Capstaff, Paudyal and Rees, 2001).

Finally, we estimated the following model:

$$AFE_{i,h,t} = \alpha + \sum_{j=1}^{J} \beta_j x_{jiht} + \sum_{l=1}^{L} \gamma_l x_{lt} + \sum_{s=1}^{S-1} \alpha_s DU_s + \sum_{c=1}^{C-1} \alpha_c DU_c + u_{it} \qquad (2)$$

with i= 1, …, I the number of securities ; t=1, …, T, the number of periods, s= 1, …, S the number of sectors and c=1, …,C the number of countries (for the European regression only), x_{jiht} corresponds to the jth micro-economic variable specific to the firm i at date t, x_{lt} corresponds to the lth macro-economic variable at date t, and DU_s and DU_c correspond to additive dummy variables corresponding respectively to the sector and to the firm's sector and country.

We adopt a two-way effect model, a specification that depends on both the cross-section and time series to which the observation belongs. The specification of the error terms is the following: $u_{it} = \upsilon_i + e_t + \xi_{it}$ where ξ_{it} is an error term with zero mean and a homoscedastic covariance matrix.

Concerning the nature of the cross-sectional and time series effects, Hausman's specification test is used to test hypotheses for inconsistency of the estimator. Given a model in which fixed effects estimation would be appropriate, a Hausman test determines whether random effects estimation would be almost as accurate. The consistency of a random effects model depends on the assumption that the υ_i are uncorrelated with regressors in the model. If they are correlated, the estimates are inconsistent.[13] In a fixed-effects case, the Hausman test is a test of the null hypothesis that random

[12]Note accounting effects are weaker in larger firms cross-listed on multiple exchanges that have generally adopted US accounting principles.

[13]Note in small samples the net result of the trade-off efficiency versus consistency is not easy to derive analytically. The GLS approach is often found to perform better overall. Moreover, fixed effects models use up all between units variation and therefore do not allow including time-invariant variables in the model, as these are collinear with the set of unit-specific indicators representing the fixed effects. The random effects model permits the use of time-invariant variables.

effects would be consistent and efficient, versus the alternative hypothesis that random effects would be inconsistent (in which case fixed effects would certainly be consistent). The result of the test is a vector of dimension k which will be distributed chi-square(k), where k is the number of explanatory variables in the model. So, if the Hausman test statistic is large, one must use fixed effects. If the statistic is small, one may get away with random effects. In Tables 2 and 3, we report these test results for the US and European regressions respectively. At 10%, we systematically decide in favour of the null hypothesis. Ultimately, we adopt a two-way random effects structure for the errors of the model (i.e. stochastic random components). The estimation method is an estimated generalized least squares procedure that involves estimating the variance components and then using the estimated variance covariance matrix obtained to apply the GLS to the data. The Wansbeek and Kapteyn (1989) method is used to handle our unbalanced data.

The first regressions convinced us of the need to modify the model, in particular by introducing sectorial dummies (and country dummies for the European zone) of a multiplicative nature. Concerning the European model, we explicitly wanted to see whether or not the country in question was an EU member; as a result, we introduced multiplicative country dummies for the macro-economic variables in the European model. For the microeconomic variables, we introduced multiplicative dummies by country and/or sector. However, in order to avoid overloading the model, we chose the European model to introduce a multiplicative dummy only for the 6 largest countries (in terms of number of companies) and the 4 largest sectors (financials, materials, consumer discretionary, and industrials). For the US model, we tested the significance of multiplicative dummy variables for all the sectors and micro-economic variables.

Furthermore, it is noteworthy that we know that some analysts do their forecasts simultaneously. For instance, anticipations at 1 and 13 month horizons (respectively named FY1 (from one to twelve months) and FY2 (from 13 to 24 months) in the IBES tables) are done simultaneously (that is also valid for the 2 and 14 month horizons …). In other words, the available information sample at a given date is the same for these horizons. One can consequently expect a strong correlation between the analysts' forecasts of these horizons. This intuition is confirmed by the recent European study of Beckers, Steliaros and Thomson, (2004) who show no distinguishable difference in analyst dispersion for FY2 and FY1 forecasts.[14] They conclude that most European analysts focus their attention on the FY1 period, with the longer term forecasts, on average, treated as an afterthought. In other words, in regressions over horizons h+12 months (h=1, …,12) , we introduced the adjusted forecasting error (named AFE*) of the corresponding horizon h, the latter coming from the estimate of the equation for the horizon h. Note that replacing the variables representing "the information sample of the analyst" with the forecasting error, which includes the forecast made for the horizon h (resp. (h+12)), makes it possible to implicitly consider the analysts' information set.

Table 2 contains US regression results for the 1 to 24 month horizons. Of course, we preserved only the significant (at 5%) explanatory variables in each model.

[14] Their study covers European countries over the period 1993-2002. They also show that a comparison with US FY2 and FY1 forecasts for the S&P 500 constituent index implies that herding may be more pronounced in Europe than in the United States.

Table 2. Regression Results US

	1 month	3 months	6 months	9 months	12 months	13 months	15 months	18 months	21 months	24 months
Intercept	0.007*	0.058	0.101	0.098	0.035*	-0.05107^{ns}	-0.04347^{ns}	0.08701	-0.05096^{ns}	0.05957
AFE*						0.319203*	0.346959	0.498364	0.647909	0.754977
Inflation Growth					0.024*	0.036543	0.039141		0.034296	
Change Growth					0.754	0.784928	0.395182*		0.675488	
Industrial Production Growth		-0.507	-0.671	-0.532*						
Slope	-0.004*	-0.008*	-0.014*	-0.017*	-0.016*					
Lcv	0.06	0.198	0.349	0.142	0.361	0.068722	-0.24203	-0.11842	-0.21451*	-0.07489
Var_P	-0.033	-0.132	-0.093	-0.087*	-0.206	-0.16659	-0.09732			
Delprev	0.054	0.06	0.059	0.058	0.049	-0.03305	-0.02279	-0.05305		
Lecart	0.001	0.004	0.004	0.005	0.004		0.002723			
Energy	0.032	0.051	0.117	0.047*	0.065		0.219762	0.200137		
Materials	0.027	0.081	0.125	0.05	0.029*				0.083091	
Consumer Discretionary	0.024		0.042							
Consumer Staples					-0.029*					
Utilities					-0.012*			-0.06695		
Industry							0.073104*	0.083503		
Adjusted R^2	0.198	0.233	0.188	0.129	0.116	0.089	0.105	0.0802	0.0684	0.0788
Endogeneous Variable mean	0.0204998	0.0438707	0.0642208	0.0639397	0.0800146	0.076	0.0856	0.0947	0.097	0.114
Endogeneous Variable std	0.0875966	0.153663	0.2038852	0.2200625	0.248034	0.2444	0.248	0.257	0.265	0.279
Variance Component for Cross Sections	0.0029	0.0035	0.0121	0.003	0.0042	0.0018	0.078	0.0089	0.0066	0.0079
Variance Component for Time Series	0.000094	0.00036	0.00127	0.0015	0.0032	0.0032	0.0026	0.0023	0.0024	0.000217
Variance Component for Error	0.0049	0.0153	0.0309	0.038	0.047	0.048	0.048	0.053	0.054	0.059
Hausman Test for Random Effects	34.38	32.35	30.58	25.7	21.12	14.02	20.97	17.47	14.91	16.7
Number of Cross Sections	286	314	312	298	283	259	263	256	252	243
Time Series Length	14	13	13	13	12	12	12	12	12	11

* signif. only at 10%. Note that the variable number of analysts was never significant because of colinearity relationships with firms' market capitalization.

Table 3. Regression Results Europe

	1 month	3 months	6 months	9 months	12 months	13 months	15 months	18 months	21 months	24 months
Intercept	0.010834*	0.016656*	0.036052	0.066824	0.113531	0.094981	0.073517	0.111482	0.080511	0.05524
AFE*						0.162603	0.457323	0.535534	0.601029	0.425738
Industrial Production Growth	-0.26063	-0.24572		-0.15601*	-0.4188	-0.42619	-0.47233			
Inflation Growth	0.006173	0.00908	0.009149				0.009636			0.01671
Change Growth		-0.12907	-0.19655	-0.16249	-0.28567	-0.43817	-0.25132	-0.4412	-0.30971	-0.25281
Slope		-0.011	-0.00961	-0.00838	-0.00668*					-0.01169
Lcv	0.065139	0.065304	0.021651		0.047834	0.015949	-0.17003	-0.41156	-0.37553	-0.07817
Var_P	-0.0845	-0.14125	-0.11097	-0.08524	-0.22415		-0.16195		0.081032	
Delprev			0.016144	0.010046	0.03355		0.073316	-0.05266	-0.04197	0.096338
Lecart	0.003343	0.004093	0.010352	0.01245	0.004937				-0.00729	
Finance						-0.06203	-0.03967			-0.07663
Materials		0.036652	0.054748		0.050183		0.041238			
Industry		0.049188	0.050737	0.043294	0.03044			0.083973	0.04796	
Consumer Discretionary		0.041398	0.059648				0.038722		0.077827	
Information Technology	0.060779	0.074972	0.078871	0.11811						
Italy				-0.08892		0.066444		-0.09751		
France						0.050715				
Finland			-0.06161		-0.06661					
Switzerland			0.034654*						0.091487	0.301896
Norway			0.039746*							
Netherlands		-0.05055*								
UK		-0.03731			-0.03993*			-0.08137		
Sweden	0.049586	0.089846	0.089825			0.072895				
Germany					-0.06473	0.168545	0.173174		0.288455	
Austria					-0.08814					
Spain					-0.03853*					
Adjusted R^2	0.181	0.155	0.149	0.119	0.123	0.094	0.103	0.1335	0.1063	0.0936
Endogeneous Variable Mean	0.055	0.067	0.074	0.077	0.09	0.088	0.095	0.095	0.088	0.099
Endogeneous Variable std	0.185	0.215	0.25	0.274	0.29	0.29	0.29	0.307	0.319	0.327
Var. Component for Cross Section	0.026	0.016	0.0094	0.017	0.0093	0.0078	0.004	0.00423	0.015	0.0209
Var. Component for Time Series	0.00055	0.000428	0.0017	0.0021	0.0034	0.00501	0.0042	0.0039	0.005	0.0045
Var. Component for Error	0.025	0.0345	0.0473	0.058	0.065	0.0638	0.066	0.064	0.066	0.073
Hausman Test for Random Effects	30.27	30.78	30.89	33.34	37.55	29.33	31.16	29.60	26.07	31.24
Number of Cross Sections	616	587	570	557	516	499	473	442	429	391
Time Series Length	14	13	13	13	12	12	12	12	12	11

*: signif. only at 10%. Note that the variable number of analysts was never significant because of colinearity relationships with firms' market capitalization.

Let us recall that we do not work with a constant sample: so the comparative results according to horizons must be interpreted with caution. Nonetheless, the dynamics of the mean and standard deviation of the endogenous variable (the bias) according to the forecast horizon appear relatively coherent. We observe adjusted R^2 going from 23% at 3 months to 7.88% at 24 months, which is weak, but it should not be forgotten that we not only work with panel data (which is a relatively heterogeneous sample) but also that our endogenous variable is a forecast bias. Moreover, we observe that the temporal dimension bias is much lower than the space dimension. As the variance decomposition indicates, heterogeneity is primarily a space component.

The coefficient signs of the macroeconomic variables are consistent with expectations. In particular, for the slope curve, the negative coefficient conveys the fact that a long-term rate higher than a short-term rate indicates good economic health and thus a mechanically weaker forecast bias (not because the analysts are less optimistic, but because the published earnings are higher). Note that the link between forecasting errors and the business cycle contrasts with the findings of Dreman and Berry (1995), who found that forecasting errors are not meaningfully affected by the business cycle.[15] Furthermore, we are in agreement with Basu, Markov and Shivakumar (2005): analysts' earnings forecast errors can be predicted using lagged inflation; analysts suffer from inflation illusion.

Regarding microeconomic variables, we find the anticipated signs for some variables, such as Var_p (the price variation between the last earnings announcement and the previous month), are always negative. However, for a range of other variables, such as Lcv (the coefficient of variation), the coefficient is positive (as expected) for short horizons and negative for horizons above 13 months, which is more difficult to explain. An interpretation of this result could lie in the introduction of the variable AFE* into regressions over long horizons, which already implicitly introduces variables such as Lcv into the regression. We may also observe that macro-economic variables intervening over short horizons and long horizons are not the same, which can be interpreted in a way similar to Lcv.

In addition, the coefficient of variation is the variable for which heterogeneity is strongest (where we have the most multiplicative dummies, for the US and Europe). For Europe, dummy countries intervene in addition to sectorial dummies. The coefficient of AFE* is always positive and increases with the horizon. There are fewer and fewer explanatory variables that are significant with the horizon and the adjusted R^2 declines quickly. All these elements tend to show that analyst forecasts over long horizons are peripheral to the forecast carried out simultaneously for the 12 month former horizon. Capitalization is never significant, which is in line with Beckers' result (2004). We obtain a similar result for the number of analysts.

Table 3 corresponds to the results obtained for our sample's European countries. For macro-economic data, the UK dummies are frequently significant, in particular for industrial production growth and inflation growth. We interpret this finding as indicative of a differentiation according to the members of the EuroZone.

4. Adjusted Earnings Forecasts

In sum, our aim is to apply a monthly expected earnings correction for each of the markets (US and Europe) over a one year period. The market's total earnings are equal to the sum of the total earnings of companies belonging to the market.

Regression models presented in the previous section are now used. Accordingly, we adopted the following step: the "1 month" model is used to estimate bias over 1 and 2 month horizons; the "3 months" model is used to estimate bias over 3, 4 and 5 month horizons, etc…

We can estimate the bias of each company at each date: $AFE^{*}_{i,h,t}$.[16] From the estimated bias, one can then correct each forecast $F_{i,h,T}$ and obtain an adjusted forecast:

---

[15] Why do investors underestimate the significance of current macroeconomic conditions for future earnings? One hypothesis is the constantly changing nature of the economic system within which market participants make earnings forecasts (see Chordia and Shivakumar, 2005).

[16] For instance, for a forecast on 31/12/94, we estimate a bias from Dec. 1993 (horizon 12) to Nov. 1994 (horizon 1).

$$F^*_{i,h,T} = \frac{F_{i,h,T}}{(1+AFE^*_{i,h,T})} \tag{3}$$

To take into account potential index rebalancing (companies going in or out of the index), we are choosing to retain the number of outstanding shares as of December. In this way, month by month, the structure weight of the market remains constant ($s = \sum_{i=1}^{n} s_i$ with s_i, the number of outstanding shares for the firm i in December). Finally, for each date, we calculated the forecasted earnings ($B_{i,h,T} = s_i F_{i,hT}$), adjusted forecasted earnings ($B^*_{i,hT} = s_i F^*_{i,hT}$) and last EPS forecast (before publication) for each firm and horizon (1-12). We deducted the forecasted earnings ($B_{h,T} = \sum_{i=1}^{n} B_{i,h,T}$) (that we named "IBES" in the following figures), adjusted ($B^*_{h,T} = \sum_{i=1}^{n} B^*_{i,h,T}$) (that we named "Adjusted Forecasts" in the following figures) and last earnings forecast before publication (that we named "Earnings") for each country and horizon.

In Tables 4 to 7, we developed forecast evaluation statistics for the 4 main countries. The RMSE (root mean squared error) and the MAE (mean absolute error) depend on the dependent variable's scale. These should be used as relative measures to compare forecasts for the same series across different models; the smaller the error, the better the forecasting ability of that model according to that criterion. The MAPE (mean absolute percentage error) is scale invariant. The Theil'U (Theil inequality coefficient) always lies between zero and one, where zero indicates a perfect fit.

Table 4. RMSE statistics

	1-24M	1M	3M	6M	9M	12M	13M	15M	18M	21M	24M
US											
IBES Forecast	11800.55	1946.91	5111.57	9608.4	10038.58	11347.76	9892.74	13992.58	14186.92	14194.58	14269.44
Adjusted Forecast	9398.33	1058.45	3641.70	4279.3	6721.96	7102.70	5064.21	9007.05	12450.65	8275.93	8385.45
France											
IBES Forecast	2204.41	1200.38	1817.53	2106.2	2193.20	2567.27	2254.82	2399.41	2327.14	2272.10	1499.26
Adjusted Forecast	1799.01	735.64	1112.25	1466.5	1547.17	1159.98	1573.53	1810.09	2352.58	2769.93	1361.59
Germany											
IBES Forecast	1318.72	882.60	1188.52	1261.4	1197.00	1376.77	1367.93	1373.41	1253.80	1067.50	1016.12
Adjusted Forecast	914.20	472.92	653.89	816.70	849.06	1025.12	1125.73	881.81	799.84	622.78	568.83
UK											
IBES Forecast	2691.58	886.44	924.66	1742.7	2107.59	2954.04	3045.89	3273.29	3185.44	3164.18	3114.34
Adjusted Forecast	1921.20	758.35	726.45	1089.2	1590.88	1661.92	1997.65	2031.66	2267.52	2270.78	2871.44

N.B.: The RMSE (root mean squared error) is defined as follows: $\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\mathrm{earnings}_t^f - \mathrm{earnings}_t)}$, where T corresponds to the number of periods in the forecasting, $\mathrm{earnings}_t^f$ corresponds to the IBES earnings forecast or to the adjusted earnings forecast and $\mathrm{earnings}_t$ is the last earnings forecast before publication. The grey areas are the cases where we don't improve analysts' forecast quality.

Table 5. MAE Statistics

	1-24M	1M	3M	6M	9M	12M	13M	15M	18M	21M	24M
US											
IBES Forecast	8739.98	1443.62	3477.63	6712.23	7279.14	8756.35	7533.25	10382.22	10678.89	11423.05	11653.59
Adjusted Forecast	5947.38	902.53	2833.39	3266.54	4932.31	4871.91	4266.89	7390.67	8360.66	6502.15	6255.38
France											
IBES Forecast	1709.08	900.95	1386.29	1699.16	1683.82	1956.02	1826.42	1906.30	1721.65	1586.73	1008.30
Adjusted Forecast	1226.18	529.23	723.67	1183.13	1015.45	904.17	1208.35	1203.08	1531.43	1678.57	947.59
Germany											
IBES Forecast	1007.89	611.01	823.98	933.01	929.71	1102.93	1119.36	1061.98	974.28	750.34	766.90
Adjusted Forecast	694.65	357.05	481.46	588.08	714.29	808.61	880.52	669.25	570.70	483.48	414.03
UK											
IBES Forecast	1698.32	648.18	713.26	1290.64	1500.88	1901.51	1867.93	1998.58	2091.91	1807.92	1710.98
Adjusted Forecast	1243.55	550.65	509.81	840.59	1122.77	1097.23	1509.87	1512.77	1515.07	1496.59	1637.73

N.B.: The MAE (mean absolute error) is defined as follows: $\mathrm{MAE} = \frac{1}{T}\sum_{t=1}^{T}\left|\mathrm{earnings}_t^f - \mathrm{earnings}_t\right|$, where T corresponds to the number of periods in the forecasting, $\mathrm{earnings}_t^f$ corresponds to the IBES earnings forecast or to the Adjusted earnings forecast and $\mathrm{earnings}_t$ is the last earnings forecast before publication. The grey area are the cases where we don't improve analysts' forecast quality.

Table 6. MAPE Statistics

	1-24M	1M	3M	6M	9M	12M	13M	15M	18M	21M	24M
US											
IBES Forecast	0.0510	0.0099	0.0198	0.0366	0.0421	0.0534	0.0470	0.0579	0.0612	0.0685	0.0752
Adjusted Forecast	0.0342	0.0063	0.0148	0.0194	0.0257	0.0289	0.0263	0.0436	0.0434	0.0381	0.0373
France											
IBES Forecast	0.1117	0.0661	0.0916	0.1147	0.1030	0.1263	0.1182	0.1281	0.1137	0.0960	0.0669
Adjusted Forecast	0.0691	0.0405	0.0503	0.0751	0.0540	0.0534	0.0677	0.0651	0.0781	0.0774	0.0526
Germany											
IBES Forecast	0.1051	0.0662	0.0764	0.0818	0.0870	0.1002	0.1035	0.0978	0.1020	0.1114	0.1333
Adjusted Forecast	0.0704	0.0419	0.0453	0.0564	0.0657	0.0669	0.0773	0.0610	0.0550	0.0682	0.0666
UK											
IBES Forecast	0.1100	0.0493	0.0452	0.0789	0.0873	0.1105	0.1064	0.1128	0.1289	0.1169	0.1506
Adjusted Forecast	0.0701	0.0354	0.0269	0.0418	0.0496	0.0501	0.0688	0.0658	0.0718	0.0871	0.1526

N.B.: The MAPE (mean absolute percent error) is defined as follows: $\mathrm{MAPE} = \left(\frac{1}{T}\sum_{t=1}^{T}\left|\frac{\mathrm{earnings}_t^f - \mathrm{earnings}_t}{\mathrm{earnings}_t}\right|\right)$, where T corresponds to the number of periods in the forecasting, $\mathrm{earnings}_t^f$ corresponds to the IBES earnings forecast or to the Adjusted earnings forecast and $\mathrm{earnings}_t$ is the last earnings forecast before publication. The grey areas are the cases where we don't improve analysts' forecast quality.

Table 7. Theil Statistics

	1-24M	1M	3M	6M	9M	12M	13M	15M	18M	21M	24M
US											
IBES Forecast	0.0302	0.0051	0.0133	0.0246	0.0259	0.0306	0.0265	0.0372	0.0380	0.0387	0.0417
Adjusted Forecast	0.0248	0.0028	0.0097	0.0113	0.0179	0.0198	0.0139	0.0250	0.0350	0.0236	0.0259
France											
IBES Forecast	0.0550	0.0299	0.0441	0.0518	0.0552	0.0673	0.0572	0.0612	0.0619	0.0619	0.0442
Adjusted Forecast	0.0457	0.0186	0.0274	0.0365	0.0399	0.0312	0.0406	0.0474	0.0640	0.0782	0.0406
Germany											
IBES Forecast	0.0539	0.0335	0.0438	0.0478	0.0476	0.0583	0.0580	0.0580	0.0610	0.0578	0.0561
Adjusted Forecast	0.0381	0.0183	0.0247	0.0315	0.0343	0.0443	0.0490	0.0388	0.0400	0.0342	0.0314
UK											
IBES Forecast	0.0577	0.0190	0.0193	0.0373	0.0456	0.0664	0.0672	0.0715	0.0735	0.0756	0.0796
Adjusted Forecast	0.0424	0.0165	0.0153	0.0239	0.0357	0.0390	0.0462	0.0461	0.0538	0.0562	0.0754

N.B.: The THEIL statistic is defined as follows: $\text{THEIL'U} = \dfrac{\text{RMSE}}{\sqrt{\dfrac{1}{T}\sum_{t=1}^{T}(\text{earnings}_t^f)^2} + \sqrt{\dfrac{1}{T}\sum_{t=1}^{T}(\text{earnings}_t)^2}}$, where T corresponds to the number of periods in the forecasting, earnings_t^f corresponds to the IBES earnings forecast or to the Adjusted earnings forecast and earnings_t is the last earnings forecast before publication. The grey areas are the cases where we don't improve analysts' forecast quality.

We greyed the cases for which our adjusted forecasts are worse than the analysts' forecasts. We observe that our forecasts make it possible quasi-systematically to improve the forecasts of the analysts, regardless of the indicator or horizon selected. Clearly, the only exceptions relate to long horizons, which is hardly surprising, as the models over these horizons were seen to be poor and the only valid explanatory variable was bias observed 12 months earlier.

In Figures 1 to 4, we deferred the last earnings forecast before publication, the earnings forecasted by analysts and the model adjusted for the four main countries of our sample, namely, the United States, the U.K., France and Germany. For each year, we deferred the 24 months to 1 month horizons. A temporal vision of the forecast adjustment is interesting. It enables us to highlight the fact that some years the adjustment is considerable, while it is weak (or even nil) for other years. Note that, in theory, the last earnings forecast should be almost constant every year. However, sample structural changes explain the non-constancy.

In the appendix, the tables show the statistical calculation related to the quality of forecasts year by year. Again, we greyed the situations for which the correction of the forecast bias does not make it possible to improve analysts' anticipations. The arrows appearing in Graphs 1 to 4 correspond to the years for which analysts' forecasts are better than our bias adjusted forecast, according to the Theil criterion. Our forecasts do not surpass analysts' forecasts in periods of strong earnings growth, in any of the countries studied.

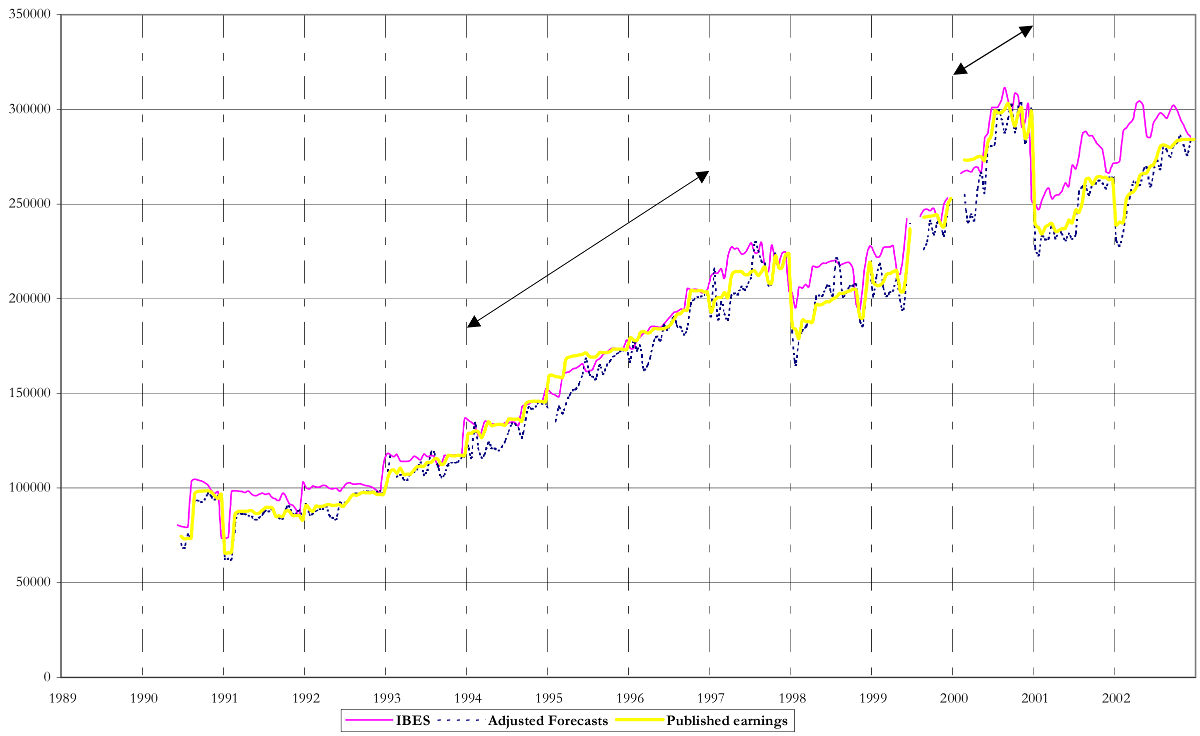

Figure 1- Last forecast before publication ("published earnings"), Forecasted ("IBES") and Adjusted Earnings ("Adjusted forecasts) for US

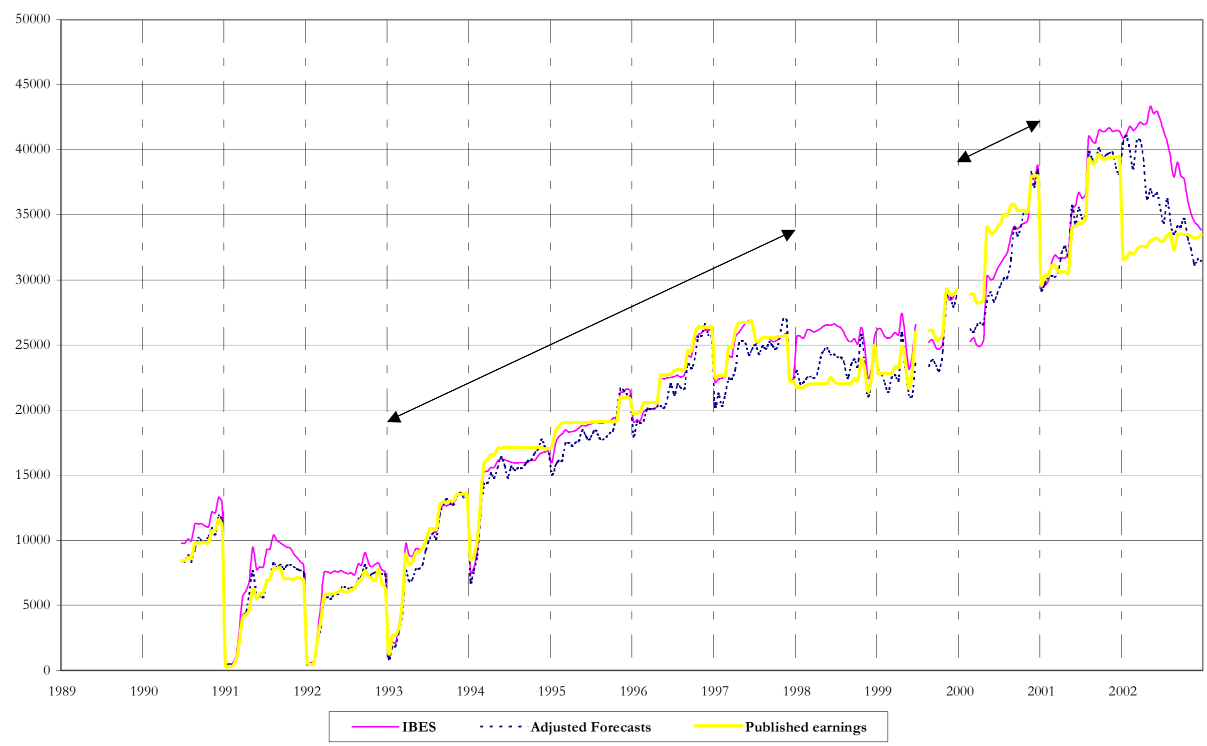

Figure 2- Last forecast before publication ("published earnings"), Forecasted ("IBES") and Adjusted Earnings ("Adjusted forecasts") for UK

Figure 3- Last forecast before publication ("published earnings"), Forecasted ("IBES") and Adjusted Earnings ("Adjusted forecasts") for France

Figure 4- Last forecast before publication ("published earnings"), Forecasted ("IBES") and Adjusted Earnings ("Adjusted forecasts") for Germany

Figures 1-4 clearly show the difficulty analysts have in integrating bad news into their forecasts during recession periods, for example as in 1991 (biases were larger following the recession in 1990-1991) or in 1997 and 1998 following the Russian and Asian crises.
A similar phenomenon was observed in 2001 and 2002 when the already gloomy economic situation was exacerbated by September 11th. Following these events, analysts adjusted their forecasts but underestimated their impact on future published earnings. These results coincide with those already presented. Indeed, bias tends to increase when there is economic decline. The introduction of macroeconomic variables into our models is justified: it is observed that in 2001 and 2002 the adjusted earnings expectations are more accurate than IBES forecasts.[17]
2003 also shows that in a cycle reversal situation, analysts have trouble revising their forecasts upwards, which led to positive surprises in 2003 and the beginning of 2004, especially for the US. This phenomenon is likely to be corrected by the activity variables introduced into the model.

Conclusion
In this paper, we developed a model which provides estimates of analysts' forecasting bias at the individual firm level. We obtain some meaningful results. In particular, the macroeconomic variables are statistically significant and their signs are as expected, which contrasts with the findings of Dreman and Berry (1995), who found that forecasting errors are not meaningfully affected by the business cycle. However, like Harris (1999), we conclude that the microeconomic variables are the main explanatory variables; a large share of analysts' forecasting error is made at the individual firm level.
From the forecast evaluation statistics (RMSE, MAE, MAPE and Theil'U) viewpoints, adjusted forecasts make it possible quasi-systematically to improve analysts' forecasts, whatever the indicator and horizon selected. The only exceptions relate to long horizons, which is hardly surprising as the models over these horizons were poor and the only valid explanatory variable was bias observed 12 months earlier.
Finally, the calculation of the forecast evaluation statistics year by year allows us to observe that the bias adjusted forecasts do not surpass the analysts' forecasts in periods of strong earnings growth, regardless of the country studied. In other words, our model corrects the bias when the latter is substantial, since in periods of earnings growth, forecast biases are, by nature, reduced.

Appendix. Forecast evaluation statistics year by year

RMSE

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
US												
IBES Forecast	8484.22	7889.87	4904.25	2611.93	6124.93	1727.31	10335.86	16086.05	9975.75	5764.85	18202.90	24677.07
Adjusted Forecast	2366.38	2635.51	3884.17	8111.35	20767.41	8187.72	9357.05	7675.36	7709.85	14437.00	6767.55	5565.03
France												
IBES Forecast	1421.46	2140.88	1851.19	1773.36	1246.25	1215.21	1193.36	778.15	615.04	3859.38	1666.32	4588.32
Adjusted Forecast	423.44	1156.59	727.51	1433.82	447.03	665.81	2185.13	1072.92	1060.72	4421.76	1526.70	2658.49
Germany												
IBES Forecast	967.35	1303.36	1325.81	269.23	473.48	482.19	1905.89	609.33	1132.41	2520.64	1684.06	711.08
Adjusted Forecast	530.18	757.70	705.90	430.81	721.94	900.75	1604.01	539.95	761.73	1308.50	1076.97	595.30
UK												
IBES Forecast	1879.14	1203.39	352.99	907.56	537.01	438.35	312.59	3494.59	1848.97	2596.03	1575.38	7405.53
Adjusted Forecast	597.34	376.90	781.09	1307.10	1429.53	1267.12	1540.77	1395.91	1342.21	3231.79	830.24	4641.28

[17]We need to be more cautious in evaluating analysts' bias prior to September 11th, as the forecasts made at the beginning of the year 2001 (for the entire year), could not possibly have foreseen the terrorist attacks. It is only natural to attribute the bias partially to exceptional events.

MAE

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
US												
IBES Forecast	8031.86	7045.65	3653.07	1671.67	5006.74	1271.17	9296.57	14791.96	7841.85	5164.98	16984.26	21547.84
Adjusted Forecast	1994.00	1746.50	3185.84	6833.48	13638.13	6242.65	6679.72	4825.37	6316.55	10243.57	5231.60	4174.69
France												
IBES Forecast	1150.42	1930.70	1660.77	1483.26	1186.38	959.39	1067.12	643.34	506.97	3424.84	1333.67	4356.47
Adjusted Forecast	369.81	1003.64	643.79	996.38	352.21	568.74	1846.48	879.25	838.44	3672.22	1308.52	2369.54
Germany												
IBES Forecast	740.17	1215.2	1219	239.77	340.55	428.23	1661.68	488.14	1002.75	2244.90	1355.78	511.84
Adjusted Forecast	436.51	559.63	612.86	322.08	619.75	766.13	1238.51	452.25	632.60	979.29	851.34	452.11
UK												
IBES Forecast	1660.58	1073.62	276.46	848.03	423.56	408.26	228.85	3236.83	1476.31	2282.88	1419.95	6533.26
Adjusted Forecast	448.15	277.40	648.93	1148.5	1211.53	1078.82	1274.59	1156.49	1069.56	2582.84	632.11	3533.19

MAPE

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
US												
IBES Forecast	0.0958	0.0767	0.0335	0.0126	0.0301	0.0069	0.0445	0.0759	0.0367	0.0180	0.0684	0.0821
Adjusted Forecast	0.0245	0.0190	0.0283	0.0511	0.0828	0.0333	0.0320	0.0246	0.0284	0.0365	0.0213	0.0159
France												
IBES Forecast	0.0927	0.2029	0.2021	0.1525	0.1080	0.0766	0.0597	0.0297	0.0183	0.0946	0.0463	0.1850
Adjusted Forecast	0.0302	0.1056	0.0789	0.1040	0.0322	0.0428	0.1046	0.0417	0.0307	0.1022	0.0456	0.1006
Germany												
IBES Forecast	0.1170	0.1994	0.2694	0.0319	0.0393	0.0372	0.1036	0.0370	0.0722	0.1217	0.1092	0.0501
Adjusted Forecast	0.0681	0.0817	0.1439	0.0438	0.0697	0.0667	0.0782	0.0334	0.0449	0.0518	0.0712	0.0462
UK												
IBES Forecast	0.3684	0.2019	0.0505	0.0564	0.0222	0.0182	0.0092	0.1461	0.0626	0.0704	0.0395	0.1998
Adjusted Forecast	0.1316	0.0600	0.1013	0.0772	0.0640	0.0473	0.0509	0.0519	0.0427	0.0776	0.0188	0.1089

U'Theil

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
US												
IBES Forecast	0.0488	0.0415	0.0219	0.0097	0.0188	0.0046	0.0244	0.0402	0.0221	0.0102	0.0360	0.0448
Adjusted Forecast	0.0144	0.0145	0.0178	0.0310	0.0653	0.0223	0.0227	0.0198	0.0176	0.0261	0.0140	0.0106
France												
IBES Forecast	0.0558	0.1054	0.1025	0.0837	0.0546	0.0455	0.0350	0.0182	0.0115	0.0562	0.0295	0.0910
Adjusted Forecast	0.0175	0.0597	0.0431	0.0700	0.0204	0.0263	0.0654	0.0253	0.0198	0.0645	0.0273	0.0549
Germany												
IBES Forecast	0.0535	0.0868	0.1171	0.0178	0.0263	0.0213	0.0612	0.0233	0.0356	0.0610	0.0684	0.0360
Adjusted Forecast	0.0310	0.0529	0.0664	0.0292	0.0405	0.0404	0.0507	0.0205	0.0247	0.0327	0.0449	0.0308
UK												
IBES Forecast	0.1409	0.0948	0.0175	0.0297	0.0143	0.0098	0.0064	0.0743	0.0369	0.0405	0.0224	0.1040
Adjusted Forecast	0.0500	0.0323	0.0397	0.0430	0.0388	0.0286	0.0321	0.0311	0.0279	0.0507	0.0120	0.0687

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