Earnings forecast bias - a statistical analysis

Karine Michalon, Sandrine Lardic, François Dossou

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Résumé : L'analyse de la pertinence des prévisions de bénéfices des analystes financiers est essentielle : non seulement les investisseurs institutionnels utilisent ces prévisions lors de leurs évaluation et sélection d'actifs, mais elles permettent également d'évaluer le mode de formation des anticipations. Une spécificité bien connue de ces anticipations a récemment été mise en exergue, à savoir l'existence d'un biais positif : les experts ont tendance à surestimer les bénéfices lors de la réalisation de leurs prévisions. Dans ce travail, nous analysons les propriétés de ce biais selon les pays et les secteurs concernés, mais également selon la taille de la firme.

Abstract: The evaluation of the reliability of analysts' earnings forecasts is an important aspect of research for different reasons: Many empirical studies employ analysts' consensus forecasts as a proxy for the market's expectations of future earnings in order to identify the unanticipated component of earnings, institutional investors make considerable use of analysts' forecasts when evaluating and selecting individual sharesand the performance of analysts' forecasts sheds light on the process by which agents form expectations about key economic and financial variables. The recent period put forward a well-known phenomenon, namely the existence of a positive bias in experts' anticipations: the latter tend to over-estimate earnings. In this paper, we study the properties of this bias according to various aspects, that is to say according to country, sector, but also according to the size of the companies.

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Introduction

Average earnings forecast errors would be expected to tend toward zero, yet analysts' forecasts have been empirically found to be positively biased (Brown 1993, O'Brien 1988, Brous and Kini 1993). Whether this optimism reflected in forecasts is intentional or unintentional could be subject to discussion between supporters of the Efficient Market Hypothesis 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 source of information for financial analysts in predicting earnings. Analysts are anxious to accept the consequences of unfavourable forecasts imposed by the management of a firm; and therefore, are eager to produce overly optimistic reports. The findings of Francis and Philbrick can be employed to demonstrate that analysts' rationality does not always coincide with semi-efficient earnings forecasting. In the described situation, alternative incentives may cause financial analysts' rational actions to result in a decrease in forecast accuracy. However, analysts' behaviour might still be explained by the Efficient Market Hypothesis - where costs of gathering, processing and reporting information are taken into consideration (cf. Jensen 1978). These transaction costs, i.e. discounted future costs of a distorted relation with the management of a company, may outweigh the benefits of increased forecast accuracy and allow for deliberately ignoring relevant, though costly information. Such an 'information perspective' partly contradicts Brown's (1993) conclusion that "...a finding that analysts ignore publicly available information is unsatisfactory to capital market researchers who advocate semi-strong form market efficiency, but it is satisfactory to behavioural researchers who maintain that people consistently overweight some cues and underweight others..." and in a measure bring some empirical evidence on earnings forecast properties into agreement with capital market based research assumptions.
- A second, more obvious explanation for a positive bias in earnings forecasts is the existence of a direct relation between a followed company's management and a *following* company's management. Investment bankers involved in forecasting earnings will force their analysts to cultivate relations with clients and on this behalf to act optimistically. Studies that notice this possibility are, for instance, those of Lin and McNichols (1993) and Dugar and Nathan (1995). Additionally, Dugar and Nathan empirically prove that private information exchanges between financial analysts faced with these incentives and the management of an investment bank's client suffice to produce forecasts that are as accurate as those of non-investment banker analysts. Finally, a distinction can be made between sell-side analysts and buy-side analysts. Most generally, sell-side analysts are employed at investment or brokerage firms, distributing their forecasts externally, whereas buy-side analysts forecast to advise their employer, i.e. banks, pension funds and insurance companies. Both types are subject to dissimilar incentives. As investment or brokerage firms participate in the underwriting of a firm's stock, a conflict of interest may arise. Managers may pressure analysts under their supervision to produce positive recommendations (Lin and McNichols 1993) that indirectly force them to report overly optimistic earnings forecasts. Conroy and Harris (1995), who examined Japanese financial analysts' earnings forecasts, confirm these results.
- Both explanations bear on conscious actions of financial analysts, thus the bias at issue may be called *reporting biases* (see Francis and Philbrick 1993). Alternative explanations relate to *processing biases*. If forecast errors are associated with unanticipated macro-economic information that is negatively affecting many firms, then, on average, financial analysts may overstate earnings (O'Brien 1988).

Note that a key issue to emerge from recent high-profile financial scandals such as Enron, Global Crossing, and Waste Management in the US, Independent Insurance in the UK, and HIH Insurance in Australia, is the so-called "revolving door," where a company hires senior financial reporting executives directly from its external audit firm (Clikeman, 1998). The Sarbanes-Oxley Act of 2002 resulted in restrictions being placed on this so-called "revolving-door." In each of these financial statement fraud cases, key corporate personnel responsible for financial reporting were hired from the company's external auditor. This legislation includes a provision (Section 206) that forbids public companies in the US from hiring senior financial reporting personnel from their external auditors for up to one year from the individual's departure from the audit firm. While such employment restrictions have been debated in the past (American Institute Of Certified Public Accountants, 1978; Independence Standard Board, 2000; Pitt 2002), the new rule is the first to specifically forbid this practice.

The paper is organized as follows. After a brief presentation of the data, section 1 is devoted to the decomposition of the bias according to country and sector. In section 2, we analyze the properties of the biais according to the year anticipations are made. Section 3 deals with the capitalization effect. Section 5 concludes.

I. Data description

We realised our study on the consensus[1] mean estimates of 21 countries for which companies belong to the MSCI universe, i.e. 239 218 monthly EPS and 2745 firms[2,3] for the period July 1987 to September 2003. After deletion of the missing data, the sample is made of 210 726 observations (either 2 472 companies).

Table 1
Description of the sample

COUNTRY	Number of firms	%
ATS	28	2.34
AUD	18	1.50
BEF	25	2.09
CAD	89	7.42
CHF	62	5.17
DEM	79	6.59
DKK	25	2.09
ESP	46	3.84
FIM	31	2.59
FRF	83	6.92
GBP	101	8.42
HKD	27	2.25
IEP	6	0.50
ITL	63	5.25
JPY	17	1.42
NLG	28	2.34
NOK	35	2.92
PTE	15	1.25
SEK	48	4.00
SGD	32	2.67
US	341	28.44

We selected all the followed companies that have, on average, at least 6 analysts take part in the consensus and at least three successive forecasts are available, so that the concept of consensus simultaneously keeps a sense from space and temporal viewpoints. 191 072 forecasts of earnings per share constitute our sample (either 1 819 companies).

[1] We do not avoid measurement bias to which a consensus is susceptible, 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 details 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. The forecasts being the same ones, we supplemented the base if necessary.

In order to make comparable the horizons, we retain only the companies whose fiscal year finishes in December. Let us note that the majority of the companies finish their fiscal year in December, except for the Japanese (87% of the companies finish their fiscal year in March) and Australian companies (66% of the companies finish their fiscal year in June). The sample is composed *in fine* of 1 199 firms (115 136 observations)[4].

The forecast errors form an invaluable indicator, allowing us to judge the quality of the analysts' estimates. On several successive horizons, the forecast errors provide information *a posteriori* for the way which analysts revise their anticipations. They enable us to see whether the analysts are mistaken on the achievements by over or under estimating them in a systematic way. Analysts' forecast error (AFE) is computed as the Average EPS forecast minus the actual EPS reported by IBES, divided by the absolute value of the actual EPS; nonzero AFE provides obviousness of bias.

$$AFE_{i,h} = \frac{(F_{i,h,T} - A_{i,T})}{\left|A_{i,T}\right|}$$

Where F corresponds to the forecast of the earning per share of company i, concerning its fiscal year T, calculated on a horizon h; A represents the realization of the earning per share being the subject of the forecast[5].

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". The bias was calculated by country, sector and horizon. Concerning the forecast horizon, we selected horizons going from 24 months to -1 month[6]. We consider the time lag between fiscal year-end and annual announcement date, as well as the IBES variable reporting lag (Cornell and Landsman, 1989): a negative horizon corresponds to a forecast carried out beyond the date of fiscal year end. Thus, a forecast in -1 month corresponds to a forecast carried out in January of the year T for a realization in December of the year (T-1).

Univariate statistics for AFE are presented in Table 2. The positive mean and median indicate that analysts' forecasts are optimistically biased.

The Mean bias decreases regularly until becoming almost null at a horizon -1, i.e. as more predisclosure information becomes available and uncertainty over the period's earnings decline (cf. Elton, Gruber and Gultekin, 1984; Brown, Hagerman, Griffin and Zmijewski, 1987). In addition, it is observed that the mean of negative bias is largely lower than that of positive bias. Furthermore, the number of positive and negative bias is almost equivalent at shorter horizons. Thus, for short horizons, the positive mean bias relates to the fact that experts with a positive bias mislead more than those which carry out a negative bias, rather than the fact that there are more experts who are mistaken positively than negatively.

Concerning the median bias, it is null at a horizon of 0 and -1 month (between the end-year date and the date of publication).

[4] We will separately study the Japanese firms that finish their fiscal year in March (14% of the total sample).

[5] We use actual earnings 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.

[6] Capstaff, Paudyal and Rees (2001) in each European country, the short horizon forecasts had considerable predictive content explaining in excess of 50% of the observed changes in EPS. At 12 months it explains only 3%. This appears to suggest that, in general, forecasts made more than twelve months before the accounting year-end have little predictive value. This apparent forecast inefficiency may offer an opportunity to investment practitioners. Investors who incorporate earnings forecasts in their stock selection procedures may be able to improve returns by explicitly adjusting their model for observed regularities in earnings forecast errors. The caveat is that these regularities differ in incidence and magnitude across the countries, companies and time studied.

Table 2
Statistics of AFE world

HORIZON	mean	mean neg	mean pos	median	median neg	median pos	obs	obs neg	nobs pos	std	std neg	std pos
24	0.214553	-0.20314	0.481131	0.074074	-0.14762	0.284483	5629	2162	3423	0.522047	0.186681	0.494277
23	0.211206	-0.19742	0.47959	0.069496	-0.14064	0.28044	6006	2354	3614	0.520028	0.182717	0.496401
22	0.210273	-0.19778	0.47585	0.065421	-0.13942	0.274497	6625	2590	4004	0.523011	0.183692	0.502192
21	0.203129	-0.19846	0.467156	0.061043	-0.14154	0.266734	6960	2718	4181	0.51653	0.184251	0.496914
20	0.208067	-0.19573	0.469509	0.062428	-0.1396	0.264329	7291	2828	4410	0.517962	0.185109	0.498146
19	0.213366	-0.194	0.467923	0.064583	-0.13562	0.266057	7563	2876	4641	0.519292	0.184842	0.50019
18	0.212288	-0.19262	0.462171	0.064014	-0.13232	0.26087	7808	2943	4813	0.51481	0.184694	0.495898
17	0.206564	-0.18987	0.459787	0.059818	-0.12941	0.257143	8329	3204	5065	0.513078	0.184261	0.497367
16	0.20315	-0.18553	0.453837	0.057143	-0.12421	0.25239	8324	3219	5042	0.506675	0.184997	0.492108
15	0.196553	-0.18286	0.445064	0.054201	-0.12107	0.245763	8474	3297	5097	0.50014	0.184979	0.488116
14	0.184621	-0.18057	0.432655	0.047441	-0.11823	0.237228	8450	3355	5006	0.489359	0.185193	0.479305
13	0.174383	-0.17849	0.422477	0.041126	-0.11654	0.223215	8691	3526	5077	0.481409	0.18343	0.47414
12	0.171029	-0.17669	0.420472	0.037196	-0.11407	0.216912	8783	3604	5087	0.481723	0.182639	0.478144
11	0.159864	-0.17487	0.409987	0.031884	-0.1126	0.207696	8885	3743	5061	0.472183	0.183173	0.469863
10	0.152505	-0.17237	0.400796	0.026966	-0.10813	0.201796	9032	3842	5089	0.464344	0.182695	0.464429
9	0.148914	-0.16678	0.394511	0.024049	-0.10272	0.195467	9168	3937	5125	0.458575	0.181461	0.462124
8	0.146095	-0.15909	0.380396	0.022222	-0.09705	0.183728	9309	3964	5233	0.448756	0.176426	0.456908
7	0.142128	-0.1546	0.366137	0.02351	-0.09035	0.168111	9459	3984	5354	0.440408	0.179942	0.449924
6	0.136017	-0.14792	0.351902	0.021712	-0.08582	0.16	9578	4037	5399	0.426378	0.173174	0.439005
5	0.12679	-0.14208	0.336784	0.017167	-0.07974	0.148243	10083	4300	5610	0.41429	0.172196	0.431002
4	0.117481	-0.13321	0.318191	0.013518	-0.07381	0.135714	10032	4302	5505	0.397331	0.167008	0.41946
3	0.107452	-0.12704	0.300792	0.010025	-0.06877	0.1233	10190	4432	5512	0.38338	0.164505	0.409712
2	0.097566	-0.11737	0.287807	0.0049	-0.05921	0.109559	10175	4553	5306	0.369061	0.15709	0.404513
1	0.085089	-0.10961	0.267157	0.00043	-0.05302	0.097826	10442	4780	5287	0.348024	0.152319	0.387704
0	0.067678	-0.10407	0.238546	0	-0.05085	0.085098	9348	4394	4569	0.319871	0.149008	0.360621
-1	0.062805	-0.11155	0.235838	0	-0.05642	0.083333	8411	3956	4111	0.319404	0.154205	0.355435

The dispersion of the analysts' forecasts also tends to decrease with the forecast horizon, but always remains much more important for the experts having a positive bias. In other words, experts who have a positive bias are less "homogeneous" than those who hold a negative bias.
The disparity of the countries and sectors lead us to a decomposition of the bias by country or sector.

I.1. Decomposition of the bias by country

We synthesized the descriptive statistics each country and various forecast horizons. In a -1 month horizon, the mean is of 0.025 for the US (median $-1.9e^{-16}$), 0.072 for France (median 0.0127), 0.085 for Germany (median 0.0026), 0.053 for Great Britain (median $-4e^{-6}$) and -0.087 for Canada (median 0).

We reproduced in Figure 1 the mean of all countries forecasts bias as well as the means of positive bias on the one hand and negative bias on the other hand. For certain countries, we have very few observations (cf. Table 2), as is the case for Ireland (6 firms) and Portugal (15 firms).

Figure 1
Bias by horizon and by country

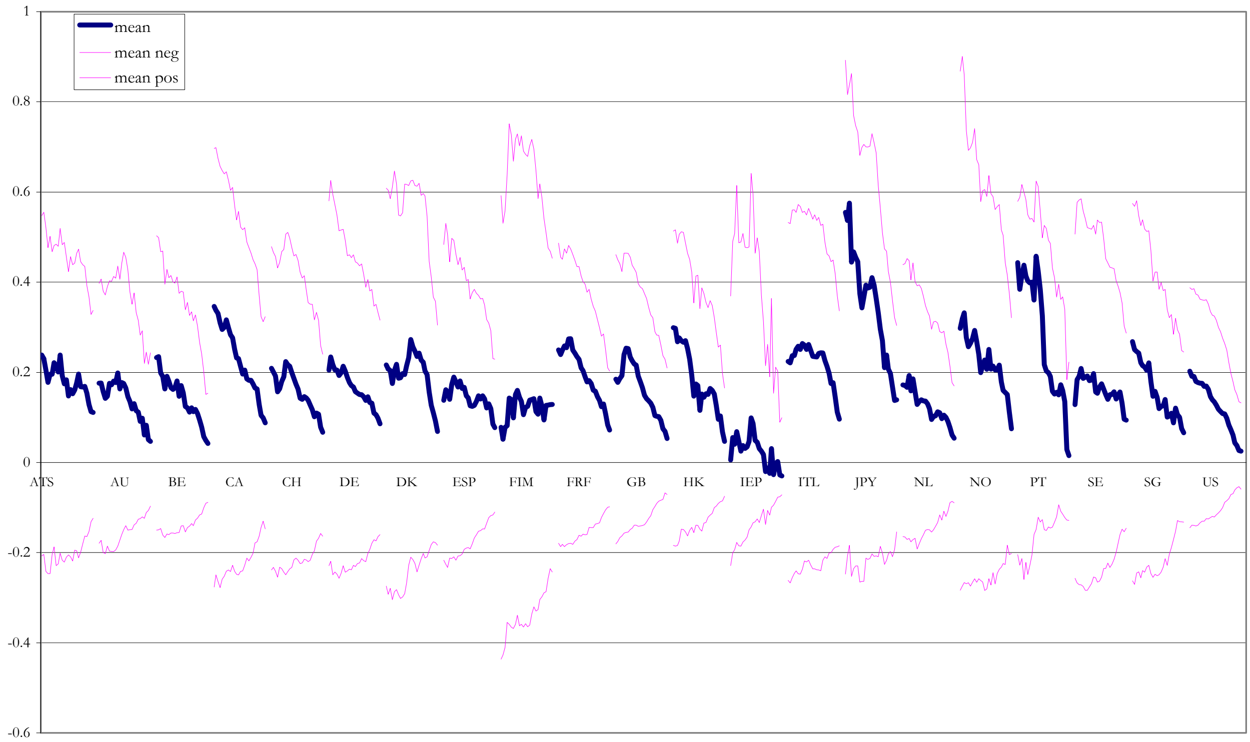


Table 3
Statistics by country

Country	Capit (%)	Number of Firms	Capit Min*	Capit Max*
ATS	0.25	28	119.9635	3030.608
AUD	0.41	18	243.6843	10966.75
BEF	0.80	25	198.8655	10349.8
CAD	3.65	89	53.51238	49276.02
CHF	4.59	62	19.01001	103410.3
DEM	6.41	79	48.81234	85273.21
DKK	0.51	25	37.51921	7584.088
ESP	1.56	46	109.7008	25603.55
FIM	1.02	31	108.7807	48283.88
FRF	6.22	83	244.054	66629.09
GBP	12.07	101	206.2583	149601.3
HKD	1.25	27	266.8892	34077.49
IEP	0.20	6	138.5009	7354.547
ITL	3.19	63	55.37956	46379.22
JPY	1.04	17	982.6461	17317.1
NLG	3.18	28	409.2178	74160.24
NOK	0.37	35	139.732	8513.281
PTE	0.40	15	97.87147	9502.182
SEK	1.77	48	314.1159	29567.06
SGD	0.71	32	101.3285	9531.257
US	50.40	341	508.3113	202538.5

Note: * in $

From Table 3, essentially American companies compose our sample, in terms of capitalization and number of firms. England is second, (12.07% of the capitalization of our sample with 101 firms), followed by Germany (6.41% of the capitalization) and then Canada (89) and France (83) in terms of number of firms.

In Figure 1, we deferred the same information by country and horizon. We observe a very atypical profile for Japan with an important bias for large horizons. The profiles of mean bias seem quasi-similar for the US and GBP. The mean bias is of the same magnitude for the European countries, yet one can observe differences in terms of positive and/or negative bias. Thus, positive and negative mean bias in the Italian and German markets appear more important than those in France, GBP or NLG. The number of observations is very diverse according to country, with a dominating weight in the United States.

Note that the behaviour of reported EPS may be influenced by accounting practices that either smooth or exaggerate the underlying earnings behaviour. Accounting practices could affect the analysts' disposable information in terms of frequency, timeless and scope of disclosure. These elements can affect the capacity of the analysts to carry out accurate forecasts.

For example, in France quarterly revenue statements are published, whereas in all the other countries, semi-annual accounts are issued, except in Switzerland where no interim accounts are required. Compared to the annual statements, the time limit for disclosure varies from five to seven months for all countries except Italy (four months) and Germany (nine months). Rees (1998) carried out a comparison of accounting measurements of seven European countries. In only two cases the countries have the same accounting practices (Sweden-Norway and UK-Ireland). Taxation is also expected to impact differently on accounting practices across the sample: Alford and Al (1993) showed that only Ireland, the Netherlands and the United Kingdom have accountings systems relatively independent from the influence of the taxes. In the other countries, one can suppose that the managers have an incentive to use accountings practices that - in the short run - depress taxable earnings (firms with tax dominated accounting practices may be expected to declare a more conservative income stream than otherwise, delaying profit recognition wherever possible). Basu and al. (1996) found that analysts' forecast errors are higher for countries with a greater degree of alignment between tax and financial reporting. An empirical relation can be due to a lack of information on accountings disclosure, tending to be lower in countries with a high alignment between tax and financial reporting (Alford and al. 1993), as there is evidence that analysts' forecasts are less accurate for firms with less informative financial disclosure policies (Lang and Lundholm, 1996).

One can expect the quality of information on the accounts to affect the quality of the forecasts (Hopwood and al 1982). Lang and Lundhohlm (1996) underlined the fact that the forecasts of the analysts are more precise for the companies having adopted more informative communication policies. Saudagaran and Biddle (1992) classified the European countries according to their policy of information communication: best quality is awarded to the U.K., followed by the Netherlands, France, Germany and then Switzerland. Basu and al. (1996) also underlined higher forecast error for countries that communicate less.

Capstaff, Paudyal and Rees (2001) showed that in Europe the three countries with the most accurate analysts forecasts (NLG, GBP and Ireland) are also those with the lowest alignment between financial reporting and taxation, and they also have the highest disclosure ranks. This is consistent with the evidence of Lang and Lundholm (1996) and Basu and al. (1996). The Netherlands and the UK also stand out as having a high degree of stock market association - with the implication that there is more pressure to produce efficient forecasts and resources will be devoted to this end.

I.2. Decomposition of the bias by sector

Figure 2
Bias by horizon and by sector

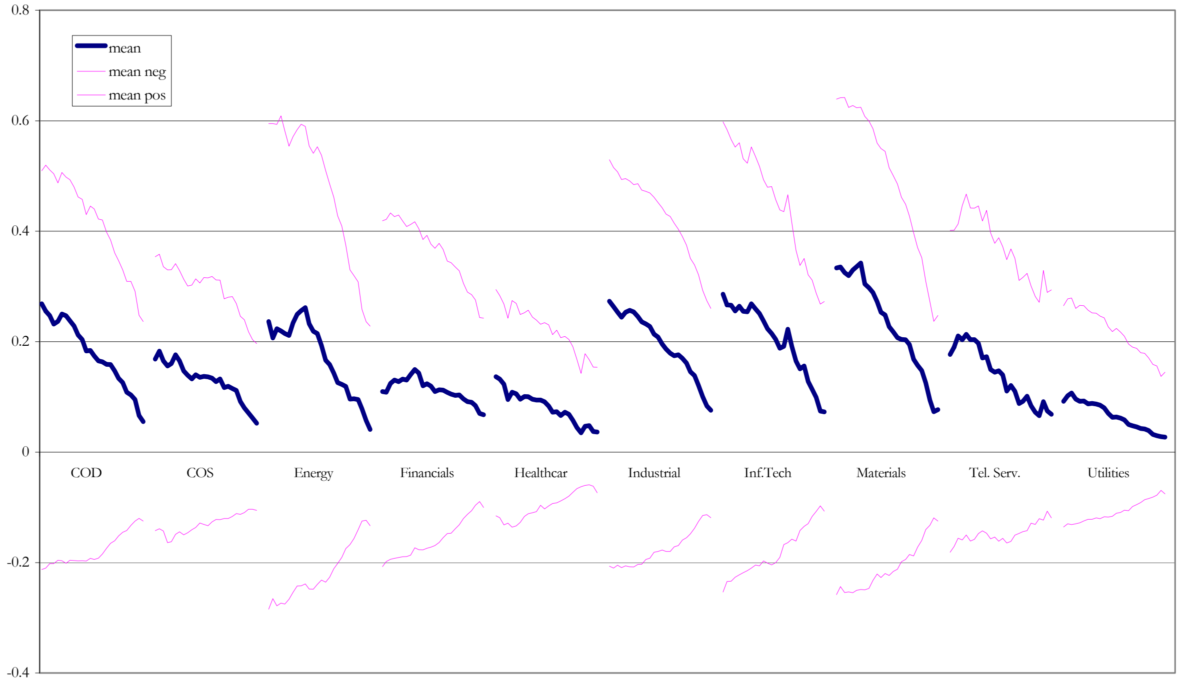


Table 4
Statistics by sector

Sector	capit (%)	Number of firms	Capit Min*	Capit Max*
consumer discretionary	11.37	193	38.40814	129325.2
consumer staples	5.71	66	37.51921	84466.25
Energy	7.15	63	138.5009	130977.6
Financials	24.81	223	119.9635	202538.5
Health care	12.85	61	108.7807	149601.3
Industrials	9.45	232	48.81234	179121.7
information technology	7.84	74	139.732	96706.25
Materials	5.43	179	19.01001	39049.37
telecommunication services	10.03	42	498.9263	87414.08
Utilities	5.37	80	216.6382	22527.38

Note : *in $

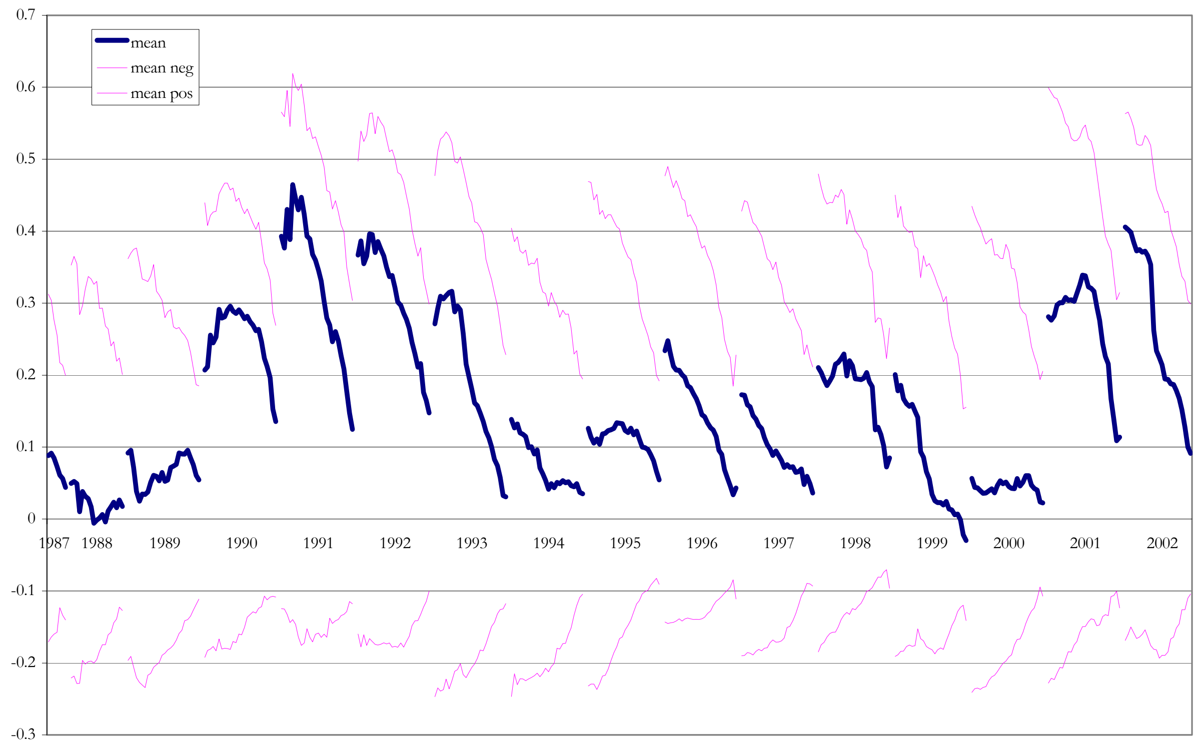
In the Figure 2, we deferred the mean bias, as well as the mean of positive bias and the mean of negative bias, by sector and horizon (from 24 to -1 month). In spite of a sometimes run up against profile, we will observe a decrease of the mean bias with the horizon. In addition, it is observed that some sectors are more prone to bias: the information technology, materials, telecom and to a lesser extent, industrials and consumer discretionary sectors. The utilities sector is characterized by the weakest mean bias regardless of the horizon. One also observes that the important mean bias observed for some sectors are more the fact of high mean positive bias than high mean negative bias. Even for weak horizons (0 or -1), mean positive bias remains about 20%, whereas mean negative biases are about -10%.

Table 4 recapitulates the sector distribution of our sample in terms of capitalisation. The sectors whose capitalisations are highest are financials (24.81%), health care (12.85%), consumer discretionary (11.37%) and telecommunication services (10.03%). In addition, the number of firms gives us an indication to the importance of sector concentration: for example, the health care and telecom sectors are very concentrated, whereas the industrials and materials sectors are characterized by a lower degree of concentration. The utilities sector has the weakest capitalisation with a high number of firms, implying the presence of many firms of mean or small size.

II. Decomposition of the bias by year

Analysts' earnings forecasts generally are optimistic and are increasingly inaccurate the longer the forecast horizon. While these results appear to hold for all countries investigated, there are country, industry and year specific differences. Further analysis of forecast bias was conducted with the sample segmented by industry, country and year.

Figure 3
World bias by horizon and by year



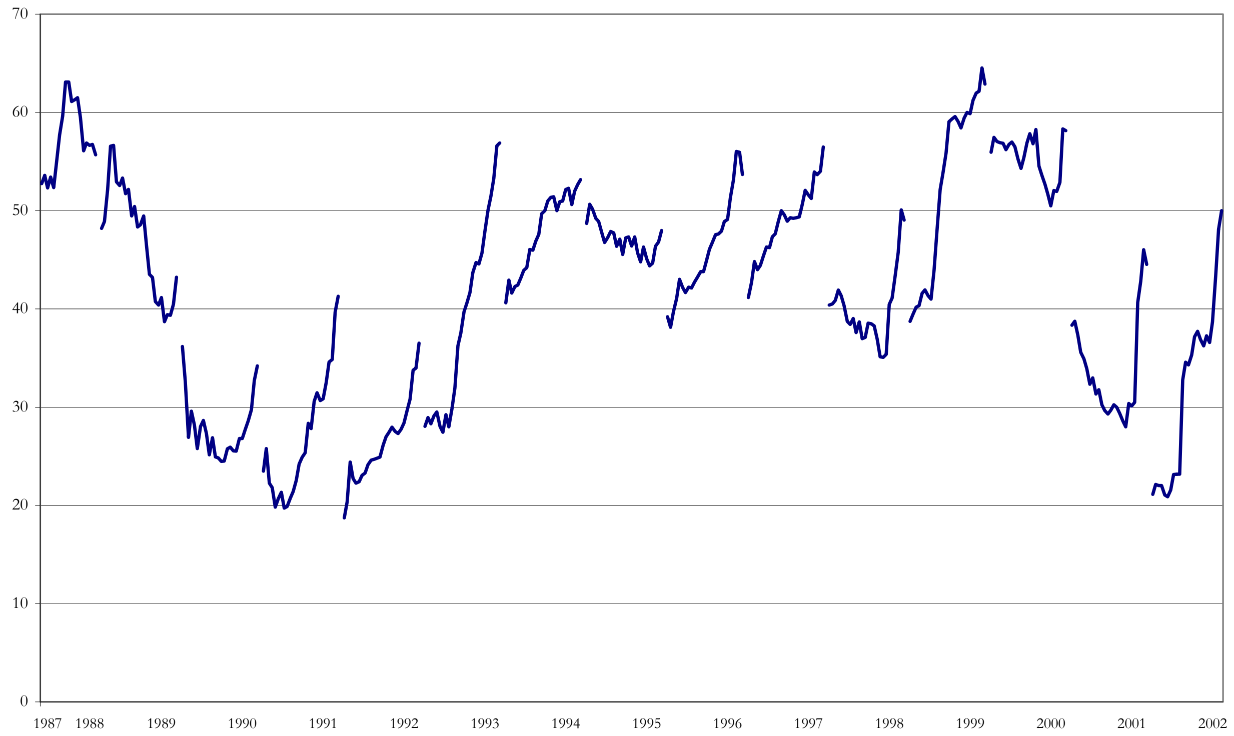
Confirming our result (cf. Figure 3), in their study, Hong and Kubik (2003) conclude there is some support for claims that Wall Street lost any self-discipline to produce accurate research during the recent stock market mania. Rewards were less sensitive to accuracy and more sensitive to optimism during the stock market boom of the late nineties. Bias in 2001 and 2002 are comparable with those obtained at the beginning of the Nineties during the housing market crisis: mean positive biases are about 55% to 30% for horizons from 24 to –1 month respectively! Note that for shorter forecast horizons, the mean bias became negative in 1999, with a positive mean bias becoming weaker (about 15 to 20%) over our sample period: however the low value of the bias is not closer related to "less biased" positive forecasts than in other years, but to realised values carried which flew away following the technological bubble[7], implying an undervaluation on behalf of the experts.

Year 2000 (correspondent with forecasts carried out over the period December 1998 (for the forecast at 24 months) to January 2001 (for the forecast at -1 months)) is the year for which the mean bias remained the weakest on the whole of the horizons, without significant revisions. Given that the profiles of mean positive and negative bias are identical to those observed during other years, this certainly implies that in 2000 the volume of negative mean bias was more important, as one can observe it in Figure 4: one notes during for the year 2000 that the proportion of negative bias is always higher than 50%, whatever the horizon. This interpretation can be related to the fact that the forecasts carried out during 1999 are

[7] Recall that the bias is indeed calculated as a difference between an anticipated and an observed values.

marked by the Russian[8] and LTCM crisis at the beginning of the year and the forecasts carried out during 2000 are marked by the bursting of the technological bubble in March.

Figure 4
Percentage of negative bias



Hong and Kubik (2003) attempt to measure the career concerns of security analysts using a panel of information on the brokerage houses employment and earnings forecast histories of roughly 12 000 analysts working for 600 brokerage houses between 1983 and 2000. Controlling for accuracy, they find that analysts who issue relatively optimistic forecasts (forecasts greater than the consensus) are more likely to experience favourable job separations: a plausible interpretation of these findings is that while accuracy matters, brokerage houses also value relatively optimistic analysts presumably because they help promote stocks and hence generate investment banking business and trading commissions. Moreover, they have cut their period of study into two sub samples and observe strong evidence that accuracy matters less for career concerns in the 1996 to 2000 period than in the 1986-1995 period. There is slightly weaker evidence that forecast optimism also matters more for career concerns during the late period. These findings are consistent with observations in the financial press that brokerage houses threw whatever concern they had for objectivity in their research out the window in the midst of the stock mania of the late 1990s, as the job description for being an analyst became more tied to promoting stocks. They are also consistent with the optimism bias having increased in the 1990s (Dreman and Berry, 1995).

Our sample is dominated by the American firms: it is thus interesting to break it down by country', in order to be able to compare the bias dynamics. However, such decomposition only makes sense for the countries that we have a sufficient number of observations. Figures 5.1 to 5.4 correspond to the mean bias observed for the United States, United-Kingdom, Germany and France[9]. Concerning the United Kingdom, we observe a dynamic bias very similar to that of the United States, with only certain levels of bias slightly higher, particularly at the beginning of the Nineties. One finds a similar phenomenon for Germany in 1993 and in France between 1991 and 1994, which one can certainly connect to the crisis of the EMS, intervened at the end of 1992, with the exit of the United Kingdom. For France and United

[8] One can also think of the consequences of the Brazilian financial crisis.

[9] For some horizons, we did not defer the mean bias value, since the number of observations was too limited. It is primarily the case for the beginning of the period and/or long horizons of forecast.

Kingdom, one finds relatively weak mean bias (even negative) at the end of 1999 and during 2000, as well as very high bias in 2001 and 2002 (because of high positive mean bias). Concerning Germany, the shaky profile (the sample is a reduced size) makes it difficult to interpret the bias dynamics over the recent years. However, one observes an increase in the positive mean bias over the last two years.

Capstaff, Paudyal and Rees, in comparing European countries, found that in the industry-based analysis the analysts' forecasts for the health care and public utilities were the most accurate, while consumer durables and transportation were the least accurate. Part of the explanation may be the low earnings volatility for the first two industries and the high volatility for the last two. They note that the four years with the least accurate forecasts are 1990-1993.

As for the study country by country, we retained only the sectors for which we have sufficient observations, namely materials, financials, consumer discretionary and industrials. In Figures 6.1 to 6.4, obviously one finds the outstanding events observed on the world figure, namely the high bias at the beginning of the Nineties, the weak bias (even negative) in 1999 and 2000 and again an extremely high bias since 2001. However, the observation of the figures shows that clear sector differences do appear. For example, bias concerning the materials and financials sectors present relatively heterogeneous profiles: for the financials sector, the years 1994 to 2000 correspond to years for which mean bias are relatively weak, whereas for the materials sector, bias is weak in 1994 and 1995 (even negative), but become high again in 1996.

The decompositions of bias per year, country and/or sector, underline the fact that an explanatory model of the world bias unaware of these various dimensions, will be clearly unaware of significant information. These three dimensions are in addition not exhaustive: the econometric models which seek to explain the behaviour of bias place importance on such variables as stock exchange capitalisation, the number of brokers or the fact that the firms carries out benefits or losses (Ali, Klein and Rosenfeld, 1992; Brous and Kini, 1993; Das, Levine and Sivaramakrishnan, 1998; Han, Manry and Chaw, 2001)… the quoted variables correspond to micro-economic information carrying out on the company itself: their importance would justify the estimate of an explanatory model of the bias on an individual level.

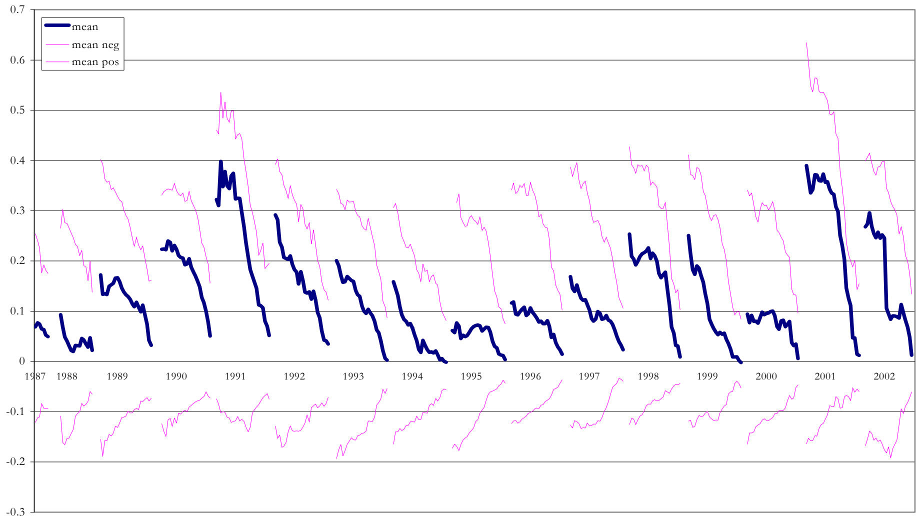


Figure 5.1. US bias by horizon and by year

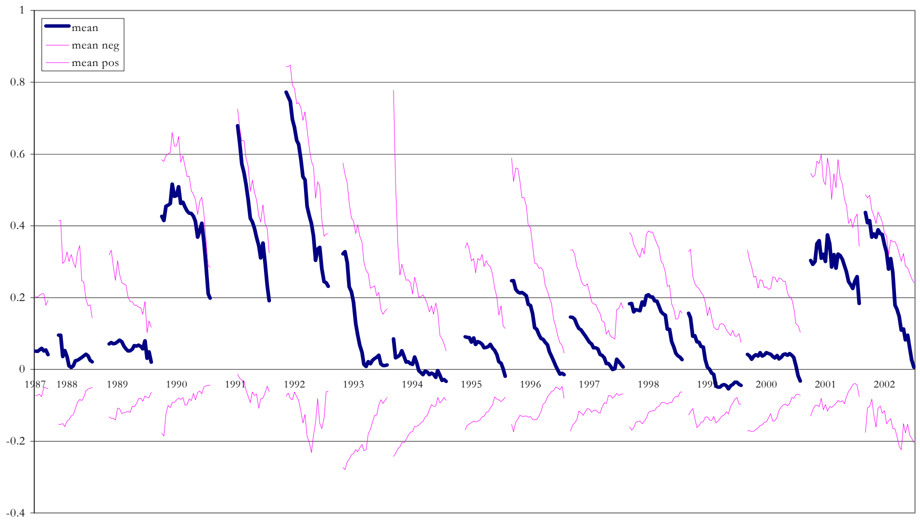


Figure 5.2. GBP bias by horizon and by year and % bias positive

Figure 5.3. DEM bias by horizon and by year

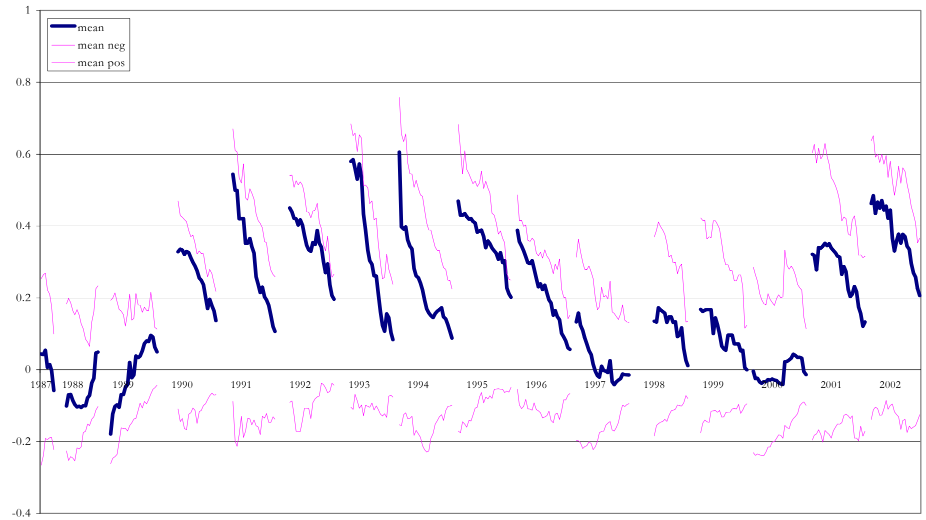


Figure 5.4. FRF bias by horizon and by year

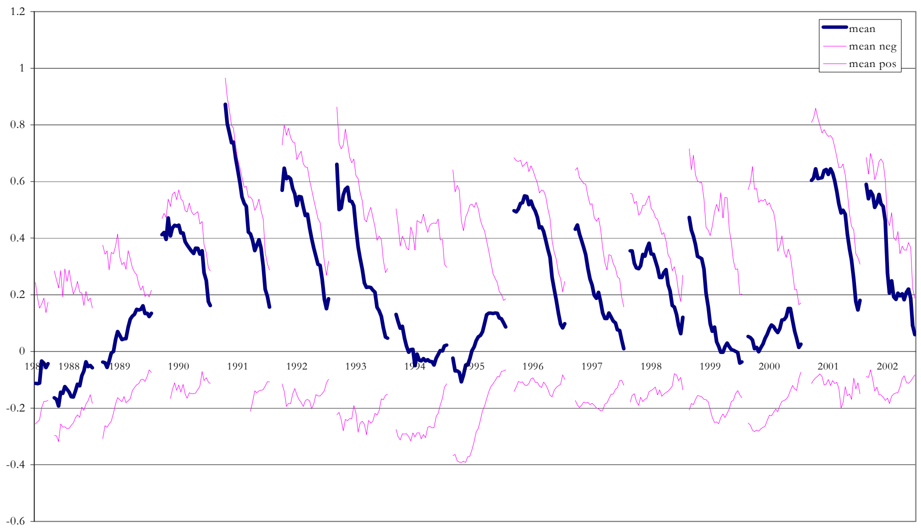


Figure 6.1. Materials bias by horizon and by year

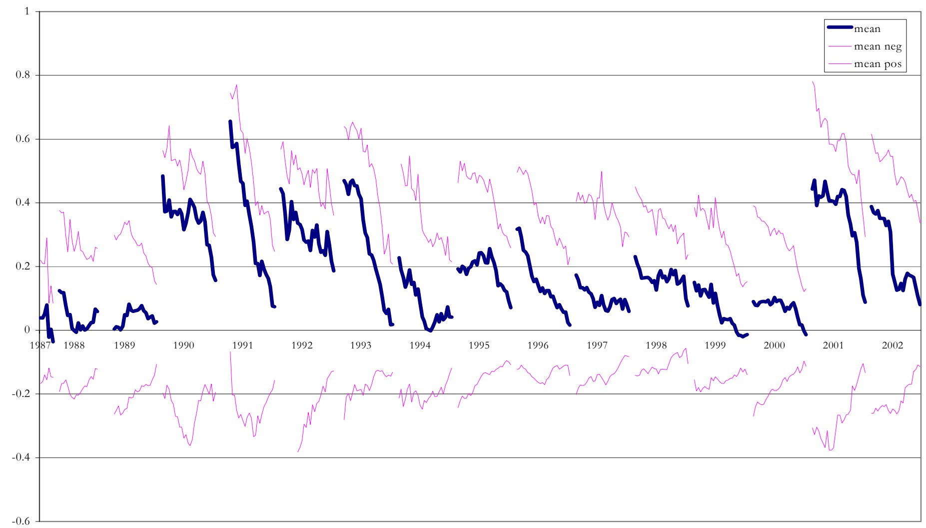


Figure 6.3. Consumer discretionary bias by horizon and by year

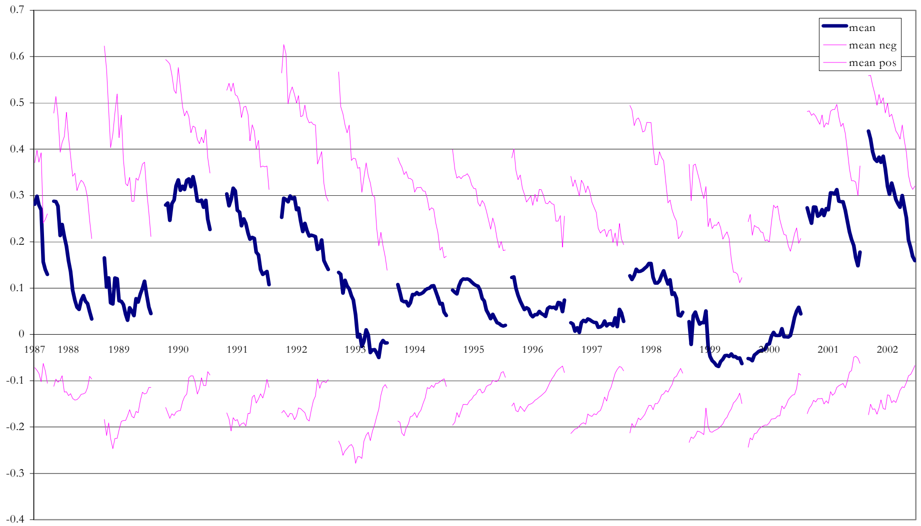


Figure 6.2. financials bias by horizon and by year

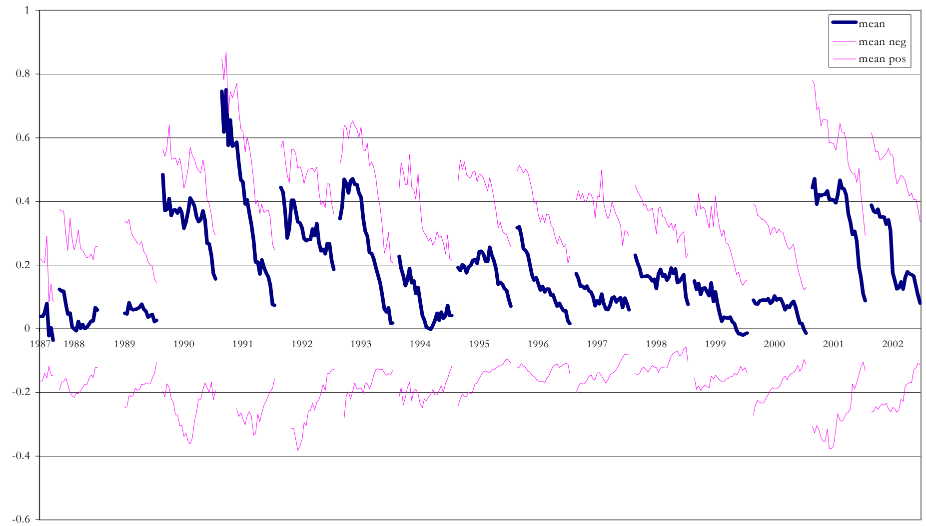


Figure 6.4. Industrials bias by horizon and by year

III. Decomposition of the bias by capitalisation

The aggregate bias based on a weighting by capitalisations is generally weaker than the equal-weighted mean of individual bias, i.e. the literature on the subject underlines the fact that small capitalisations are characterized by mean bias higher than large capitalisations. Brown (1997) showed that optimistic bias decreased over time and that it is negatively associated with firm size and analyst following. An explanation is that the accuracy of analysts' earnings forecasts declines as the complexity of the forecasting task increases. Das and al. (1998) 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.

We gathered bias in two sub samples (large and small) by retaining as "large" capitalisations the higher third. Naturally, a decomposition by country is essential if one does not want the sub sample of "large capitalisations" to be made up of only American firms. The same concern is also at the origin of sector decomposition: the telecommunication sector is primarily composed of large capitalisation (the percentile at 66.7% is 23806.32), whereas the utilities sector is composed of companies whose capitalisations are weaker (the percentile at 66.7% is 7288.86) [10].

Figures 7.1 to 7.4 describe the dynamics of the bias according to countries and horizons for the two sub-samples. Concerning the United States, one observes, as waited, that the mean bias is weaker for large capitalisations than for the others, the spread however tending to reduce itself with the forecast horizon . In addition, the spread is essentially the fact of the positive mean bias: the experts tend to over-estimate the benefits for moderate sized companies . One can put this phenomenon on the account of the public information available concerning each group of firms: the less information the experts have, the more they will tend to overestimate their forecasts in order to "ensure themselves" not to underestimate the benefit carried out.

One observes a similar behaviour of the bias for the United Kingdom, but for Germany and France, the spread in terms of bias for the two sub-groups of capitalization are 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 industrials sectors, bias associated with the most important capitalisations are weaker than those associated with moderate capitalisations. On the other hand, for the consumer discretionary and financials sectors, sub sample bias is indistinguables whatever the horizon for finance and on long horizons for the consumer discretionary sector.

[10] The percentiles at 66.7% for the sectors financials, materials and industrials and consumer discretionary are respectively: 9743.66, 3143.68, 2961.97 and 4108.32.

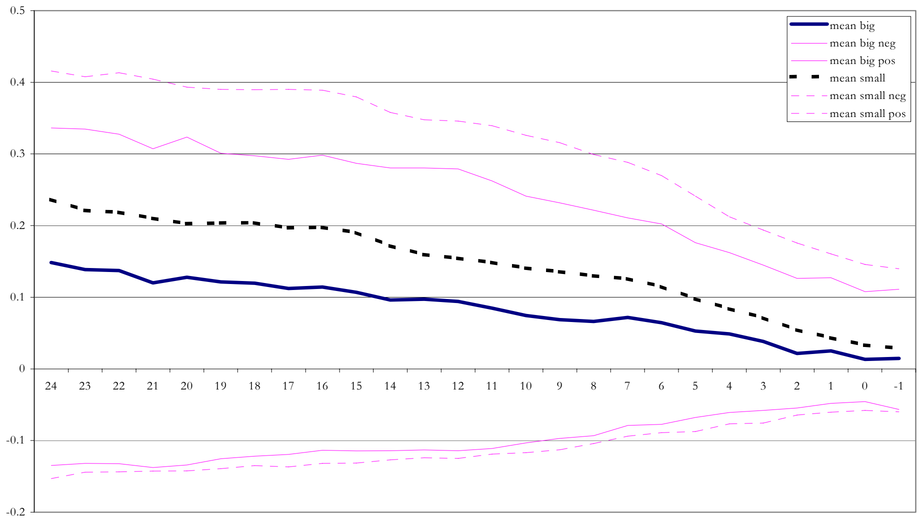


Figure 7.1. US bias(by capitalisation)

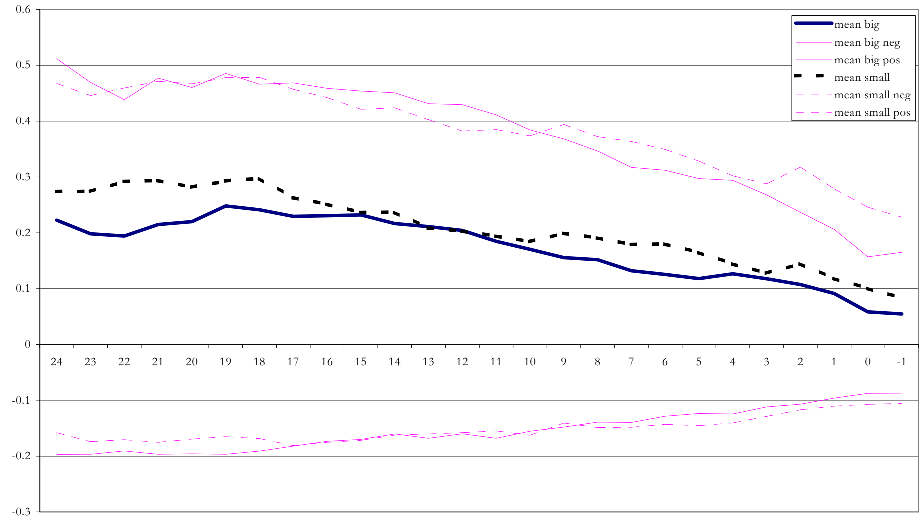


Figure 7.3. FRF bias (by capitalisation)

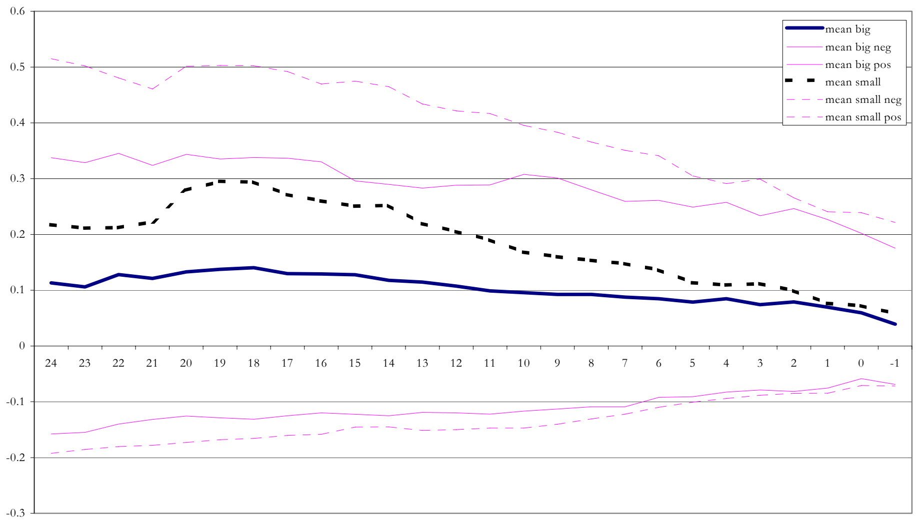


Figure 7.2. GBP bias(by capitalisation)

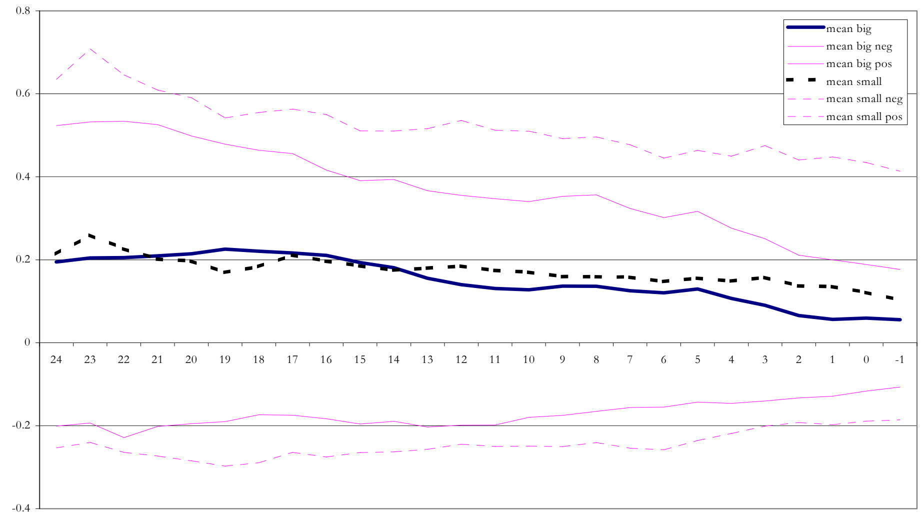


Figure 7.4. DEM bias (by capitalisation)

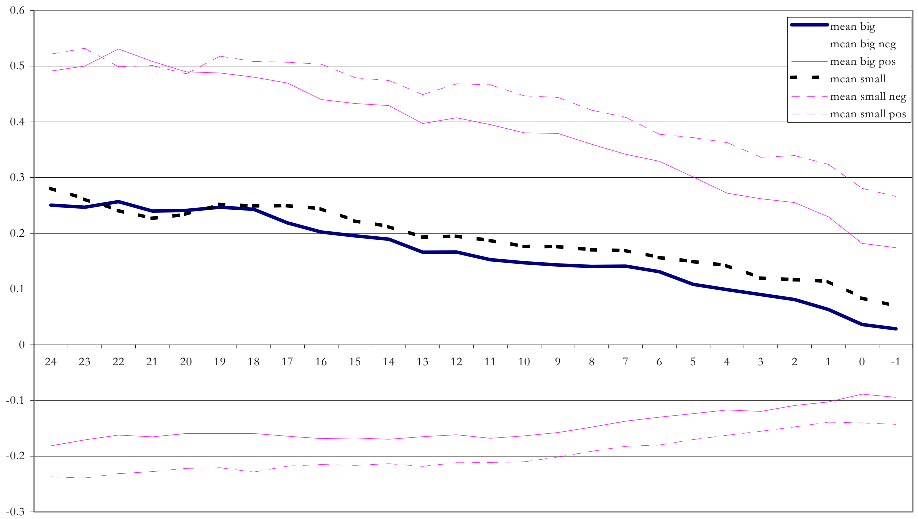


Figure 8.1. COD bias(by capitalisation)

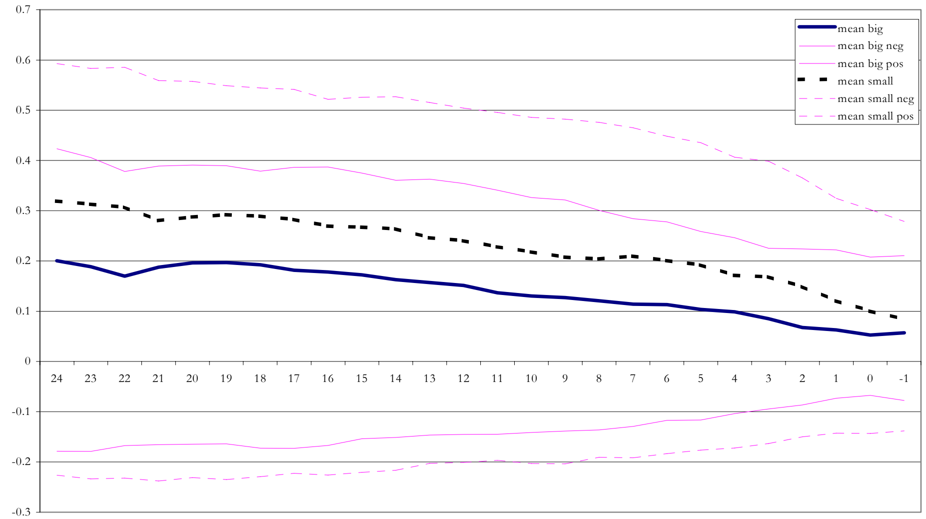


Figure 8.3. industrials bias (by capitalisation)

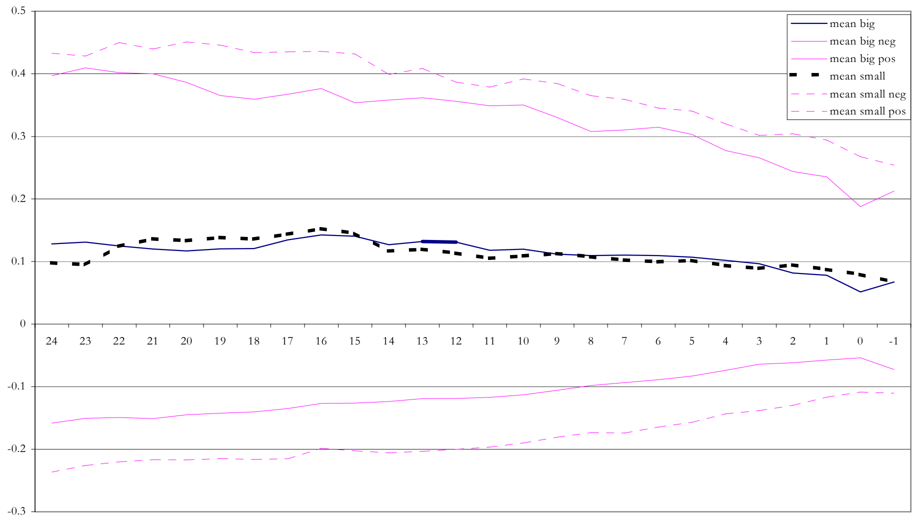


Figure 8.2. Financials bias (by capitalisation)

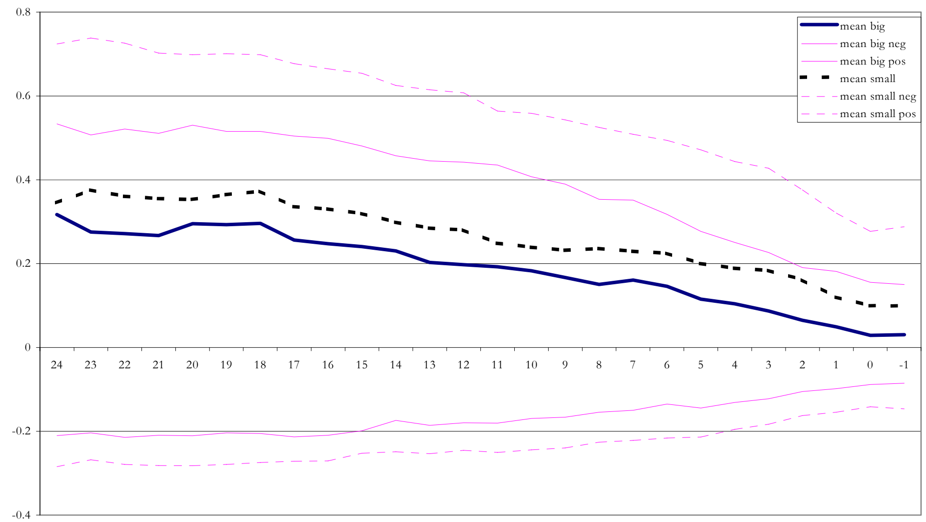


Figure 8.4. Materials bias (by capitalisation)

IV. Summary

We realised our study on the consensus mean estimates of 21 countries for which companies belong to the MSCI universe, for the period July 1987 to September 2003. The bias was calculated by country, sector and horizon. Concerning the forecast horizon, we selected horizons going from 24 months to -1 month. We notably observed that:

- the mean of the bias decreases regularly with the horizon, becoming almost null at a horizon -1, i.e. as more predisclosure information becomes available and uncertainty over the period's earnings decline,
- the behaviour of reported EPS may be influenced by accounting practices that either smooth or exaggerate the underlying earnings behaviour,
- some sectors are more prone to bias: the information technology, materials, telecom and to a lesser extent, industrials and consumer discretionary sectors. The utilities sector is characterized by the weakest mean bias regardless of the horizon,
- there is some support for claims that Wall Street lost any self-discipline to produce accurate research during the recent stock market mania.

References

Alford, J. Jones, R. Leftwich and M. Zmijewski, The relative in formativeness of accounting disclosures in different countries, Journal of Accounting Research (Supplement), 1993, 183-223.

Ali, A., A. Klein and J. Rosenfeld, Analysts' use of information about permanent and transitory earnings components in forecasting annual EPS, The Accounting Review 67, 1992, pp.183-198.

Basu Sudipta, Ching-Lih Jan and LeeSeok Hwang, Loss firms and analysts' earnings forecast errors, Journal of Financial Statement Analysis, Vol. 1, Winter 1996, 18-30.

Brown, L.D., Earnings forecasting research: its implications for capital markets research, International Journal of Forecasting, 1993, pp.295-320.

Brown L.D, Earnings Surprise Research: Synthesis and Perspectives, Financial Analyst Journal, March/April 1997, pp.13-19.

Brown, L.D., R.L. Hagerman, P.A. Griffin and M.E. Zmijewski, Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings, Journal of Accounting and Economics, 1987a, pp.6 l-87.

Brous P and Kini O, A reexamination of analysts' earnings forecasts for takeover targets, Journal of Financial Economics, 33, 1993, 201-225.

Capstaff, J., K. Paudyal and W. Rees, A comparative analysis of earnings forecasts in Europe. Journal of Business Finance & Accounting 28, 2001, 531–562.

Clikeman Paul M., "Auditor Independence, Continuing Controversy," The Ohio CPA Journal, April 1998.

Collins, W. A. and Hopwood, W. S., A multivariate analysis of annual earnings forecasts generated from quarterly forecasts of financial analysts and univariate time-series models, Journal of Accounting Research, 18, 1980, 390 406.

Conroy, R.M. and R.S. Harris, Analysts' earnings forecasts in Japan: Accuracy and sell-side optimism, Pacific-Basin Finance Journal 3, 1995, pp.393-408.

Cornell, B. and W. Landsman, Security Price Response to Quarterly Earnings Announcements and Analyst Forecast Revisions, The Accounting Review, 64, 1989 (October), 680-692.

Das, S., C.B. Levine and K. Sivaramakrishnan, Earnings predictability and bias in analysts' earnings forecasts, The Accounting Review 73 (2), 1998, 277-294.

Dreman, David, and Michael Berry, "Forecasting Errors and Their Implications for Security Analysis," Financial Analysts Journal, May/June, 1995.

Dugar, A. and S. Nathan, The effect of investment banking relationships on financial analysts' earnings forecasts and investment recommendations, Contemporary Accounting Research 12, 1995, pp.131-160.

Elton, Edwin J., Martin J. Gruber and Mustafa N. Gultekin, Professional expectations: accuracy and diagnosis of errors, Journal of Financial and Quantitative Analysis, 19, 1984, 351-363.

Francis, J. and D. Philbrick, Analysts' decision as products of a multi-task environment, Journal of Accounting Research 3 1, 1993, pp.2 16-230.

Han Bong H., Manry David and Wayne Shaw, Improving the Precision of Analysts' Earnings Forecasts by Adjusting for Predictable Bias p.81-98, Review of Quantitative Finance and Accounting, 17 (1), July 2001, pp.81-98.

Hong Harrison and Jeffrey D. Kubik, Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts, Journal of Finance, 58, February 2003, 313-351.

Hopwood W.S., P. Newbold and P. Silhan, The Potential for Gains in Predictive Ability through Disaggregation: Segmented Annual Earnings. Journal of Accounting Research 20, 1982, pp.724-32.

Jensen, M.C., Some anomalous evidence regarding market efficiency, Journal of Financial Economics 6, 1978, pp.95-101.

Lang M. and R. J. Lundholm, Corporate Disclosure Policy and Analyst Behaviour, Accounting Review, October 1996, pp. 467-92.

Lim, Rationality and Analysts' Forecast Bias, Journal of Finance, 2001.

Lin, H. and M. McNichols, Underwriting relationships and analysts' research reports, Working Paper, Stanford University, 1993.

O'Brien, Analysts' forecasts as earnings expectations, Journal of Accounting and Economics 10, 1988, pp.53-83.

Rees, Lynn. "Realized Benefits From Foreign Listings," Journal of International Accounting, Auditing and Taxation, Vol. 7, No. 1, 1998, pp. 1-20.

Saudagaran, Shahrokh M., and Gary C. Biddle, Financial Disclosure Levels and Foreign Stock Exchange Listing Decisions, Journal of International Financial Management and Accounting 4, Summer 1992, pp. 106-148.