Earnings Forecasting Bias and Accuracy in the Italian Stock Market

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Abstract

The aim of this study is to evaluate the financial analysts' earnings forecast bias and accuracy. We focus on annual earnings per share forecasts issued on Italian listed firms by brokerage analysts and find that (1) analyst are on average optimistic about the future prospects of covered firms; (2) median optimistic bias as well as forecast dispersion decline during the forecasting period toward the actual realization; (3) earnings forecasts are on average inaccurate; (4) accuracy increases with the firm size, actual profit realization, brokerage size, analyst's specific experience on firm and, in general, during bull markets, while it declines with the number of firm the analysts follows and when the time from the forecast date to the release of actual earnings increases; (5) forecasts are less accurate for technological listed firms, compared to firms in other sectors.

JEL Classification: G14
Keywords: forecasting accuracy, over-optimism, analysts, earnings, stock market.

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1.
INTRODUCTION

This research investigates analysts' forecasting bias and accuracy in the Italian stock market.

Based on a large sample of earnings per share forecasts issued by brokerage analysts on Italian listed firms between 1988 and 2004 we infer a temporal pattern of forecast bias and focus on how various factors can affect the individual accuracy of financial analysts.

The forecast bias, defined as the difference between forecasted and realized earnings, is the magnitude of the earnings surprise and is the main indicator of optimism/pessimism in the analyst's forecasting process. While an *ex-post* analysis indicates if analysts' forecasts have exceeded or fell short the actual earnings per share, the absolute value of the earnings surprise is called forecast error and captures how accurate the forecasts are. We therefore decided to perform two distinct analyses in evaluating not only the level of optimism/pessimism in analysts' forecasts but also accuracy.

It appears that the Italian stock market, similarly to the US and European markets, suffers from an overall optimistic bias in earnings forecasts. The mean forecast bias for the entire sample period is in fact about 13% (median 10%) suggesting that analysts tend to issue too optimistic earnings per share forecast compared to actual realizations. In general, positive bias accounts for a large part of the observations. More than 51% of the computed signed forecast errors are positive while the negative ones are about 45%. Further analyses based on the forecast bias distributional characteristics confirm that large positive signed error (high optimism) occurs more often than small negative forecast errors (low pessimism).

Our results are consistent computing the forecast bias in different calendar and sub-samples periods. Mean signed forecast errors seems to follow a decreasing path moving from earlier calendar periods toward the actual earnings release date. The mean forecast bias computed one year before earnings announcement is 25% (median 7%) and it gets close to zero one month prior to the release date (mean 3%, median equal to zero). This pattern suggests that analysts are able to gather and process new information and therefore adjust their estimates in the right direction. The evidence is confirmed by the level of dispersion in earnings estimates which is larger in earlier period and decreases gradually. The results for analysts' accuracy show a similar pattern: earnings forecasts appear to be inaccurate, on average. The mean unsigned forecast error is 31% (median 15%), over time decreasing and suggesting that accuracy improves moving from an absolute value of about 40% one year before the release date to 20% one month before it.

To investigate the variables affecting analysts' accuracy, we conduct two distinct regression analyses to capture the effect of firms-specific, brokers/analysts and sectorial characteristics. The results confirm that accuracy improves when analysts issue forecasts on big companies, firms that record profits instead of losses, and in general in bull markets. Taking into account both analysts' individual skills and the peculiarities of brokers for which they work for, the unsigned forecast error decreases with broker size, analyst's specific experience, while it increases with the number of covered firms. Moreover, sectorial specification highlights that during the sample period technological listed firms experienced the less accurate earnings forecasts while energy and health care sectors showed lower forecast errors.

The present research is organized as follows: the second paragraph reviews previous studies in the literature; the third one presents the databases used; the fourth shows the methodology chosen to calculate signed and unsigned forecast errors; the fifth proposes the evidences of optimistic/pessimistic bias and individual accuracy; the sixth describes the regression models and the main results while the seventh concludes.

2.
REVIEW OF THE LITERATURE

There is a relevant empirical and theoretical literature on analysts' earning forecasts. Analysts from brokerage houses and investment banks issue sell-side forecasts, while buy-side analysts are typically employed by mutual or pension funds and issue forecasts primarily for internal investment decisions. While both buy-side and sell-side analysts usually issue earnings forecasts, most research in financial markets and in accounting examines forecasts of the latter category since these are publicly available.

This huge literature can be divided into two broad categories of analysis: analysts' optimism and forecasting accuracy.

The first line of research examines analysts' consensus defined as the median or mean earnings forecast. The main topic of this research stream is analysts' optimism, i.e. the evidence that, on average, forecasts are greater that actual earnings. The second category, instead, focuses on individual analysts' characteristics, either on a cross-section or time-series perspective, examining whether personal skills do affect accuracy.

Many studies in the literature report evidence that analysts' forecasts are optimistic, although optimism appears to be declining in recent years [Brown (1996, 1997, 2001b); Matsumoto (2002); Ramnath et al. (2005); Richardson et al. (1999, 2004)].

There are at least three hypotheses consistent with the decline in optimism: analysts learn from evidence of past biases [Mikhail et al. (1999, 2003, 2004); Clement (1999); Jacob et al. (1999)]; analysts' incentives have changed [Hayes and Levine (2000); Jacob et al. (2004); Agrawal and Chen (2005); Cowen et al. (2006)]; the quality of data used in the researches examining analysts' forecast characteristics has improved (e.g. it suffers less from survivor or selection biases).

Research on analysts' accuracy has focused on two main attributes: the nature of the forecast itself, for example, whether the forecast reflects new information or whether the analyst is merely herding with the consensus; analyst's characteristics, e.g. affiliation or prior experience.

In considering forecast characteristics, it is clearly established in the literature that recent forecasts are more accurate [O'Brien 1988]. Furthermore, Sinha et al. (1997) recognize the effect of forecast age on accuracy and find that it differs across analysts, but only after controlling for the relative age of the forecasts. They find that analysts identified as superior *ex ante*, on either firm-specific or industry levels, continue to provide more accurate forecasts in the subsequent year. Other papers examine the characteristics of individual analyst's forecast superiority [Mikhail et al. (1997), Jacob et al. (1999) and Clement (1999)]. The results suggest that firm-experience, as measured by the length of time over which analysts made earnings forecasts for a firm, the size of the brokerage firm that an analyst works for, and the complexity of the analyst's task (number of firms and industries followed by an analyst) affect forecast accuracy.

The evidence on general experience appears mixed, in part because of data problems. Accuracy seems to increase when analysts' firm–specific experience increases, consistent with analysts learning over time and when analysts are affiliated with large brokerage houses, or are covering fewer firms [Clement (1999)]. Therefore, resources available to the employer and specialization also seem to increase forecast accuracy.

Interestingly, the turnover is higher when analysts perform worse than their peers suggesting that brokerage houses do evaluate analysts based on their accuracy [Mikhail et al. (1997)].

It should be emphasized that all the studies just quoted have taken into account US markets. However, there are some examples of empirical analysis on analysts' accuracy and forecast bias focused on European markets as well.

The same pattern for optimism documented by Brown (1997) and the importance of broker/analyst characteristics in term of forecast accuracy has been found for equity markets in the United Kingdom [Capstaff, Pauyal and Rees (1995); De Bondt and Forbes 1999], Germany [Capstaff et al. (1998)] and Europe as a whole [Capstaff et al. (2001); Becker et al. (2004), Bollinger 2004; Bagella et al. (2006)].

3.
DATABASE DESCRIPTION

It is relatively easier to check for bias in earnings estimates, compared to other outputs from analysts' research. Recommendations, as well as target prices and estimates of long-term growth rates, in fact, extend over an unspecified horizon. As a result, it is hard to reconcile them with realized performance in order to detect biases. Earnings estimates, on the other hand, are generally issued each month so they can be compared against realizations on a regular basis when earnings are announced.

In choosing between different forecast data provider, it is necessary to remember that annual consensus forecasts are compiled according to each provider's procedures and definitions. In general, the procedures used by these providers are designed to exclude certain non-recurring items (e.g. "one time" charges/gains associated with acquisitions), special items, and non–operating items from reported earnings, to eliminate components of earnings that the analysts, generally, do not attempt to forecast. Abarbanell and Lehavy (2003), in this respect, state that "the practice of excluding certain items from I/B/E/S definition of reported earnings have been in place since 1985. First Call Corporation implemented a similar practice from the inception of its forecast tracking service in 1992."

We base our analysis on two different datasets that we call "Detail" and "Consensus".

The Detail dataset contains all earnings estimates issued by brokerage analysts while the Consensus database includes the average monthly analyst's consensus estimates on earnings calculated by Thomson Financial.

In both databases we used data from 1988 to 2004 (referred to fiscal years 1987-2003). For the purpose of descriptive statistics we refer to the issue years, while for other purposes we use the fiscal year. After having eliminated erroneous data, forecast referred to savings and preferred shares or for which the company name was not reported, we end up with the following number of observations:

Synthesis	Consensus	Detail
Initial sample	30,458	69,538
Without date/Erroneous date	(3,451)	(5,279)
1st Sub-sample	27,007	64,259
Empty, Erroneous	(200)	(5,126)
2nd Sub-sample	26,807	59,133
Saving or Preferred Shares/Without Name	(1,175)	(240)
Final sample	25,632	58,893

Table 1 and Figure 1 show, in parts A and B respectively, the splitting of the firms included in the two databases among macro-sectors, using the classification proposed by I/B/E/S, in each year of the sample and on average.

Part A shows that in the Detail database, the two most covered sectors are "Finance", representing almost one third of the total (31.93%), and "Capital Goods" (17.81%), the two accounting for about a half of the total number of estimates. Considering the third sector in order of importance, “Basic Industries” (14.28%), one reaches almost two thirds of the total. Adding “Consumer Non-Durables” (12.70%) more the three fourths of the estimates are represented in the first four sectors, while the following seven sectors represent less that one fourth of the total. Looking at part B of table 1 it is possible to observe how the results for the Consensus database are similar to the Detail one.

Table 2, instead, summarizes the most important information of the Detail database that includes all the companies listed in the Italian Stock Exchange. The percentage of covered over listed companies is rather relevant across all the years in the database, with the exception of 1988, in which we only have four companies followed by analysts.

Since year 1988 is not very relevant, we focus our main comments starting from 1989. The coverage degree ranged between about 30% (50% in terms of market capitalization) in the late 80s/early 90s and around 50% in the 90s, reaching peaks of about 60% (80/90% in terms of market capitalization) after 2000.

The number of brokers has grown steadily over time, from 28 in 1989 to levels close to 70 at the end of our sample period. Therefore, we have evidence that both the number of brokers and the number of covered companies has grown over time.

The same trend can be observed for the number of analysts that has grown from 63 in 1989 to 546 in 2004, about nine times the initial value.

The number of analysts per covered firm, instead, has not steadily grown over time. Looking either at the average or at the median value, in fact, analyst coverage increased until 1993 with high rates of growth (from 2.25 to 9.60), decreased heavily in 1994 and 1995 (at about 5), increased in 1996 at about 10% and there remained quite stable until 1999, decreased in 2000 until 2002 and finally increased in 2003 and 2004.

The analysis of the number of covered companies per analyst gives us further insights. In the late 80s/early 90s, on average, an analyst was following about five companies (three if we take the median). From 1994 to 1999 the number decreases to about four (two in median) and to about three (one in median) since 2000. This decreasing pattern could be due to the decision of focusing the attention on fewer stocks, rather than dividing the time dedicated to researches in many stocks.

The number of brokers per covered company shows an interesting pattern: it increased in late 80s/early 90s, from four brokers per covered company in 1989, to eleven in 1993 (using the median), then remained quite stable until 1998, when it decreased until 2004 with six brokers per covered companies.

Figure 1 A. Detail Database: Summary description of databases

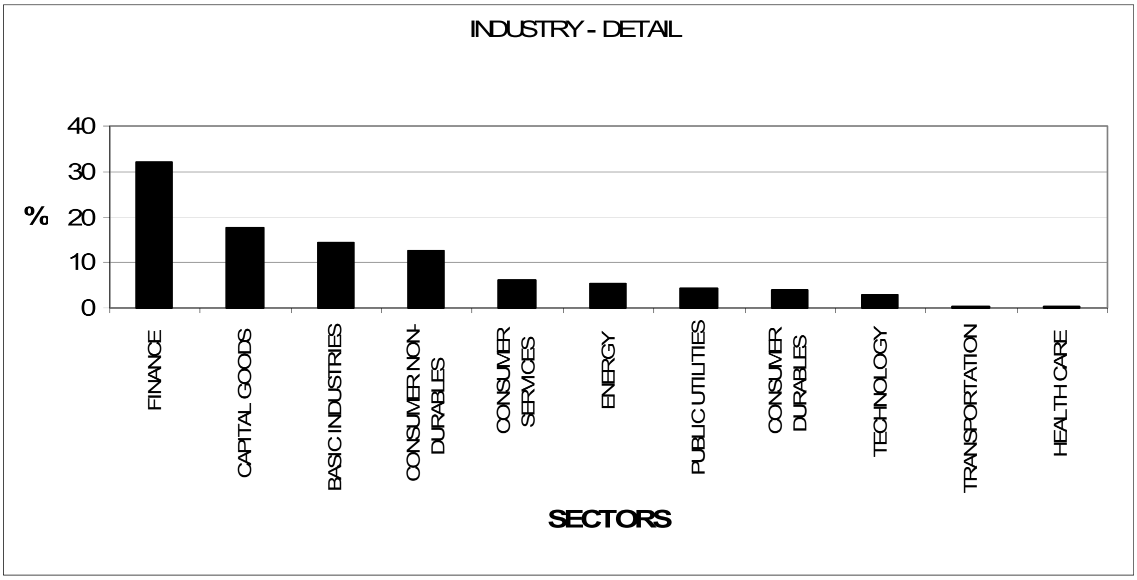


Figure 1 Part B. Consensus Database: Summary description of databases

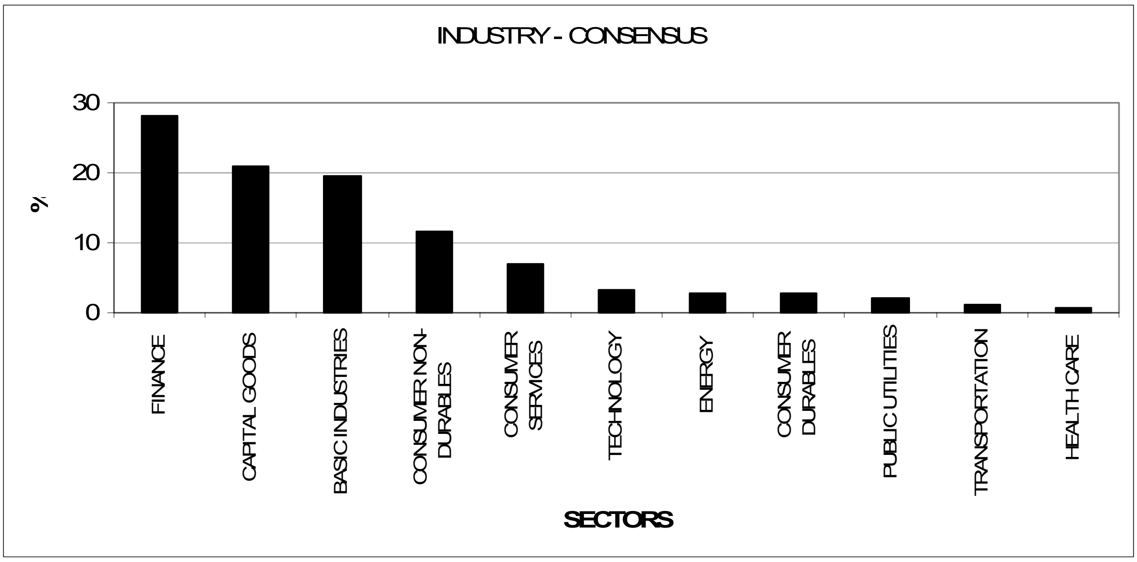


Table 1. Summary description of databases

Part A (Detail database)

PART A- DETAIL	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	TOTAL	%
FINANCE	8	210	238	481	593	1,332	986	1,181	1,449	1,443	1,479	1,457	1,137	1,265	1,599	1,361	1,368		17,587	31.93
CAPITAL GOODS	4	156	269	544	729	1,121	866	761	778	859	819	666	530	473	360	402	475		9,812	17.81
BASIC INDUSTRIES	3	151	293	520	549	1,011	721	734	735	770	648	536	333	262	268	153	179		7,866	14.28
CONSUMER NON-DURABLES		62	129	245	318	537	503	439	464	562	613	604	404	457	521	579	540	20	6,997	12.70
CONSUMER SERVICES		20	24	47	58	153	125	174	188	246	298	289	233	301	414	324	393		3,287	5.97
ENERGY		12	21	16	44	111	74	103	133	216	284	311	263	267	397	383	441		3,076	5.58
PUBLIC UTILITIES		8	30	38	47	136	112	81	154	212	200	160	136	149	259	287	277		2,286	4.15
CONSUMER DURABLES		52	76	113	37	121	115	146	144	182	175	131	139	162	230	188	195		2,206	4.01
TECHNOLOGY		41	80	78	102	106	108	93	88	94	87	70	17	92	189	117	195		1,557	2.83
TRANSPORTATION				3	15	33	1					22	44	39	60	28	5		250	0.45
HEALTH CARE										11	34	18	11	18	19	13	30		154	0.28
TOTAL	15	712	1,160	2,085	2,492	4,661	3,611	3,712	4,133	4,595	4,637	4,264	3,247	3,485	4,316	3,835	4,098	20	55,078	100

Part B (Consensus database)

PART B - CONSENSUS	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	TOTAL	%
FINANCE	10	218	236	290	340	428	430	460	464	467	498	498	557	526	499	417	407		6,745	28.23
CAPITAL GOODS	27	251	257	271	353	388	369	357	318	315	377	306	317	319	301	256	235		5,017	21.00
BASIC INDUSTRIES	23	256	285	299	364	397	403	331	317	307	298	278	274	246	239	226	147		4,690	19.63
CONSUMER NON-DURABLES		64	94	117	135	135	126	130	139	144	195	244	260	267	268	237	206	7	2,768	11.59
CONSUMER SERVICES		39	22	32	51	87	92	66	75	81	84	92	108	172	245	239	177		1,662	6.96
TECHNOLOGY		12	12	11	12	10	12	12	9	12	15	22	25	129	193	171	110		767	3.21
ENERGY		22	24	21	24	24	22	24	23	23	46	60	47	59	78	87	85		669	2.80
CONSUMER DURABLES		25	34	35	36	48	41	47	45	42	23	25	43	59	46	52	44		645	2.70
PUBLIC UTILITIES		10	12	10	12	20	22	12	17	23	23	27	48	62	66	60	69		493	2.06
TRANSPORTATION				4	13	26	23	12	11	11	9	23	21	38	46	42	16		295	1.23
HEALTH CARE										6	12	12	10	23	36	28	12		139	0.58
TOTAL	60	897	976	1,090	1,340	1,563	1,540	1,451	1,418	1,431	1,580	1,587	1,710	1,900	2,017	1,815	1,508	7	23,890	100

Table 2 Detail database: relations between listed firm, covered firms, brokers and analysts

					Covered firms		Analysts per covered firm		Covered firms per analyst		Brokers per covered firm		Covered firm per Brokers		Analysts per broker		Brokers per analyst	
Year	**No. listed firms**	**No. covered firms**	**No. Brokers**	**No. Analysts**	**As % of listed firms**	**As % of Mkt. Cap.**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**	**(19)**
1988	262	4	9	8	1,53	2,91	2,25	2	1,13	1,0	3,25	2	1,44	1,0	1,44	1,0	1,63	1
1989	270	78	28	63	28,89	49,08	4,17	3	5,16	3,0	5,46	4	15,21	8,5	3,79	1,5	1,68	1
1990	266	84	33	82	31,58	48,09	5,92	5	6,06	3,5	7,69	6	19,58	16,0	4,06	2,0	1,63	1
1991	272	112	35	156	41,18	53,46	7,41	6	5,32	3,0	8,96	7	28,69	24,0	6,51	3,0	1,46	1
1992	266	119	37	190	44,74	56,16	8,41	8	5,27	3,0	10,62	9	34,16	32,0	7,89	5,0	1,54	1
1993	259	131	44	253	50,58	67,56	9,60	8	4,97	3,0	13,28	11	39,55	36,0	9,61	7,5	1,67	1
1994	260	122	46	165	46,92	62,84	5,45	3	4,03	2,0	12,48	10	33,09	28,5	5,33	4,5	1,48	1
1995	254	140	47	194	55,51	60,76	5,83	4	4,21	2,0	12,87	9	38,34	35,0	5,68	4,0	1,38	1
1996	248	140	49	343	56,45	74,76	10,44	7	4,26	2,0	13,25	10	37,86	31,0	8,92	7,0	1,27	1
1997	239	132	49	337	55,23	82,07	10,29	7	4,03	2,0	13,34	11	35,94	31,0	8,35	7,0	1,21	1
1998	243	139	48	353	57,61	81,81	10,51	7	4,14	2,0	13,09	10	37,90	36,5	8,60	9,0	1,17	1
1999	270	143	54	357	53,33	77,04	10,22	7	4,10	1,0	11,63	9	30,80	19,5	7,54	4,0	1,14	1
2000	297	151	62	413	50,84	80,27	9,12	6	3,33	1,0	10,88	7	26,50	16,5	7,42	4,0	1,11	1
2001	294	178	65	418	60,54	81,75	7,37	4	3,14	1,0	8,88	5	24,31	7,0	7,20	4,0	1,12	1
2002	295	165	72	426	55,93	85,77	7,57	4	2,93	1,0	9,24	6	21,17	7,0	6,58	3,0	1,11	1
2003	279	173	69	549	62,01	91,62	8,92	5	2,81	1,0	8,14	5	20,42	9,0	8,49	6,0	1,07	1
2004	278	153	68	546	55,04	81,90	10,41	6	2,90	1,0	9,56	6	21,37	9,5	8,34	7,0	1,04	1
Mean	267,76	127,29	47,94	285,47	47,52	66,93	7,88	5,41	3,99	1,91	10,15	7,44	27,43	20,47	6,81	4,68	1,34	1

4.
METHODOLOGY DESCRIPTION

4.1.
Optimism/Pessimism

Forecast optimism is inferred from a systematic positive difference between forecast and actual earnings per share.

In the literature on analysts' optimism, different variables have been advanced, but most of them rely on the concept of forecast bias, i.e. the difference between actual and forecast earnings (or vice-versa).

Dreman and Berry (1995), for example, use different variables to measure the degree of analysts' optimism. They propose two main measures called, respectively, SURPE and SURPF. The first one is the consensus earning surprise as a percent of the absolute value of actual Earning Per Share (EPS); the second measure, instead, is the consensus earning surprise as a percent of the absolute value of forecasted earnings per share.

Both measures are often called "percent earning surprise" and they are signed forecast errors, meaning that while at the denominator it is taken the absolute value of (actual or forecasted) earnings per share, at the numerator it is important to keep the sign, to know the direction of the error, optimism or pessimism. When the measure of signed forecast error is positive (percent positive surprise), we know the percentage of time the actual EPS exceeded the forecasted EPS. If it is negative, we have the fraction of times the actual EPS is below the estimate, when is zero, the times the forecast is correct.

Optimism has been documented using Value Line, I/B/E/S, and Zacks data sources for analysts' forecasts [Lim (2001)]. The estimates of analyst's optimism vary across studies in part because of differences in research designs, variable definitions, and time periods examined. Lim (2001), Brown (1997, 2001b), and Richardson et al. (1999, 2004), for example, are studies based on firm-quarter observations and analyzes I/B/E/S forecasts from approximately the same time period from 1983 or 1984 to 1996 or 1997. However, whereas Lim (2001) uses the median of the unrevised estimates of a quarter's earnings across all brokerage firms (although the use of the mean of analysts' forecasts is not uncommon in the literature), Richardson et al. (1999) use individual analyst's forecast and average the forecast errors each month, while Brown (1997) reports results using only the most recent analyst forecast.

With regard to the method of calculating forecast errors, instead, Lim (2001) uses the difference between forecasted and actual earnings per share as reported on *Compustat*, based on the evidence in Philbrick and Ricks (1991) that actual earnings reported by I/B/E/S suffer from the so-called ''alignment problem''. This problem is the evidence that I/B/E/S forecasts appear to exclude special items, while I/B/E/S reported earnings are inconsistent in the treatment of such items. Large discretionary accounting charges could generate extreme negative earnings that skew measures of overall forecast bias. Brown (1997), instead, went in the opposite direction, deciding to use I/B/E/S actual earnings ''for comparability with the forecast'' [Richardson et al. 1999].

To evaluate analysts' optimism, we calculate two measures of forecast errors:

$$FE_1 = \frac{(EST - ACT)}{|ACT|} \qquad (1)$$

$$FE_2 = \frac{(EST - ACT)}{|EST|} \qquad (2)$$

where:

ACT: actual earning realized;
EST: earning forecasted or estimated;
FE_1: forecast error calculated with method 1;
FE_2: forecast error calculated with method 2.

Both measures of forecast errors use the difference between the estimated and the actual (realized) earnings as numerator. It is however necessary to scale this difference to standardize the forecast error, otherwise we could not compare errors referred to different companies, since the magnitude of these errors depends on the absolute levels of the earnings.

Analysis without a deflator implicitly assumes that the magnitude of undeflated or unscaled forecast error is not related to the level of earnings per share (i.e., forecast errors are not heteroskedastic): Brown (1997), Degeorge et al. (1999), and Kasznik and McNichols (2001), for example, do not use a deflator in calculating forecast errors. In contrast, use of earnings or stock price deflation implicitly assumes that the deviation of the actual from forecasted earnings depends on the level of earnings or price per share and that the deflation mitigates heteroskedasticity. Stock price is often used as the appropriate deflator when regressing rates of returns at the time of earnings announcements on "earnings surprises" (predicted minus actual earnings). In this case, the use of any other deflator seems to lead to biased, inconsistent estimators of regression coefficients [Christie (1987)].

To justify the homoskedasticity assumption other variables could be used as deflator. For example, book values of equity or total assets per share seem to be more stable and much less correlated with movement of the financial market. Use of earnings per share or stock prices as deflator could generate artificially small scaled errors during stock market boom years relative to errors in declining years. For example, some firms might have very large EPS simply because they have a very small share base. Comparing unscaled forecast errors across firms in this case could generate potential bias.

The two measures that we use are different for the denominator: in both cases we take absolute values, but in the first one, we scale for actual earnings; while in the second one for estimates. We use the absolute value to avoid affecting the sign of the numerator. If the forecast error is positive, then realized earnings are smaller than earning forecasts, i.e. analysts, on average, are said to be "optimistic" since their estimates lie above actual earnings. If instead forecast error is negative, then pessimism prevails among analysts, since their estimates are below realized earnings.

Performing our calculation, we had to exclude outliers like in previous researches. Lim (2001) excludes absolute forecast errors of $10 per share or more; Degeorge et al. (1999) delete absolute forecast errors greater than 25 cents per share; Richardson et al. (1999, 2004) exclude price-deflated forecast errors that exceed 10% in absolute value.

We decided to exclude forecast errors computed following method 1 and 2 that are greater or lower than three times the actual earning per share (EPS +/- 300 percent). This choice reduces the number of observations in our Detail sample to 47,393. The same procedure applied to the Consensus database permits us to keep only 19,598 observations. This is the first reason for which we decided to focus on the Detail sample, instead of the Consensus one. The second one is that we can use the detailed database to construct our own analysts' consensus.

The great advantage of this choice is that we can check that no errors are made in the construction of the median or mean forecast while taking the consensus calculated by others does not permit this degree of control. Lastly, we found similar results using the two databases, and the differences are not worthy of mention.

4.2.
Distributional characteristics of the signed forecast error

Table 3, panel A, shows descriptive statistic on the distribution of signed forecast errors in the Detail database obtained using method 1. The phenomena of "right tail asymmetry" and of "middle asymmetry" [Abarbanell and Lehavy (2003); Cohen and Lys (2003); Gu and Wu (2003)], instead, are displayed in panel B and C, respectively.

Table 3. Descriptive statistic on the distribution of FEs

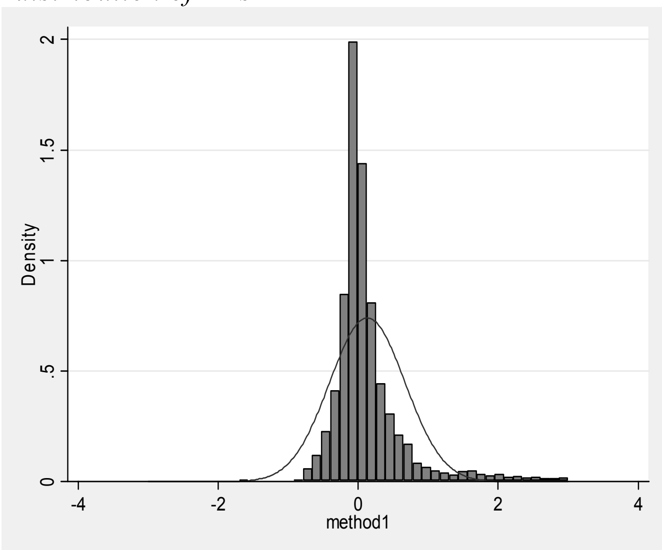
Panel A. Descriptive statistics on distribution of method 1 signed FE		
Number of observations		47,393
Mean		0.13
Median		0.01
% Positive		52%
% Negative		44%
% Zero		4%
Panel B. Statistics on the "tail asymmetry"		
P1		-0.709
P5		-0.431
P10		-0.285
P25		-0.109
P50		0.007
P75		0.222
P90		0.644
P95		1.178
P99		2.382
Panel C. Statistics on the "middle asymmetry"		
Range of forecast errors	**Ratio of positive to negative forecast errors**	**% of total number of observations**
[1]	**[2]**	**[3]**
Overall		100%
Forecast error = 0		4%
[-0.1, 0) & (0, 0.1]	0.83	34%
[-0.2, -0.1) & (0.1, 0.2]	0.92	21%
[-0.3, -0.2) & (0.2, 0.3]	0.96	12%
[-0.4, -0.3) & (0.3, 0.4]	1.22	9%
[-0.5, -0.4) & (0.4, 0.5]	0.99	5%
[-1, -0.5) & (0.5, 1]	2.58	10%
[min,-1) & (1,max]	7.89	6%

Panel B shows that the absolute value of the forecast error in the 99th, 95th and 90th percentiles is approximately 3.36, 2.76 and 2.26 times as large as the forecast error in the 1st, 5th and 10th percentiles. This evidence is generally interpreted as indicative of the presence of the right-tail asymmetry. In fact, the right tail is longer and fatter than the left tail, i.e. far more extreme forecast errors of greater absolute magnitude are observed in the *ex-post* optimistic tail of the distribution than in the pessimistic tail.

Panel C, instead, highlights the so-called "middle asymmetry" of the forecast error distribution, i.e. the evidence that the frequency of small negative FEs is larger than the one of small positive FEs. In order to verify this evidence, we used the methodology proposed by Abarbanell and Lehavy (2003), computing the ratio of positive (optimistic) errors to negative (pessimistic) errors for observations that fall into increasingly longer and non-overlapping intervals moving out from zero forecast error. If middle asymmetry exists we should observe an increasing pattern of the ratio moving from the smallest forecast error interval [-0.1, 0) & (0, 0.1] toward the larger one, [min, -1) & (1, max], in that values of the ratio less than 1 show prevalence of negative (pessimistic errors) versus positive (optimistic errors).

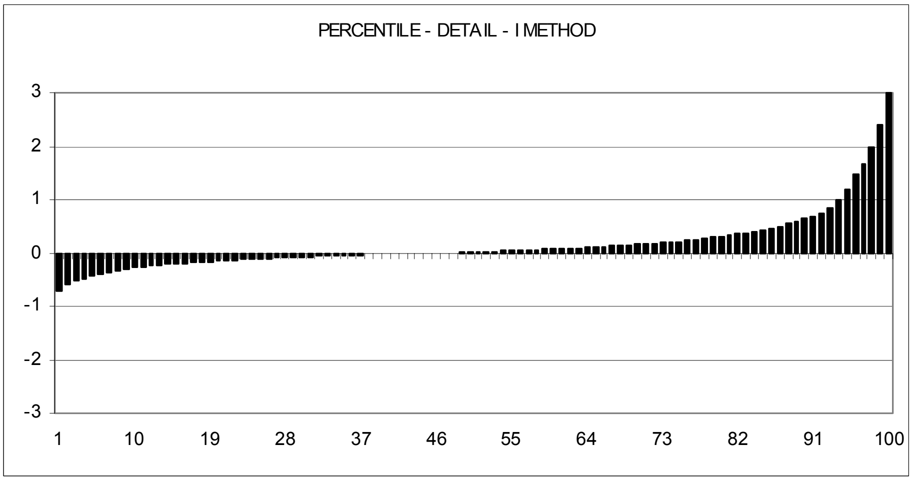
While our evidence for right tail asymmetry is consistent with the prior literature, the results for middle asymmetry are mixed. The ratio follows as expected an increasing pattern from the first category (i.e. error close to zero) to the last (larger error in value). Only the middle category shows an inverse pattern, different changes of the sign of growth, even if the ratio correctly increases toward extreme class of forecast errors.

Figure 2 Frequency distribution of FEs



Figures 2 and 3 graphically show the relevant aspects about the distributions of signed forecast errors used to assess the level of analysts' optimism/pessimism bias. We focus our analysis on forecast error computed with method 1 on the detail database. Using method 2 or the consensus database gives very similar results. The distribution appears to be not normally distributed exhibiting high occurrences of extreme positive forecast errors (high optimism) and of small negative forecast errors (low pessimism).

Figure 3 Cumulative frequency distribution of FEs



4.3. Accuracy

As mentioned, the literature on forecast errors and analysts' accuracy is literally huge [e.g. O' Brien (1988); Kang, O' Brien, and Sivaramalrrishnan (1994); and Das, Levine, and Sivaramalrrishnan (1997)].

To measure accuracy, instead of optimism/pessimism, it is necessary to consider the Unsigned Forecast Error (UFE), defined as the ration between the absolute value of the difference between estimated and actual earnings and the absolute value of either actual or predicted earnings. Thus, depending on the deflator, we have two measures:

$$UFE_1 = \frac{|EST - ACT|}{|ACT|} \tag{3}$$

$$UFE_2 = \frac{|EST - ACT|}{|EST|} \tag{4}$$

where:

ACT is the actual earning realized;
EST is the earning forecasted or estimated;
UFE_1 is the unsigned forecast error calculated with method 1;
UFE_2 is the unsigned forecast error calculated with method 2.

These measures are similar to those used to study analysts' optimism/pessimism, but at the numerator we take the absolute value. In this way, we can only find positive values and therefore calculate analysts' accuracy.

5. RESULTS
5.1. Optimism/Pessimism

We want to analyze the trend of forecast errors starting one year before the release date. We expect the forecast error to decrease approaching the actual earning release date since, as time goes by, new information is given to the market and to analysts that can adjust their estimates in the right direction. We first take the signed forecast errors since we are interested in studying how the optimism of analysts varies over time. The results are contained in table 4.

Table 4 Detail: Optimism and Pessimism with method 1 and 2 over time

FORECAST ERROR DETAIL (Excluding Observation -/+300%)

		MEDIANs		MEANs		STD. DEV.s		OPTIMISM - PESSIMISM			
Months	N	Method 1	Method 2	Method 1	Method 2	Method 1	Method 2	% > 0	% < 0	% = 0	Opt-Pes
12	3,079	0.071	0.066	0.246	0.103	0.644	0.613	59.63	38.36	2.01	21.27
11	3,633	0.039	0.038	0.203	0.069	0.619	0.627	55.35	42.77	1.87	12.58
10	3,935	0.060	0.056	0.209	0.098	0.600	0.608	58.07	40.74	1.19	17.33
9	3,726	0.036	0.035	0.180	0.076	0.576	0.579	55.18	43.51	1.32	11.67
8	3,850	0.028	0.028	0.162	0.066	0.545	0.562	54.03	43.87	2.10	10.16
7	4,589	0.024	0.024	0.130	0.041	0.551	0.551	53.56	44.15	2.29	9.41
6	4,201	0.012	0.011	0.120	0.029	0.539	0.549	51.34	46.56	2.09	4.78
5	4,067	0.000	0.000	0.103	0.024	0.535	0.545	50.01	46.87	3.12	3.15
4	3,860	0.002	0.002	0.094	0.044	0.471	0.546	50.39	46.14	3.47	4.25
3	3,837	0.000	0.000	0.071	0.011	0.486	0.486	48.16	47.07	4.77	1.09
2	4,469	0.000	0.000	0.054	-0.017	0.446	0.457	46.41	47.04	6.56	-0.63
1	4,147	0.000	0.000	0.034	-0.018	0.405	0.417	41.55	45.89	12.56	-4.34

N	47,393

Figure 4 graphically represents the content of table 4: median forecast errors are about 7% one year before the release date (7.1% and 6.6% for method 1 and 2) and decrease over time hitting the level zero three months before that date.

The same trend is observed considering mean forecast errors, even though, as means are more influenced by extreme value, there is a difference in magnitude.

As shown in figure 4bis, twelve months before the release date, the mean FE is 24.6% using method 1, and just 10.3% using method 2. They both decline over time, but while for the first method it remains positive, for the second it becomes negative two months before the actual earnings are announced.

Furthermore, figure 5 shows FEs' standard deviations starting at a high level (over 60% for both methods) and gradually declining as time goes by to about 40% one month before the release date.

The pattern followed by FEs' standard deviation seems to suggest that the dispersion of forecasts decreases over time, in line with the intuition that analysts adjust earnings estimates as new information becomes available approaching the release date.

Figure 4 Median Forecast Errors before the release date (Detail database)

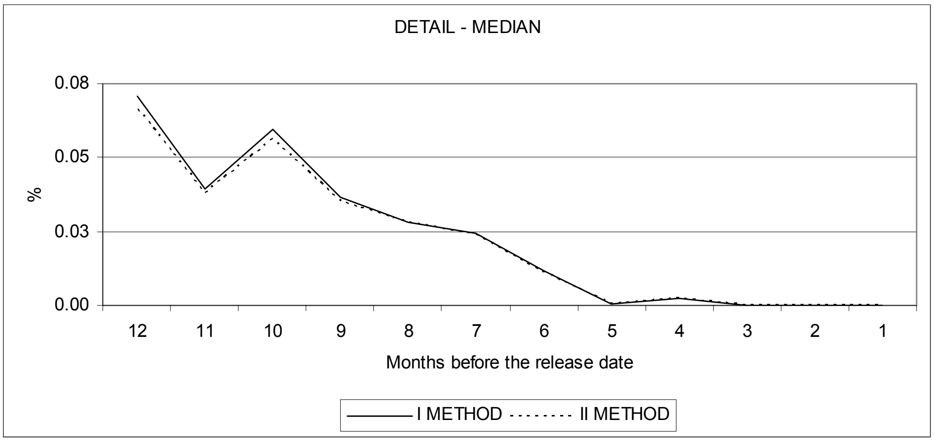


Figure 4bis Mean FEs before the release date (Detail database)

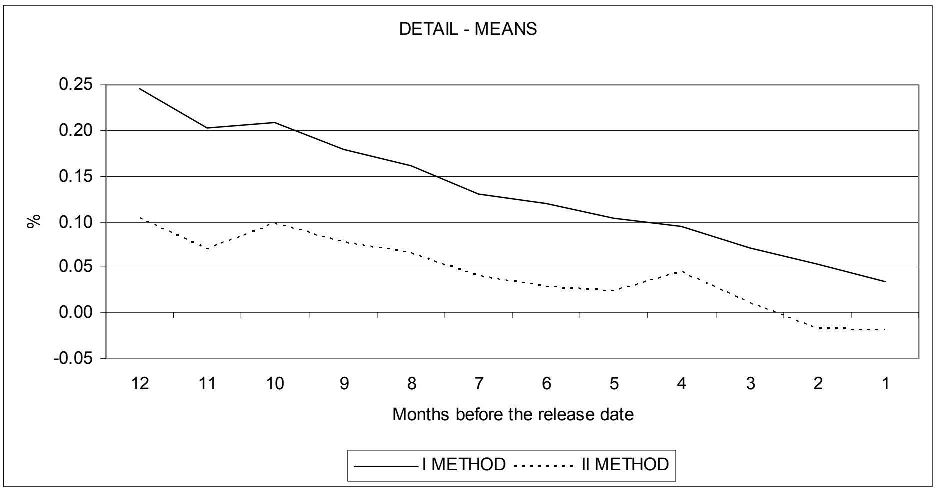
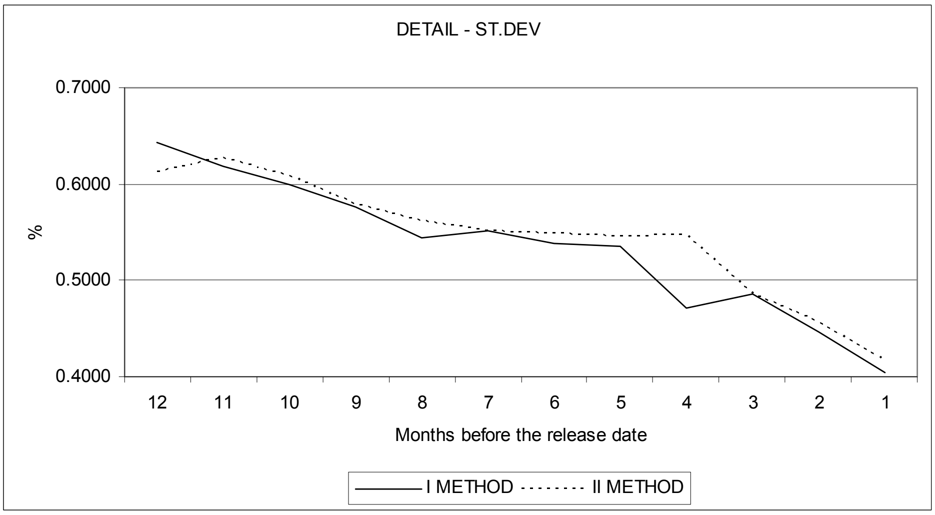


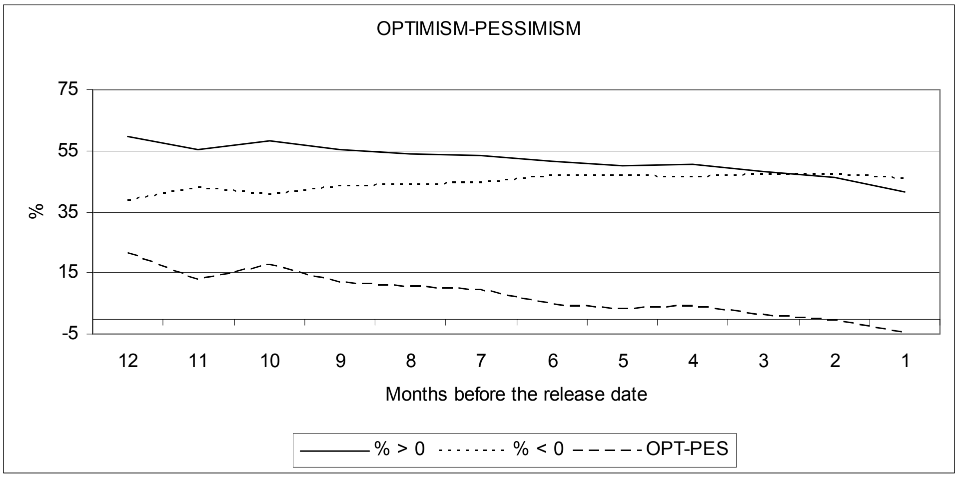
Figure 5 FEs Standard Deviations before the release date (Detail database)



The variable "OPT-PES", displayed in figure 6, is just the difference between the fraction of positive FEs (%>0), displaying optimism, and the percentage of negative ones (%<0), showing pessimism, as calculated in table 4. As can be noticed, this variable passes from positive to negative values two months before the release date, meaning that analysts shift from optimism to pessimism. Optimism is based on uncertainty; therefore, as new information arrives in the market, the degree of optimism should decrease.

Two different explanations can be advanced to explain optimism: behavioural and traditional. The behavioural one claims that psychological traits push analysts to be overly optimistic in their estimates. The traditional view, instead, states that analysts are rationally optimistic, i.e. their behaviours perfectly match with their objective function. It should be kept in mind, in fact, that the remuneration of analysts basically depends of two factors: reputation and the amount of business they can bring to their bank.

Figure 6 Optimism/Pessimism (Detail database)



4.1.1. Clusters for Optimism-Pessimism

Table 5 shows an additional analysis performed aggregating forecast errors in four clusters, permitting us to divide in longer sub-periods the analysis. The reason to do this is that the division in months is somehow limitative, in a sense that estimates issued at the end of one month should probably be considered together with the ones issued at the beginning of the previous one.

Consider, also, that quarterly earnings reports are in general not available for Italian listed firms so our research design employs annual earnings announcements.

An additional problem is that often earnings are released with a substantial delay after the fiscal year-end. By the time earnings are publicly announced, investors probably already had a good grasp of what actual earnings would end to be. The implication is that many individuals already have access to the information on actual earnings before the public announcement date. The clusters are built to contain each three months: the first from month one to three, the second from the fourth to the sixth month, the third from the seventh to the ninth, and the last one from the tenth to the twelfth.

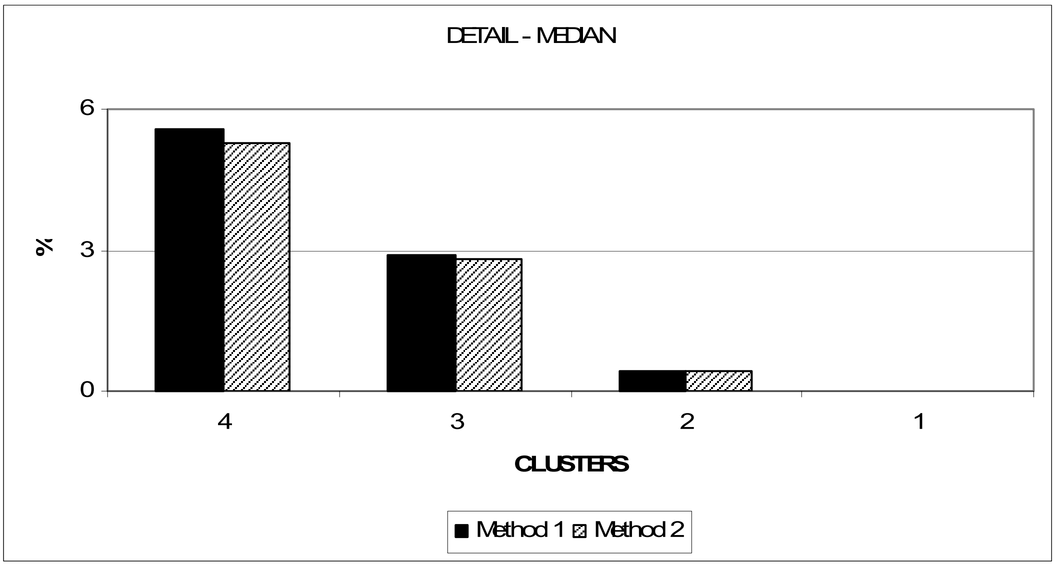
Table 5 Detail database: FEs calculated with method 1 and 2 over time clusters

FORECAST ERROR DETAIL (Excluding Observation -/+300%)

		MEDIANs		MEANs		ST. DEVs		OPTIMISM - PESSIMISM			
Cluster	N	Met. 1	Met. 2	Met. 1	Met. 2	Met. 1	Met. 2	% > 0	% < 0	% = 0	OPT-PES%
4	10,647	5.56	5.26	21.76	8.98	61.95	61.62	57.59	40.74	1.66	16.85
3	12,165	2.89	2.82	15.52	5.96	55.73	56.32	54.20	43.86	1.93	10.34
2	12,128	0.44	0.44	10.60	3.20	51.71	54.68	50.59	46.53	2.88	4.06
1	12,453	0.00	0.00	5.27	-0.91	44.61	45.35	45.33	46.66	8.01	-1.33
N	47,393										

The median forecast error for method 1 in the clusters displays a pattern similar to the one showed in figure 2 where all months before release date were represented. Cluster 4, the most far in the past, shows that analysts start with a high degree of optimism, given a forecast error of about 5%. In cluster 3, FE decreases to less than 3%, a quite relevant decline compared to cluster 4, suggesting a sharp revision of forecasts from the last quarter to the following one. From cluster 3 to 2 the decline is even more dramatic, falling to a FE of 0.44%, dropping to zero in cluster 1. This pattern suggests that in the last months a lot of information is disclosed to the market and becomes available to the analysts, allowing them to improve their estimates, dramatically reducing FE.

Figure 7 Median Forecast Errors before the release date in Clusters (Detail database)



The pattern followed by mean FEs is similar to the one observed for medians, except for two facts: method 1 always records values significantly greater than method 2; while for method 1 in cluster 1 the FE is still positive (about 5%), with method 2 it becomes negative, showing pessimism.

Figure 7bis Mean FEs before the release date (Detail database)

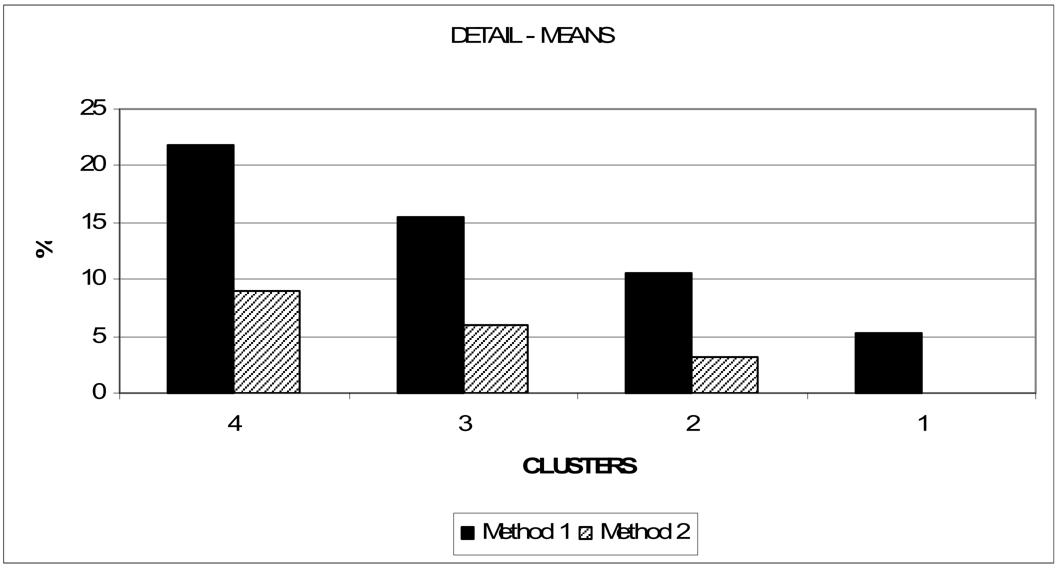
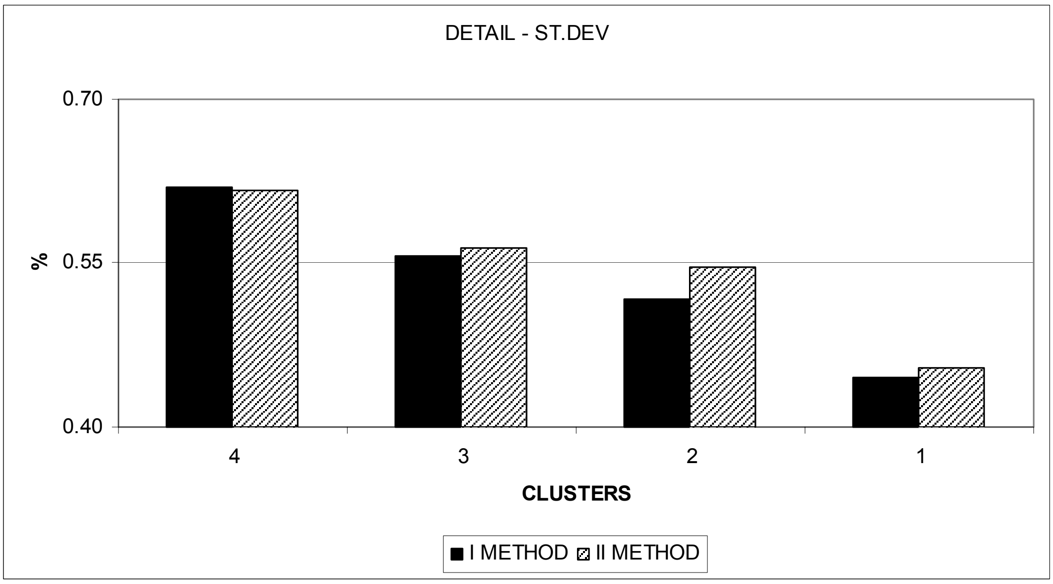


Figure 8 FEs Standard Deviations before the release date in Clusters (Detail database)



The FEs standard deviation, starting from a high level of about 60% in cluster 4 declines quite gradually over time to a level of about 45% in cluster 1. This seems to suggest that, in clusterizing by quarters analysts' forecasts, the precision increase over time, but not in a dramatic fashion.

Figure 9 shows three series, clusterized by quarter. The first one is the percentage of positive FEs (%>0), i.e. the situation in which the forecast is greater than actual earnings, displaying optimism. The second one is the fraction of negative FEs (%<0) that is when analysts are pessimistic, issuing earnings forecast below actual realizations. Finally, the variable "OPT-PES" is just the difference between the two, highlighting eventual shifts from optimism to pessimism. This happens in cluster 1, i.e. in the three months before the release date. In other words, even if median FE remains positive until the end, this new result suggests that the percentage of pessimistic forecasts is greater than optimistic one in the last months preceding the release date. This can be due to the fact that, even if the fraction of negative FEs is greater than the percentage of positive ones, the magnitude of optimistic forecasts is much higher. This evidence seemingly supports the idea the also in the Italian market the so-called "earning guidance game" is verified, even if not as much as the evidence in the US suggests.

Figure 9 Optimism/Pessimism before the release date (Detail database)

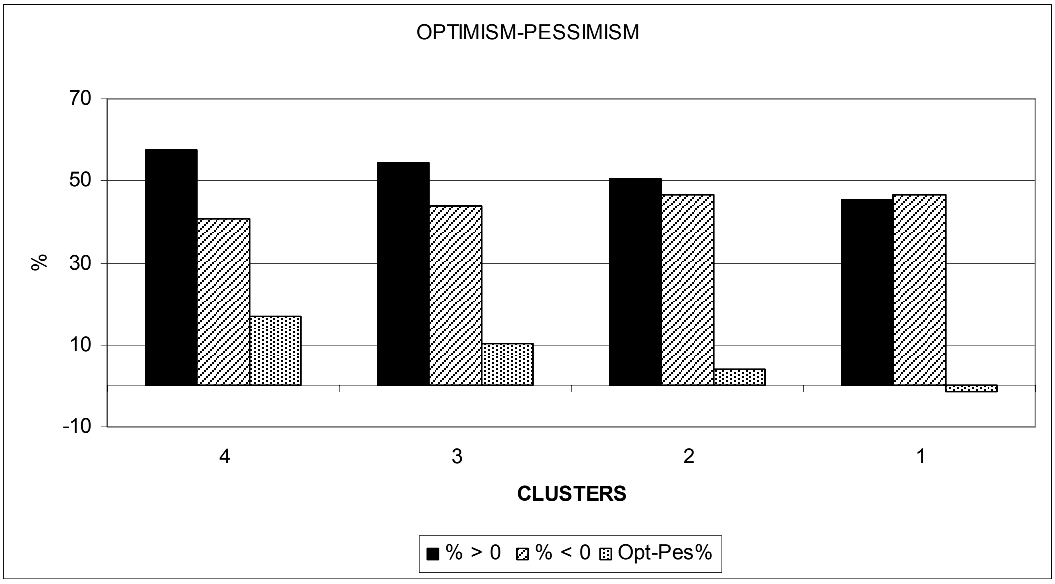


Table 6 shows FEs (medians, means, and standard deviations) as well as optimism *versus* pessimism for all the years in our sample.

While table 6 gives some detailed information, it is immediate to see that the number of observations in each year is quite volatile, rising statistical problems. Thus, we decided to clusterize median FEs by years. Table 7 shows the results. Subdividing the sample in sub-periods containing three years each basically has two advances: first, it solves, at least in part, statistical problems due to lack of data; second, it gives us a better grasp of different degrees of optimism among analysts in different periods in time.

As can be seen from the figures, the sub-period 96-98 show negative FEs since the beginning. This can be due both to the fact that in those years analysts where actually pessimistic, but can also be caused by statistical problems due to lack of data.

It seems in fact that analysts were more optimistic at the end of the '80s and early '90s than in late 90's or in last years where the degree of optimism was the lower.

Table 6 Detail database: Median, Mean FEs and Optimism-Pessimism per year

FORECAST ERROR DETAIL (Excluding Observation -/+300%)

		Medians		Means		Standar Deviations		Optimism – Pessimism			
Year	N	Method 1	Method 2	Method 1	Method 2	Method 1	Method 2	% > 0	% < 0	% = 0	Opt-Pes
1987	13	0.09	0.08	0.14	0.10	0.21	0.16	69.23	23.08	7.69	0.46
1988	692	0.00	0.00	0.10	0.04	0.40	0.37	51.73	43.21	5.06	0.09
1989	1,126	0.06	0.06	0.14	0.07	0.32	0.27	65.81	31.08	3.11	0.35
1990	1,995	0.05	0.05	0.22	0.10	0.48	0.32	63.71	32.53	3.76	0.31
1991	2,214	0.00	0.00	0.11	0.01	0.49	0.49	51.63	46.25	2.12	0.05
1992	3,812	0.10	0.09	0.29	0.26	0.57	0.66	66.89	27.73	5.38	0.39
1993	3,186	0.00	0.00	0.10	0.07	0.59	0.60	51.51	44.16	4.33	0.07
1994	3,304	0.04	0.04	0.15	0.07	0.58	0.70	55.63	40.47	3.90	0.15
1995	3,796	0.00	0.00	0.08	-0.02	0.47	0.50	46.63	51.63	1.74	-0.05
1996	4,358	0.01	0.01	0.10	0.02	0.50	0.40	52.13	47.32	0.55	0.05
1997	4,313	-0.03	-0.03	0.04	-0.07	0.49	0.41	39.14	60.86	0.00	-0.22
1998	1,244	0.00	0.00	0.11	0.00	0.54	0.40	47.51	46.70	5.79	0.01
1999	3,062	0.00	0.00	0.10	-0.03	0.53	0.45	42.78	48.11	9.11	-0.05
2000	3,334	-0.02	-0.02	0.06	-0.07	0.51	0.47	42.17	51.71	6.12	-0.10
2001	3,852	0.09	0.08	0.27	0.18	0.66	0.65	62.62	33.36	4.02	0.29
2002	3,207	0.04	0.03	0.14	0.02	0.59	0.72	54.29	41.38	4.33	0.13
2003	3,883	-0.01	-0.01	0.07	0.01	0.49	0.54	45.45	50.58	3.97	-0.05
2004	2	0.07	0.13	0.07	0.13	0.29	0.36	50.00	50.00	0.00	0.00
Total	47,393	0.01	0.01	0.13	0.04	0.54	0.55	51.71	44.58	3.71	0.07

Table 7 Detail database: median FEs per cluster-years

FORECAST ERROR DETAIL (Excluding Observation -/+300%)

N.	87-89		90-92		93-95		96-98		99-01		02-04	
	Met. 1	Met. 2	Met. 1	Met. 2	Met. 1	Met. 2	Met. 1	Met. 2	Met. 1	Met. 2	Met. 1	Met. 2
4	0.0841	0.0776	0.1791	0.1519	0.0634	0.0596	-0.0085	-0.0086	0.0800	0.0741	0.0000	0.0000
3	0.0617	0.0581	0.0813	0.0752	0.0364	0.0351	-0.0203	-0.0207	0.0435	0.0417	0.0116	0.0115
2	0.0538	0.0511	0.0680	0.0636	0.0000	0.0000	-0.0160	-0.0163	0.0000	0.0000	0.0000	0.0000
1	0.0017	0.0017	0.0000	0.0000	0.0000	0.0000	-0.0044	-0.0044	-0.0106	-0.0107	0.0000	0.0000

Figure 10.A Median FEs in Clusters per years (Detail database) – Method 1

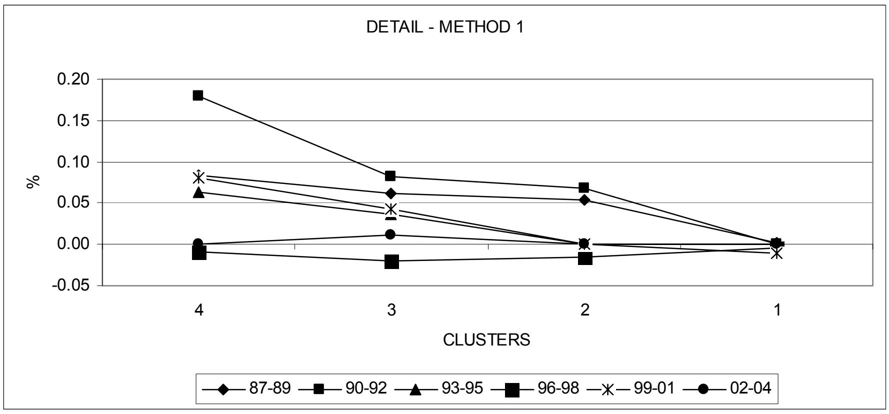
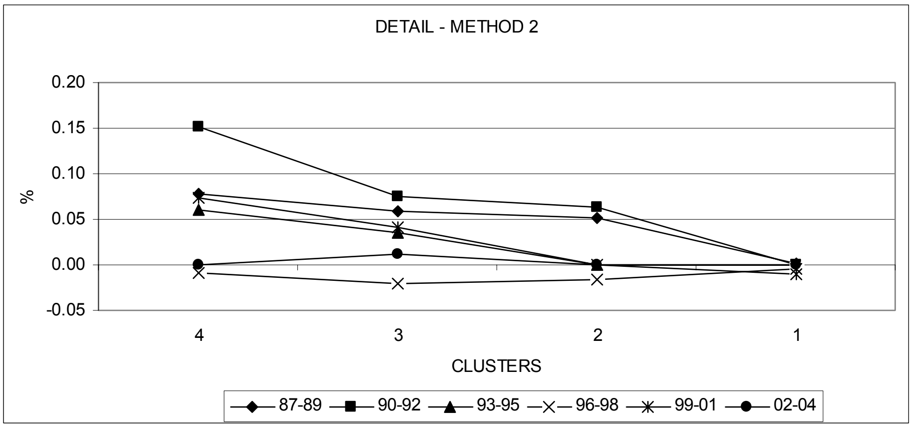


Figure 10.B Median FEs in Clusters per years (Detail database) – Method II



5.2. Accuracy

In what follows, we focus on the Detail database, analyzing forecast accuracy, as measured by the Unsigned Forecast Error (UFE).

Table 8 shows how accuracy changes over time. One year before actual earnings are released, the median UFE is about 19% (with both methods), remaining quite stable for the following five months, and then gradually decreasing to almost 8%.

While, analyzing the degree of optimism, we highlighted that the signed forecast error reached zero as early as two months before the release date; the unsigned forecast error does not go to zero, but remains positive. This means that, while optimism vanishes just before the release date, analysts still commit errors, even though their accuracy increases over time.

Furthermore, standard deviations decrease over time, supporting the idea of greater consensus among analysts and more accuracy as new information arrives to the market and is incorporated in analysts' forecasts.

Figures 11 and 12 show, respectively, UFE's medians and standard deviations in the twelve months before the release date.

Table 8 Detail database: Medians, Means, Standard Deviations for UFEs

UNSIGNED FORECAST ERROR DETAIL (Excluding Observation -/+300%)							
		MEDIANs		MEANs		STANDARD DEVIATIONs	
Months	**N**	**Method 1**	**Method 2**	**Method 1**	**Method 2**	**Method 1**	**Method 2**
12	3,079	0.194	0.189	0.401	0.356	0.561	0.510
11	3,633	0.195	0.192	0.386	0.363	0.525	0.516
10	3,935	0.195	0.186	0.376	0.353	0.512	0.505
9	3,726	0.191	0.186	0.357	0.337	0.486	0.476
8	3,850	0.180	0.178	0.336	0.323	0.459	0.464
7	4,589	0.167	0.161	0.321	0.311	0.467	0.457
6	4,201	0.164	0.161	0.315	0.313	0.453	0.451
5	4,067	0.154	0.153	0.307	0.309	0.451	0.450
4	3,860	0.143	0.141	0.272	0.297	0.396	0.461
3	3,837	0.134	0.133	0.267	0.266	0.413	0.407
2	4,469	0.107	0.107	0.233	0.239	0.384	0.390
1	4,147	0.077	0.078	0.196	0.202	0.356	0.365
N	47,393						

Figure 11 Accuracy: Median UFEs before the release date

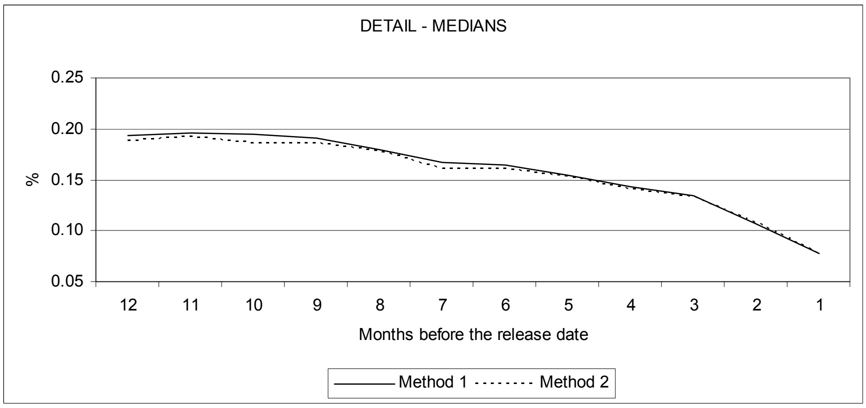


Figure 12 Accuracy: UFEs' Standard Deviations before the release date

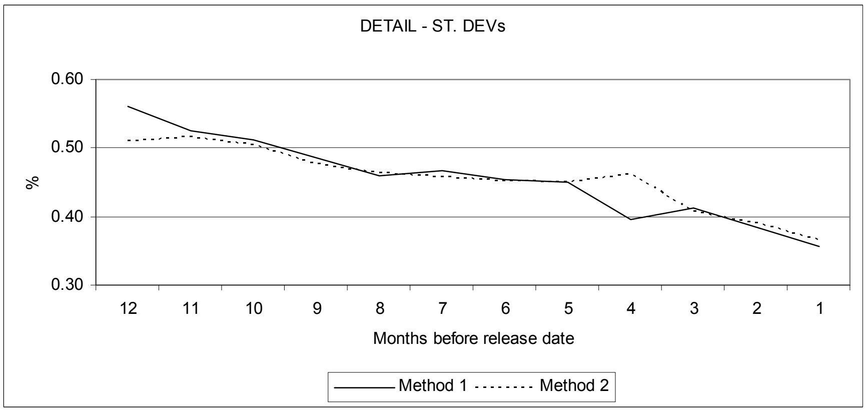


Table 9 Detail database: Medians, Means, Standard Deviations for UFEs

UNSIGNED FORECAST ERROR DETAIL (Excluding Observation -/+300%)

		MEDIANs		MEANs		STANDARD DEVIATIONs	
CLUSTER	N	Method 1	Method 2	Method 1	Method 2	Method 1	Method 2
4	10647	0.1947	0.1895	0.3865	0.3575	0.5308	0.5099
3	12165	0.1770	0.1739	0.3365	0.3231	0.4706	0.4652
2	12128	0.1528	0.1515	0.2986	0.3067	0.4352	0.4538
1	12453	0.1055	0.1064	0.2313	0.2349	0.3850	0.3881
N	47393						

Table 9 is obtained dividing the year preceding the release date in four clusters, each of three months. For each cluster, we calculated UFE's means, medians and standard deviations as in table 8. As it possible to see in figures 13 and 14, the pattern followed by UFE's means and standard deviations closely resembles the ones pictured in figures 11 and 12.

Figure 13 Accuracy: Median UFEs before the release date, divided in clusters

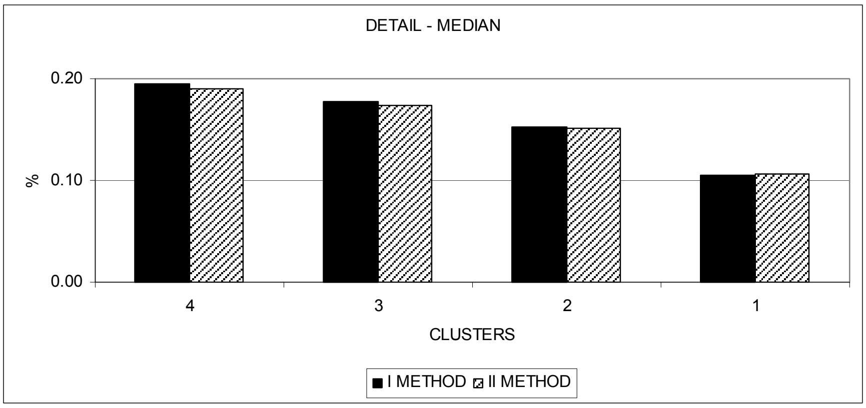


Figure 14 Accuracy: UFEs' Standard Deviations before the release date, in clusters

It could be interesting to investigate if analysts' accuracy changed over time. This is done in table 10, summarizing medians, means and standard deviations for UFEs in all sample-years.

Table 10 Detail database: Medians, Means, Standard Deviations for UFEs over time

UNSIGNED FORECAST ERROR DETAIL (Excluding Observation -/+300%)							
		MEDIANs		**MEANs**		**STANDARD DEVIATIONs**	
Year	**N**	**Method 1**	**Method 2**	**Method 1**	**Method 2**	**Method 1**	**Method 2**
1987	13	0.094	0.086	0.181	0.143	0.174	0.120
1988	692	0.080	0.078	0.198	0.175	0.357	0.328
1989	1,126	0.117	0.110	0.217	0.172	0.275	0.217
1990	1,995	0.126	0.119	0.293	0.200	0.440	0.267
1991	2,214	0.136	0.134	0.272	0.270	0.425	0.413
1992	3,812	0.186	0.174	0.377	0.383	0.516	0.597
1993	3,186	0.170	0.169	0.345	0.342	0.486	0.499
1994	3,304	0.197	0.193	0.349	0.405	0.490	0.573
1995	3,796	0.139	0.141	0.261	0.275	0.402	0.422
1996	4,358	0.141	0.143	0.288	0.240	0.425	0.317
1997	4,313	0.108	0.111	0.238	0.234	0.429	0.348
1998	1,244	0.113	0.119	0.276	0.220	0.481	0.337
1999	3,062	0.157	0.158	0.290	0.261	0.453	0.372
2000	3,334	0.167	0.169	0.291	0.286	0.421	0.373
2001	3,852	0.195	0.185	0.423	0.376	0.577	0.564
2002	3,207	0.224	0.216	0.378	0.437	0.476	0.579
2003	3,883	0.170	0.171	0.292	0.310	0.395	0.444
2004	2	0.206	0.252	0.206	0.252	0.102	0.189
Total sample	47,393	0.155	0.154	0.310	0.303	0.459	0.456

UFEs, as well as the number of observations, vary a lot from year to year causing problems in terms of statistical significance. To avoid this problem and have a better idea of how accuracy changed over time, we divided the sample in sub-periods of three years, as shown in table 11.

Table 11 Detail database: Medians, Means, Standard Deviations for UFEs over time

UNSIGNED FORECAST ERROR DETAIL (Excluding Observation -/+300%)												
Cluster	**87-89**		**90-92**		**93-95**		**96-98**		**99-01**		**02-04**	
	Met. 1	**Met. 2**	**Met. 1**	**Met. 2**	**Met. 1**	**Met. 2**	**Met. 1**	**Met. 2**	**Met. 1**	**Met. 2**	**Met. 1**	**Met. 2**
4	0.1821	0.1773	0.2325	0.2165	0.2116	0.2029	0.1441	0.1496	0.2143	0.2000	0.1947	0.1948
3	0.1384	0.1399	0.1762	0.1671	0.1992	0.1966	0.1338	0.1363	0.1880	0.1883	0.2086	0.2142
2	0.1096	0.1058	0.1633	0.1573	0.1724	0.1732	0.1151	0.1181	0.1507	0.1503	0.1884	0.1815
1	0.0400	0.0404	0.0649	0.0657	0.1031	0.1044	0.1023	0.1037	0.1315	0.1321	0.1714	0.1687

The results contained in table 11 are graphically shown in figures 15.A and 15.B, respectively for method 1 and 2. It seems that the sample period can be divided in two main sub-periods: the first from 1987 to 1995 and the second one from 1996 to 2004. The first sub-period is characterized by the fact that unsigned forecast errors start quite high (around 20%) one year before the release date, but then decrease quite heavily in a range between 4% and 10%. In the second sub-period, instead, the starting level is almost the same, but the unsigned forecast errors declines more gradually, remaining quite high, between 10% and 17%.

Figure 15.A Median FEs in Clusters per years (Detail database) – Method 1

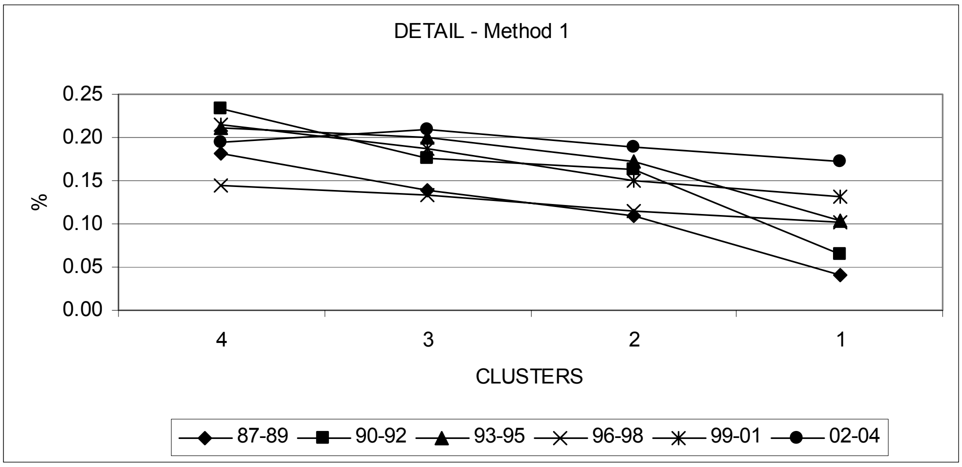
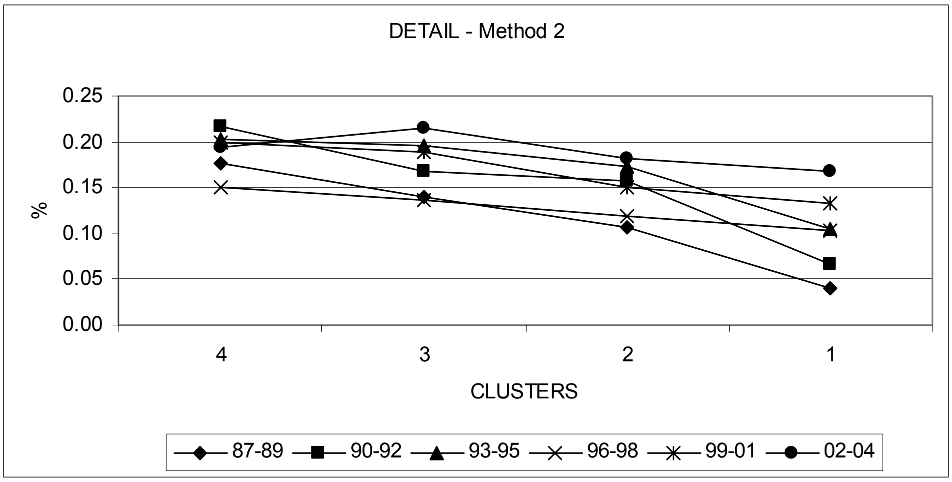


Figure 15.B Median FEs in Clusters per years (Detail database) – Method 2



In other words, it seems that until mid '90s analysts started their forecasts showing low levels of accuracy, but then increasing it substantially approaching the actual earnings release date. In the second sub-periods, instead, analysts seem not to improve accuracy that much, even when news is probably to occur as the release date approaches.

6.
REGRESSION ANALYSIS
6.1.
Variables and models description

In order to analyze the variables that contribute to explain analysts' forecast error, we performed two regressions. The first one, the "complete" model, includes all the considered variables, while the second, the "restricted" model, excludes all the variables referred to brokers or analysts. The reason is that even though these variables are important for the analysis, we have several missing values in our database notably reducing the number of observations.

The dependent variable in both regression analyses is the unsigned forecast error (UFE_1). We also performed the two regressions using the alternative measure of unsigned forecast error (UFE_2) but, as we obtained very close results, we chose not to report them.

In what follows, we describe the explanatory variables used in our regressions, highlighting our expectations in terms of their effect on the unsigned forecast error.

Explanatory variable	**Description**	**Expected relation with Unsigned Forecast Error**
months	Number of months between forecast and release date	**Positive**: the more far in the past is the forecast, the larger the UFE
ln_cap	Natural logarithm of market capitalization of the firm in the preceding year (proxy of size)	**Negative**: the bigger the company, the lower the UFE
profit	Dummy variable equal to 1 if the firm records a profit (0 if loss)	**Negative**: profit firms usually record lower UFEs
prev_ profit	Dummy variable equal to 1 if the firm records a profit in the previous year	**Negative**: for firms already in profit, analysts' optimism can increase UFEs
Bull	Dummy variable equal to 1 if there is an increase in market index price in the fiscal year of reference	**Negative**: an increase in general level of market prices is associated with lower UFEs
Size_broker	Number of analysts employed by the broker in the fiscal year of reference	**Negative**: the bigger the broker, the lower the UFE
general_experience	Number of years of general experience for the analyst	**Negative:** the bigger the experience, the lower the UFE
firm_experience	Number of years of firm-specific experience for the analyst	**Negative**: the bigger the firm experience, the lower the UFE
companies	Number of companies followed by the analyst in the fiscal year of reference	**Positive**: more companies followed by the analyst should result in bigger UFEs
sectorial dummies	We considered ten dummies, one for each sector	**Different, depending on sector**

The variable "months" permits to understand the impact of time on forecasts. We decided to insert it in our regression analysis to further support the evidence found in the literature that, approaching the actual earnings release date, analysts' forecasts become more precise, given the fact that additional information reaches the market as time goes by.

The market capitalization is taken one year before the fiscal year to which the forecast refers. The reason is that analysts can decide to cover or not a firm, depending on the expected level of commissions that could be earned on it. Typically, analysts decide to cover bigger firms since the level of expected commissions is high [Richardson, Teoh, Wisocki (2004)]. Of course, the decision is taken before the release date, i.e. one year in advance with respect to the actual earning is known. This variable is important since we can analyze how firm size affects analysts' forecasts. Given the evidence that bigger companies are followed by a greater number of analysts, we can expect a greater degree of accuracy. Besides, bigger companies have more stringent transparency requirements, thus increasing the information transmitted to the market.

"Profit" is a dummy variable that is equal to 1 if, in the fiscal year of reference, the covered company records a profit, and zero otherwise. It is well-known in the literature that, on average, forecast error is greater for firms that record a loss, given the optimistic bias of analysts that tend, on average, to issue positive earning forecasts. "Prev_profit", is instead a dummy variable equal to 1 if the covered company recorded a profit in the year preceding the one of reference. It can be that for firms already in profit, analyst' optimism is greater, increasing forecast errors and decreasing accuracy. While Das (1998) use year specific effects to account for differences in bias or accuracy that could be attributed to macroeconomic factors, we use the dummy variable "bull" that equals 1 (bull markets) if the market has increased with respect to the previous year.

"Size_broker" permits to understand how broker size affects analysts' forecast ability. Since we take broker size as a proxy for analysts' quality, thinking that bigger brokers could hire more accurate analysts; we expect that bigger brokers issue more accurate forecasts, on average.

As mentioned earlier "general_experience" is expected to reduce the unsigned forecast error. However, looking at previous studies in the literature, it is not clear if general experience is the right proxy to measure analysts' accuracy, since it often appears not to be statistically significant [Mikhail et al. (1997, 2004)].

"Firm_experience" has a negative impact on forecast errors, i.e. more specialized analysts should be more accurate. In the literature, it is shown that specific experience of a particular company is statistically significant. If an analyst follows more companies, this could mean a lower degree of specialization, increasing the forecast error.

The dummy variables for sectors are included to consider the differences in accuracy across industries [O' Brien (1990); Sinha, Brown, and Das (1997)].

Following the I/B/E/S sectorial classification, we use ten dummy variables to distinguish the sectors, namely: capital goods; consumer durables; consumer non durables; consumer services; energy; finance; health care; public utilities; technology; transportation. The dummy used as benchmark, and therefore excluded from the regression, is "basic industries".

Then, while the complete regression model considers all the variables above-described; the restricted model excludes those related to brokers or analysts' characteristics, i.e. "size_broker", "general_experience", "firm_experience", and "companies". As in this model we do not consider analysts-related variables, we excluded all the observations for which the codes identifying the analyst are not available on the I/B/E/S dataset. The complete and restricted model equations are presented below, respectively, in equations (5) and (6):

$$\begin{aligned} UFE = b_0 &+ b_1(months) + b_2(ln\_cap) + b_3(firm\_experience) + b_4(prev\_profit) + b_5(bull) \\ &+ b_6(size\_broker) + b_7(general\_experience) + b_8(firm\_experience) + b_9(companies) \\ &+ \sum_{i=10}^{19}(sectorial\ dummies_i) \end{aligned} \tag{5}$$

$$\begin{aligned} UFE = b_0 &+ b_1(months) + b_2(ln\_cap) + b_3(firm\_experience) + b_4(prev\_profit) + b_5(bull) \\ &+ \sum_{i=6}^{16}(sectorial\ dummies_i) \end{aligned} \tag{6}$$

6.2. Results

In what follows, we present our models that, as it is possible to notice, according to the F-test and to the value of the R-squared, are both well specified.

Complete Regression Model

Number of obs.	25,899
F(19, 25879)	130.51
Prob > F	0.0000
R-squared	0.1355
Root MSE	0.4167

UFE_1	Coef.	Robust Std. Err.	t	P>|t|	[95% Confidence Interval]	
months	0.0174	0.0008	22.4200	0.0000	0.0158	0.0189
Ln_cap	-0.0098	0.0020	-5.0100	0.0000	-0.0136	-0.0060
profit	-0.5093	0.0225	-22.6500	0.0000	-0.5533	-0.4652
prev_profit	0.0427	0.0190	2.2400	0.0250	0.0054	0.0800
bull	-0.0578	0.0056	-10.3700	0.0000	-0.0687	-0.0468
size_broker	-0.0007	0.0004	-1.7900	0.0730	-0.0016	0.0001
general_experience	-0.0017	0.0020	-0.8200	0.4140	-0.0056	0.0023
firm_experience	-0.0070	0.0027	-2.5700	0.0100	-0.0123	-0.0017
companies	0.0021	0.0006	3.5400	0.0000	0.0009	0.0033
capital_goods	-0.0550	0.0122	-4.5100	0.0000	-0.0789	-0.0311
consumer_durables	-0.0921	0.0174	-5.3000	0.0000	-0.1261	-0.0580
consumer_non_durables	-0.1450	0.0124	-11.6800	0.0000	-0.1693	-0.1207
consumer_services	-0.1627	0.0133	-12.2200	0.0000	-0.1889	-0.1366
energy	-0.2158	0.0127	-17.0500	0.0000	-0.2406	-0.1910
finance	-0.1053	0.0117	-8.9800	0.0000	-0.1282	-0.0823
health_care	-0.1717	0.0406	-4.2200	0.0000	-0.2513	-0.0920
public_utilities	-0.1191	0.0141	-8.4300	0.0000	-0.1468	-0.0914
technology	0.0851	0.0318	2.6800	0.0070	0.0228	0.1473
transportation	-0.1663	0.0719	-2.3100	0.0210	-0.3071	-0.0254
_cons	0.8340	0.0253	33.0100	0.0000	0.7844	0.8835

Restricted Regression Model

Number of obs	43092
F(15, 43076)	247.62
Prob > F	0.0000
R-squared	0.1189
Root MSE	0.4324

UFE_1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
months	0.0191	0.0006	30.6000	0.0000	0.0179	0.0203
ln_cap	-0.0144	0.0015	-9.4000	0.0000	-0.0173	-0.0114
profit	-0.4411	0.0167	-26.3800	0.0000	-0.4738	-0.4083
prev_profit	0.0581	0.0145	4.0100	0.0000	0.0297	0.0864
bull	-0.0512	0.0043	-11.9100	0.0000	-0.0597	-0.0428
capital_goods	-0.0705	0.0092	-7.6900	0.0000	-0.0884	-0.0525
consumer_durables	-0.0703	0.0136	-5.1600	0.0000	-0.0970	-0.0436
consumer_non_durables	-0.1479	0.0095	-15.6200	0.0000	-0.1665	-0.1294
consumer_services	-0.1707	0.0102	-16.7800	0.0000	-0.1906	-0.1507
energy	-0.2189	0.0101	-21.6400	0.0000	-0.2387	-0.1991
finance	-0.1154	0.0088	-13.0700	0.0000	-0.1327	-0.0981
health_care	-0.0923	0.0378	-2.4400	0.0150	-0.1664	-0.0183
public_utilities	-0.1294	0.0108	-11.9800	0.0000	-0.1505	-0.1082
technology	0.0686	0.0248	2.7700	0.0060	0.0201	0.1172
transportation	-0.0664	0.0567	-1.1700	0.2410	-0.1775	0.0447
_cons	0.7675	0.0166	46.2300	0.0000	0.7350	0.8000

Since we obtained the same regression coefficient's signs (positive/negative) from the two models, we chose to report only the comments referred to the complete model, highlighting, in case, eventual differences.

The advantage of the restricted over the complete model is just that, excluding the variables referred to brokers or analysts, it permits to perform the regression analysis on a larger number of observations (43,092 against the 25,899 of the complete model). On the other hand the results are quite the same, while the adjusted R-square is slightly lower (0.1189) compared to the complete model (0.1355). Our models' R-square is satisfactory, compared to previous studies in the literature. In the reference paper by Clement and Tse (2005), for example, the authors found for their model R-squares ranging from 17% to 18%, however not considering the sectorial and firm-specific effects; for Mikhail et al. (2003) the same figure is 10.10%, while for Jacob et al. (1999) is even lower, in the range between 5.31% and 6.03%.

Our methodology is directly comparable to theirs, since we perform a cross-sectional analysis that in the field of earning forecasting, generally record not very high R-squares.

Before commenting our results, we refer to two reference papers in the earning forecasting literature, Das (1998) and Brown (1998), to compare our findings with the existing ones.

Das (1998) highlights two effects: the "loss firms' effect" and the "horizon effect". The first is the evidence that the optimistic bias for loss firms is, on average, greater than for non-loss firms, i.e. the unsigned forecast error is larger (less accuracy) for loss firms than for non-loss firms. The second effect, as also presented in previous studies in the literature [O' Brien (1988), Kang, O' Brien, and Sivaramalrrishnan (1994)] suggests that the staleness of the forecast affects accuracy. The closer is the forecast to the actual earnings announcement date, the more accurate it is likely to be. Brown (1998), instead, claims that when analysts expect a firm to report a profit but it then actually reports a loss, their earnings forecasts are optimistically biased. Furthermore, he suggests that small firms or followed by few analysts show more optimistic bias basically because they are much more likely to report losses. On the contrary, larger firms and companies followed by more analysts show less optimistic bias.

In what follows we present our results for every explanatory variable.

Explanatory variables	**Results**
Months	As expected, the time horizon significantly and positively affects analysts' forecasting ability. This is in line with the existing literature: the greater is the difference in months between the forecast and the release date, the higher is the forecast error. This is reasonable since as time goes by new information is available to analysts to improve their forecasts.
ln_cap	As expected, the coefficient associated with this variable is negative, highlighting that the bigger the company, the lower the unsigned forecast error, and the bigger analysts' accuracy.
profit	This dummy variable has a negative coefficient, and seems to be the one that mostly affects UFE, confirming what found in previous studies. Thus, there is a positive relation between this variable and analysts' forecasting ability.
prev_ profit	This dummy variable, with a positive value, increases the level of unsigned forecast errors. Therefore, it seems that analysts are less precise on firms with a positive profit in the previous year. This could be due by the fact that the degree of optimism increases for profit firms.
bull	This dummy variable, as a proxy for the trend followed by the market, displays results in line with previous studies in the

	literature. The negative coefficient suggests that during market booms, analysts' forecast errors are lower. This variable gives insights similar to the dummy "profit", at an aggregate level.
size_broker	This variable, with a slight negative value, reduces forecast errors and increases accuracy. Therefore, as expected, it seems that biggest brokers issue more precise forecasts.
general_experience	As shown in previous researches, we find that the coefficient associated with analysts' general (non-specific) experience is not statistically significant, i.e. it seems not to affect analysts' forecasting ability. This result suggests that a general level of knowledge is not enough to improve forecasts' accuracy.
firm_experience	Since the coefficient associated with this variable is negative, it seems that analysts' firm specific experience is the variable really affecting their forecasting accuracy. Our result, in line with our intuition and with the previous literature, shows that a greater knowledge of a specific company leads to a progressive improvement in analysts' forecasts.
companies	The number of companies followed by the analyst in the fiscal year of reference negatively influences analysts' accuracy. The positive coefficient, in fact, points out that more specialized analysts issue more accurate forecasts.
sectorial dummies	All the ten dummies considered seem to be significant for the model. The coefficient of the technology sector is positive, the others show negative signs. As expected, UFEs are higher for these companies since it seems to be more difficult to forecast their earnings compared to others in mature sectors.

The comments regarding the distinct effect of the belonging to different sectors deserves a more detail discussion. The coefficients that we found are in line with our expectations.

Energy is the sector characterized by the lowest unsigned forecast error, given the high predictability of their earning streams.

For the complete model, we classified the sectors in order of increasing difficulty of earning forecasting, finding the following order: health care, transportation, consumer services, consumer non durables, public utilities, finance, consumer durables, capital goods and technology. Only technological firms have a positive coefficient, increasing the unsigned forecast error. With regard to other sectors, the classification is in line with our intuition and with real world evidence, except for the transportation sector. In the complete model, in fact, it seems that this sector is one in which earning forecast are relative easier. In reality, however, the composition of this sector is quite heterogeneous, and the forecasting activity not so easy.

If, instead, we take into account the restricted model, the transportation sector seems to be the most difficult to forecast, if we exclude the technological sector that even increase UFEs, but is not statistically significant. In this case, it seems therefore that, at least for the Italian market, the transportation sector is not so easy to forecast.

In general, however, even if the classification for the restricted model is slightly different from the one calculated for the complete model, energy is still the sector for which we record the greatest degree of accuracy, while the technological sector is the one for which unsigned earning forecast errors are greater.

This behaviour and other potential specific Italian sectorial effects on analysts' forecasting accuracy could however be investigated more deeply in future researches.

7.
CONCLUSIONS

We investigated two distinct issues related to sell-side analysts' coverage of firms listed in the Italian stock market.

First, we examine analysts' forecast bias in different calendar and sub-samples periods. Our results suggest that financial analysts suffer from an overall optimistic bias. The mean forecast bias computed one year before earnings announcement is quite high and it gradually decreases until it gets to zero a month before the release date. This pattern suggests that analysts are able to gather and process information, thus adjusting their estimates in the right direction. The evidence is confirmed by the level of dispersion in earnings estimates which is larger in earlier period and decreases gradually. Second, we focus on forecast accuracy and found a similar behaviour: earnings forecasts appear to be inaccurate, on average. The mean unsigned forecast error is very high one year before the release date. Accuracy then improves approaching the release date and his standard deviation, usually a proxy for investor uncertainty prior to information events, declines over time.

Sectorial differences are important in explaining earning forecast accuracy that is higher in the, more predictable, energy sector, while it is lower for technological firms.

We also defined firm or broker/analyst-specific and sectorial characteristics and analyze their impact on individual forecast accuracy. Consistent with prior literature it seems that analysts' specific experience on firm is more important in explaining accuracy than his general experience.

A possible extension of the present analysis could be to focus the attention on some other individual brokers/analysts' characteristics. Past accuracy, forecast timeliness, deviation from the consensus estimates and herding behaviour among financial analyst should be associated with the level of experience in explaining cross-sectional differences in forecasting accuracy. In particular focusing on whether analysts' earnings forecast revisions may bring their previous forecast closer to the current consensus (generally referred to as herding), or they may diverge from the existing consensus could add more insight to the relation between forecast accuracy and price impact.

The analysis of brokers/analysts' tracking records is however difficult given the high number of missing values in the database, and also due by the fact that we do not know the names but only the codes associated with every broker or analyst. Having the possibility of identifying brokers/analysts' name would allow to better distinguish among leaders and followers, but also among independent and affiliated analysts with respect for example to particular operations like Initial Public Offerings.

Another possibility could be to consider the effect of regulatory changes, such as new rules regarding transparency provided in the Italian Banking Act or the Financial Intermediation act, on forecasting accuracy.

Last, but not least, it should be highlighted the present research follows the traditional view of corporate finance, based on the efficient market hypothesis and the rational behaviour of the agents.

However, more recently, behavioural explanation have been advanced to explain the evidence of analysts' optimistic bias. In other words, optimism would not be only the effect of a rational calculus linked to the earning-guidance-game, but could also be explained by the psychology of the analysts. In this respect, it would be important to insert in future researches the dimension offered by the so-called Behavioral Finance.

8.

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