Target Price Accuracy in Equity Research

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Abstract

Analysts' target prices have received very limited attention in academic research. In this paper we try to fill the gap by developing an innovative multi-layer accuracy metric that we test on a novel database. Our analysis shows that forecasting accuracy is very limited with a mean target price accuracy of 12%. Prediction errors are large (up to 46%) and significant, and positively correlated with research intensity. Controlling for market and company factors, we still document large and consistent prediction errors. Our results suggest that research activity may be used strategically by issuing firms to artificially drive market prices.

Security research provides investors with information on the current and future prospects of listed companies. Research is typically performed by high-status entities like investment banks, consultancies or private research firms, whose reputation influences investors' behaviour significantly. Analysts make predictions on earnings (earnings forecasts), forecast long-term stock prices trends (stock recommendations) and try to anticipate future stock prices (target prices).

While a great deal of academic research and business press attention has been devoted to the effect of analyst recommendation on stock returns or trading volumes, and to the accuracy of stock recommendations, the ability of target prices to predict future stock prices consistently has remained essentially unexplored.

Yet, we believe that understanding analysts' forecasting accuracy is relevant for three reasons: First, target prices are self-contained statements incorporating stock recommendations and earnings forecasts, making them a more comprehensive prediction.

Second, since gathering and managing information conveyed by research reports is a delicate, costly and time-consuming process,[1] target prices may be a simple and practical way[2] to create portfolio strategies by looking at the implicit returns embedded in each target. Implicit returns, i.e. the difference between the predicted price and the issuing date stock market price, convey a straightforward prediction of the potential return for an investment, and intuitively this prediction is more attractive the higher the reputation of the issuer and the lower the sophistication of the investor. Less informed investors may also tailor their investment strategies on the information inferred from target prices. Analysts therefore may have an incentive to shift risk from skilled and informed investors to the less informed by issuing overstated target prices.

[1] On average, over 50,000 reports are published every year worldwide. Scattered evidence on the cost of gathering research shows that, when available, a report can be purchased at an average price of 30 USD.
[2] Typically, information is spread in the market by means of simple statements such as "Morgan Stanley analysts have set a medium-term upside target of 17,7 euro per share in Deutsche Telekom" (Frankfurter Allgemeine Zeitung, January 13, 2005) or "Amazon.com: Shares of the online retailer rose 3.5 percent after Bear Stearns raised its investment rating to 'outperform' from 'peer perform' saying it was poised for a very strong fourth quarter [...] target price 57 dollars", (Yahoo Finance, US stock watch, December 28, 2004).

Third, previous studies - Barber et al. (2001) and Jagadeesh et al. (2004) - have shown a degree of differential ability among analysts in predicting earnings and recommending stocks that have outperformed the market. No study, though, has provided evidence of the accuracy of analysts in forecasting future market prices. Limited evidence is shown by Asquith et al. (2005) who, adopting a simple binary metric show that on average 46% of targets are not met. Evidence on this accuracy could help draw a better picture of the security research industry, which is receiving growing attention from regulators worldwide. In this spirit, more stringent information disclosure rules and more effective requirements for granting independence of research have been issued.[3]

Target prices should reflect, at or around the publication date, the analyst's best estimate of the company "intrinsic value". At the issue date, each target price may differ from the current market price for a number of reasons: First, the market is not yet discounting the full company's value emerging from the latest information available to analysts. Second, the analyst is making assumptions on the company's future cash flows which differ from assumptions shared by the majority of investors and are implied in the current market price. In both cases, which can also occur simultaneously, if markets are sufficiently efficient, we can expect prediction errors to be, on average, not far from zero, given that market prices should fully reflect investors' strategies based on any available information[4] and that the market assigns a value to accurate predictions by either increasing reputation for consistently anticipating price movements and/or linking analysts compensation packages to some accuracy measure.

Surprisingly, empirical evidence by Stickel (1990,1992,1995) Cooper, Day and Lewis (2001) and Bernhardt, Campello and Kutsoati (2004), show that both analysts'

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[3] In the US research activity regulation is based on SEC (Regulation analyst certification), NYSE (rule 472) and NASD (rule 2711) regulations. In 2002 the Sarbanes-Oxley Act established more stringent requirements and obligations for analyst research and defined harsher penalties for rule breaches. The main goal is to have firms fully disclose information about sell-side analyst remuneration policy, relevant ties between analysts and companies and relationships between companies and other banking divisions. Italian rules establish that if information is suitable for influencing prices of financial instruments, must be released to the market by immediate publication on publicly accesible media..

[4] Thomson Financial data show that 92% of market trade is given by insititutional investors who are generally the most active issuers of research reports.

ranking criteria by independent institutions[5] and published compensation schedules by banks, do not include target price accuracy as a factor in determining analysts' salaries.

Target prices therefore, appear to be a powerful but largely unregulated influence on driving investment decisions.

In this paper we argue that since forecasting target prices is an opaque activity, research analysts (and the institutions they work for) have an incentive to use them "strategically", i.e. , by issuing target prices that, rather than conveying a fair estimate of the future price, are consistently over/underestimated, as recently shown by Bernhardt, Campello and Kutsoati (2005) on earnings' forecasts. The rationale for this behaviour is that since no monitoring occurs on this part of the research activity which flows continuously to the market at large, analysts, independently or on behalf of the companies they work for, may try to exploit the price effect associated with the release of new information as documented, among others, by Abdel-Khalik and Ajinkya (1982). For instance over-optimistic target prices can create positive momentum on some stocks that firms can anticipate for rebalancing their own portfolios or transferring risk from more informed to less informed investors by appropriate trading strategies. If this behaviour holds, we should expect a consistent overestimation of target prices for positive recommendations (buy/strong buy) and, conversely, a large underestimation for negative ones (sell/strong sell). Furthermore, the magnitude of the over/under estimation should increase with liquidity: since large caps are less sensitive to trading activity, in order to generate a sizeable price effect on this asset class, over/underestimation needs to be sufficiently large to induce a significant number of investors to trade.

Measuring accuracy is not straightforward: Barber et al. (2001) check whether analysts have superior forecasting ability by creating portfolios based on analyst recommendations and comparing them with an investment in the index. Brown and Mohd (2003) also try to measure analyst accuracy in forecasting earnings. Both approaches share the characteristic of measuring relative performance at the end of a fixed period (12 months or the release of actual earnings by companies). Unfortunately, when dealing with target prices this approach would lead to biased results: a target price

[5] See Institutional Investors All America research or Investar ranking.

is generally assumed to be a prediction that is realized within a specified period, not necessarily at the end of that period. Since no similar studies testing target price accuracy are available and given this peculiarity of target prices, we introduce a comprehensive four-fold accuracy measure: we jointly measure the accuracy of price forecast at the end of the forecasting period and at any moment in between. We then compare this measure with the actual returns realized by each stock. Our results suggest that the frequency of accurate prediction is surprisingly low and the size of the prediction error is impressively large. Consistently with our expectation, liquidity is positively related with the size of the error as well as with market momentum, with mixed results for other industry variables. Our findings are consistent with Bradshaw and Brown (2005) which recently addressed target price accuracy with a simpler methodology.

An innovative part of this paper is the choice of the sample base: Italy requires, since 1999, mandatory publication of research reports on the stock exchange website for the purpose of granting investors access to price-sensitive information. Other countries do not share similar regulations. Italy, therefore is an ideal testing ground for our research. Since research publication is mandatory for all intermediaries authorized in the market, if a strategic behaviour in issuing research exists, we expect firms to try to avoid truthful disclosure by, for example, issuing research from foreign branches.

This hypothesis seems to be supported by our findings which show the largest trading firms in the market issuing relatively less research, with some companies, representing 10% of market turnover not publishing at all.

Finally, our research adds to the existing literature because we choose to study prediction errors in every target price/report instead of focusing on aggregate measures like consensus forecasts. This approach helps to support the hypothesis that research activity is largely inefficient effort and is widely influenced by research firms' strategic choices.

The remainder of the paper is structured as follows: Section II reviews the literature; Section III describes data collection; Section IV introduces variables and research hypothesis; Section V presents results; Section VI concludes and introduces future research agenda.

II Related research

Security analysts' research has received growing attention from both academics and regulators. Early studies have mainly focused on market's reaction to analysts' earnings forecasts, recommendations and revisions. Almost uniformly, these analyses show non-zero, robust abnormal returns for earnings forecast revisions or new buy/sell recommendations. Abdel-Khalik and Ajinkya (1982) find significant abnormal returns around the publication week of revisions issued by Merrill Lynch analysts. Analogously, Lys and Sohn (1990) and Stickel and Scott (1990) document an information content associated with forecast revisions

The sign of abnormal returns was examined originally by Lloyd-Davies and Canes (1978). Additional evidence is provided by Bjerring, Lakonishok and Vermaelen, (1983); Elton, Gruber and Grossman, (1986); Liu, Smith and Syed, (1990); Beneish, (1991); Stickel, (1995).

Womack (1996) documents a significant initial price and volume reaction: size adjusted prices increase by 3% for buy recommendations and drop 4.7% for sell recommendations in the event window. Furthermore he finds a significant post-recommendations stock price drift in the direction forecast by the analysts: buy recommendations earned an adjusted mean return of 2.4% for the first post-event month, sell recommendations caused a post-recommendations drift of –9.1% over a longer six-month post-event period.

Recent research investigates simultaneous changes in both earnings forecast and recommendation revisions. Francis and Soffer (1997) show that both factors fail to fully convey the information of the other signal. Their findings support the hypothesis that investors rely more heavily in their investment decisions, on repeated signals like revisions rather than an absolute forecast. Stickel (1995) performs similar tests also controlling for the magnitude of the recommendation revision, the analyst's reputation, the size of the analyst's firm and the company’s information. His results are consistent with those of Francis and Soffer while both show low statistical significance.

Target prices have been included in academic research only in recent studies. Bradshaw (2002) focuses on the joint publication of target prices and recommendations:

on a sample of 103 reports, finding that the publication of a target price is positively correlated with more favourable recommendations. The paper closer in spirit to ours is Bradshaw and Brown (2005), who provide evidence of a differential ability by analysts in accurately predicting prices: Yet, as in Asquith et al. (2005), they look at the analysts' ability in predicting prices through a binary metric rather than developing a quantitative metric for interpreting the size and sign of forecast errors.

Brav and Lehavy (2003) show that target prices significantly affect market prices. The effect is unconditional on the simultaneous issuance of recommendations, similarly to Francis and Soffer (1997).

The effects associated with a lack of independence are similar to those found in Michaely and Womack (1999), which documents that mean excess returns around a buy recommendation revision are lower when the recommendation is made by an underwriter rather than by an unaffiliated brokerage.

Asquith, Mikhail and Au (2005) examine the complete text of a large sample of actual analyst reports and provide information beyond earnings forecasts, recommendations and price targets. They show that other information, such as the strength of the analyst's justifications, is also important and when considered simultaneously reduces, and in some models eliminates, the significance of the information available in earnings forecasts and recommendation revisions. By controlling for the simultaneous release of other information, they show that analyst reports provide new and independent analysis to the market.

Jegadeesh, Kim, Krische and Lee (2004) investigates the source of the investment value provided by analyst stock recommendations and changes in recommendations. They also assess the extent to which sell-side analysts make full use of available information signals in formulating stock recommendations. They find that analysts do not fully take into account the ability of various stock characteristics to predict returns. Moreover, their evidence shows that the direction of the bias in analyst recommendations is in line with economic incentives faced by sell-side brokerage firms.

Evidence on the Italian Market shows similar results. Belcredi, Bozzi and Rigamonti (2003) have studied stock market price and volume reaction following upgrade (downgrade) recommendations. The authors observe abnormal returns around stock recommendation release (+1;-1 days) but not in prior or subsequent period.

Barucci Bianchi and Passaporti (2003) document market reactions to the release of new analyst recommendations. They show that positive/negative recommendations (buy, strong buy/sell, strong sell) yield positive/negative abnormal returns.

Finally Cervellati (2004), documents potential conflicts of interest by non-independent research analysts issuing research on recently listed companies. By analyzing 1099 reports on 63 companies that went public in the period 1 January 2000 – 29 December 2001, he shows that IPOs recommended by independent analysts perform better than those recommended by non-independent analysts.

III. Data Collection

A. Regulatory issues

We are motivated in the selection of a non-US sample of target prices by observing that Italy is the only country to require mandatory publication of any research issued by authorized financial intermediaries. Research activity is ruled by the TUF (Testo Unico della Finanza) approved by the Italian Parliament in 1998. Section IV (Comunicazioni al pubblico),[6] article 114 states that all non-public information which, if revealed to the market, may affect market prices of financial instruments, must be compulsorily transmitted to the public. It also established that CONSOB (Italian Stock Exchange Commission) must set and update, when necessary, rules concerning what is considered to be "price sensitive" information.

In 1999, CONSOB issued regulation #11971. Article 69 states that research reports on listed companies must be sent to CONSOB and to Borsa Italiana on the day they are issued for immediate publication in full format on the Borsa Italiana website. Exception is given to research privately produced for financial institutions or specific customers which has to be transmitted to CONSOB and Borsa Italiana within 60 days of the issuing date. This delay is granted in order to preserve value for clients who pay for additional research.

[6] *Comunicazioni al pubblico* i.e. "Information released to the market".

This unique regulation provides a fertile testing ground for our research hypothesis for two reasons: first, we should not expect a sample bias due to discretionary disclosure of research activity by analysts. Second, given the existing regulation, intermediaries not willing to reveal information to the market have an incentive to circumvent the Stock Exchange requirement by publishing from overseas branches. In contrast, publication of US research is generally provided through agreements between research firms and non-financial institutions such as Thomson Financial or Investar. Therefore the risk of incurring in significant selection bias would be greater.

B. Database construction

We collected over 13,000 reports published from 1 January 2000 up to 31 December 2003, on the Borsa Italiana website. We then selected 9690 reports published by 47 distinct research firms.[7] Selected reports cover 98 companies listed on the Milan Stock Exchange[8] representing approximately 405.32 bn€ or 81.96% of the overall market cap. Surprisingly, over 140 stocks are not covered or marginally covered by research. This suggests that their representation in investors' portfolios and the relative trading activity is rather small.

Reports were included in the first sub sample of 9690 if they satisfied three criteria: first each report accepted for inclusion in the database ought to represent companies continuously listed in the whole period of analysis, therefore we have excluded delisted companies' reports. Second, reports focusing on firms that went public later than January 1999 were excluded due to the potential for upward bias, as showed by Michaely and Womack (1999) and Cervellati (2004). Third, for any research firm, we exclude "single report companies", i.e. companies for which only one report has been published across the time interval of analysis. These three criteria resulted also in the exclusion of all reports targeting companies listed in the technological stock market "Nuovo Mercato".

[7] Consistently with previous studies we define research issuers as "firm(s)" and target companies as, simply "companies"
[8] Out of a total of 262 as of 31 December 2003.

We then applied two further filters: the first excluded from the database all "damaged"[9] reports and all "mirror"[10] reports, a total of 1825 reports or 18.83% of the original set. The second filter was applied to generate an "informationally efficient" sample aimed at solving quasi-duplications: whenever two reports on the same company by the same research firm were available with publishing date less than or equal to 14 days, we excluded either the former or the latter according to the following principle: if the two reports presented an identical recommendation and target price we excluded the latter because we assumed a duplication or error in the publication; if the two reports expressed different recommendations or target price, we excluded the former assuming that an unanticipated, extraordinary event had occurred.[11] This filtering excluded a further 865 reports.

Jointly, the two filters reduced the sample to 7036 reports which we consider to be a consistent representation of publicly available information for our research perimeter.

Additional information about reported companies – such as market capitalization, daily closing prices, daily trading volumes - has been collected by Datastream. Industry classification is based on FTSE Global Classification system "Economics group" level 3. Stock Market Index Composition was extracted from Datastream.

Tables 1 provides details of the sample.

TABLE 1 PANEL A HERE

TABLE 1 PANEL B HERE

[9] By damaged we mean: unreadable, empty, compiled in formats unsupported by standard readers such as Acrobat, MS Word, Wordperfect etc. and/or with missing information.

[10] Mirror reports have been defined as identical reports published twice under two different filenames or classifications.

[11] Some examples include: mistakes in publication, corrections in data originated and released by the reported company.

Table 1, panel A shows descriptive statistics of the 98 companies included in the database. Six companies total over 200 reports each, being the most represented in the sample. The relative number of reports per company shows that the most-analysed company, tops 225 reports, forming only 3,198% on the total sample, therefore allowing us to exclude major concentration biases in sample representation.

Table 1, panel B shows summary statistics for reports distribution by companies and industry. Companies are researched on average by 72 reports, but data on standard deviation and median hint at some skewness in distribution. Standard deviation is high 66.08 and median is 46.5. At the Industry level, data show that Financials is the most represented industry with 29 companies and 2109 reports; Cyclical industries are also well represented both in terms of companies and reports. A measure of the thinness of the Italian Stock Exchange is given by figures on Non-cyclical services and Resources which, with only 2 and 3 firms respectively, show the highest mean coverage of the sample.

Table 2 provides evidence on yearly and monthly reports distribution. Research intensity steadily grows over the sampling horizon. Within each year, four accumulation points exist around the months of March, May, September and November which typically host major corporate events like shareholders' meetings, dividend distribution decisions or budget approval for future fiscal years. This pattern is consistent with the hypothesis that analysts update research with the arrival of new information.

TABLE 2 PANEL A HERE

TABLE 2 PANEL B HERE

Selected reports have been classified according to the original recommendation ranking adopted by each individual research firm. Since each firm adopts an individual scale, we reclassified recommendations on a standard five-point scale: "strong sell-sell-hold-buy-strong buy", in order to perform comparative analysis. The conversion criterion goes as follows: if the original scale is a five-steps scale with a central recommendation indicating a "stand-by" on the investment (such as 'neutral' or 'hold') we have converted the recommendation straightforwardly in our standard scale; if the original scale is a three-steps scale we have converted the central recommendation into a 'hold' and looked at both the recommendation and the target price for the upside and downside indications. We convert a buy with an implicit return above 20% into a strong buy and keep a buy for implicit returns below that level. Analogously we convert 'sell' recommendations into strong sells only when implicit loss is larger than -20%. Table 3 shows scales conversions.

TABLE 3 HERE

Table 4 provides recommendations transition matrix. Recommendations considered are less than total recommendations because we have excluded the last recommendation issued by each firm and reports published only once by a firm on a company.

TABLE 4 HERE

Most reports (*n*=3845) reiterate the previous recommendation. Reiterations are represented in bold on the diagonal of the matrix in Table 4. 'Strong buy' and 'buy' reiterated recommendations account for 56% of total unchanged reports. Upgrade recommendations are defined as upward revisions of previous recommendations: they include all reports below the matrix diagonal. Similarly, downgrades are defined as downward revision of previous recommendations and include all reports above the matrix diagonal.

The two tables show that upgrades and downgrades are most often towards near recommendations: buy to hold (*n*=385), hold to buy (*n*=294), strong buy to buy (*n*=241) and buy to strong buy (*n*=182). The relative transition matrix indicates that across all recommendation classes, the most frequent update is a reiteration of the previous recommendation. When positive recommendations (strong buy/buy) change, they are often downgraded to the nearest-class recommendation (buy/hold) and, similarly, when negative recommendations change it is most often an upgrade to the nearest superior recommendation class.

IV. Accuracy metrics

Our analysis addresses the accuracy of analyst target prices.[12] No previous studies have developed a comprehensive methodology for assessing forecasting accuracy. In a recent paper Asquith et al. (2005) test accuracy by a simple metric which considers "accurate" a target if the underlying share price reaches or exceeds the target at the end of the time horizon. In the same spirit, Bradshaw and Brown (2005) extend the analysis by checking whether the price is met also at any time during the report time horizon.

In this paper we aim to develop a multidimensional benchmarked metric for testing accuracy. We first address the issue dealing with each analyst's forecasting time horizon. Analysts generally do not make explicit assumptions on the time required by market prices to adjust towards the predicted target. Most of the time, when an explicit time is provided, it is equal to 12 months from the report's issue date. A second concern is whether we should adjust time horizons for target price revisions. If a new report is issued before the end of the (implicit or explicit) time horizon, two options are available for defining time horizons: time horizons can be left unchanged, and accuracy measured on two partially overlapping periods or time horizons can be reset i.e. stopping the initial accuracy measure at the time of update and generating a new measurement adopting the update's new time horizon (again, implicit or explicit). In our analysis we have opted for the second approach for the following reason: a rational individual would revise his/her prediction only if new information arrives implying a consistent change in his/her judgment. If this translates into a new price forecast, rational investors have the

[12] Throughout this paper we are interested in trying to understand the predictive ability of each research firm. We therefore analyze every recommendation as a stand alone investment indicator. We exclude, differently from other papers, investment strategies based on either static portfolio diversification or a fortiori dynamic portfolio allocation. Clearly, any consensus-driven or deep-diversified investment strategy reduces the non-systematic risk for any investor but risk reduction actions are out of the scope of this research. We believe this approach to be more consistent with small, uninformed investors' strategies which are more subject to sub-optimal diversification and to be driven in their allocation decisions by analyst recommendations. Furthermore, results in terms of analyst's individual performance are not affected by this assumption.

option to adjust their portfolio holdings based on the new credible signal issued to the market. Obviously, the former forecast loses any meaning both for the analyst and for the investors. Accordingly, we believe that it would be misleading to measure accuracy without adjusting for report updates.

We make then the following assumptions:

Assumption 1: If target prices are issued with an explicit time horizon we check whether the market price reaches the target price at any moment between the issue date and the time-horizon final date, unless a new report is issued. In this case we consider the final prediction date to be the new report date minus three days.[13]

Assumption 2: if reports are issued without an explicit time horizon, we consider the time horizon to be the lesser between 12 months or the following report update minus three days.

A second issue is given by the very meaning of accuracy. *Ex-ante* target prices convey an immediate performance prediction that we define "implicit return" which is given by the algebraic difference between the target price and the current market price.

Formally, we define implicit return (IR) as:

$$IR = [TP_{t0}/P_{t0}]-1$$

This prediction is met if at some point during or at the end of the time horizon, the underlying share price reaches the target price. Market prices, though, may not perfectly match the target;[14] in this case the accuracy of a target price is given by the degree of proximity of the share price to the target. To capture accuracy at this level we develop two metrics, named "Ideal Strategy" (IS) variables, because it is dubious whether this level of accuracy can be exploited by investors, since understanding when a price is at its maximum level is almost impossible:

[13] This last adjustment is made to take into account any possible information leakage around the new report date. A second motivation is given by the fact that, as in Welch (2000) and Barucci et al. (2003), analysts tend to concentrate publishing reports around the same date. This last evidence is also supported by the data in Table, Panel A

[14] And indeed we show that this is not typically the case.

$$\delta_1 = [P_m / P_{t0}]-1$$

$$\delta_2 = \left((TP_{t0} / P_m) - 1 \middle| TP > P_{t0};\ 1 - (TP_{t0} / P_m) \middle| TP < P_{t0}; \right)$$

where:

t_0: report issue date by firm *i* on company *j*

t_1: report update publication (minus 3 days) by firm *i* on company *j*

P_{t0}: stock market price at the research report publication date t_0

TP_{t0}: target price given by analyst at the research report publication date t_0

P_m: maximum/minimum price level within the prediction time horizon[15]

$\boldsymbol{\delta_1}$ is defined as the "ideal" return control variable calculated as the difference between the maximum/minimum price over the time horizon and the issue date share price. A different way to interpret δ_1 is the maximum potential return an investor could earn if (s)he could perfectly foresee future prices along the investment time-horizon and identify a maximum/minimum.

$\boldsymbol{\delta_2}$ measures the *IS* prediction error for any report as the difference between the issued target price at t_0 and the maximum/(minimum) market price in the relevant prediction time-horizon. This variable expresses ex-post analyst prediction error compared to stock market price. To compute prediction errors we look at target prices at the report issue date for each report: when at t_0 the target price is larger than the current market price we interpreted a positive difference between TP_{t0} and P_m as "upside overshooting", i.e., a prediction of greater increase in the maximum market price than eventually realized by each share. Conversely, a negative difference is considered to be a "conservative" prediction. Analogously, when at t_0 the target price is smaller than the market price, a negative difference between TP_{t0} and P_m means that the analyst has predicted greater downside than the real price downside observed ex-post on the stock market. We name this phenomenon as "downside overshooting" and the opposite sign phenomenon as "conservative".

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[15] Recommendation can be divided into two groups inferring the expected outcome: positive or neutral performance (Strong buy/buy and hold recommendations) and negative performance (sell and strong sell). Accordingly, when calculating all δ variables implicit returns, we use the <u>maximum</u> price if, at t_0, $TP_{t0} > P_{t0}$. Alternatively, we use the <u>minimum</u> price if , at t_0, $TP_{t0} < P_{t0}$.

Feasible investment strategies, though, do not allow investors to anticipate future market prices. Assuming that investors cannot effectively predict when a maximum/minimum price is achieved on the market, we model two alternative "Feasible Strategy" (FS) variables:

$$\delta_3 = [P_{t1} / P_{t0}] - 1$$

$$\delta_4 = \left((TP_{t0} / P_{t+1}) - 1 \middle| TP > P_{t0};\ 1 - (TP_{t0} / P_{t+1}) \middle| TP < P_{t0}; \right)$$

where:

P_{t+1} : stock market price at the research report releasing date t_1

δ_3 is the second control variable measuring the "feasible" return as the difference between the price at the end of the time horizon and the report's issue date share price. Analogously with ***δ_1*** we can interpret it as the return yielded to investors by a buy-and-hold strategy in the share over the whole time horizon.

δ_4 measures the *FS* prediction error for any report as the difference between the issued target price and the stock market price at the end of the investment time-horizon. Prediction error interpretation goes the same way as for δ_2: when the target price is bigger than the market price at t_0 we interpreted a positive difference between TP_{t0} and P_{t1} as "upside overshooting", i.e., a prediction of greater increase in market price than eventually realized by each share at the end of the time horizon. Conversely, when the target price is smaller than the market price at t_0, a negative difference between TP_{t0} and P_m is defined as "downside overshooting".

Figure 1 gives a graphical representation of the four variables.[16]

INSERT FIGURE 1 HERE

[16] The case represents a positive implicit return target price forecast.

Figure 2 shows variables' sign interpretation: if TP is greater than market price at t_0 (top side of the graph), a positive sign for variables δ_2 and/or δ_4 means that the issued TP has proved to be greater than the realized market price at the end of the time horizon. We name this event as "overshooting". A negative sign means that the realized market price has exceeded the issued TP: we define this recommendation to be "conservative". For the bottom part of the graph (when TP is lower than current market price at t_0), overshooting occurs when we obtain a positive sign, i.e., when the issued TP is lower than the realized market price.

INSERT FIGURE 2 HERE

In Table 5, we show summary statistics for these metrics. In column 1 we report predicted implicit returns computed as the difference between target price and the market price at the issue date. In Column 2 we report the quantitative change in Target Price revisions measured as the percentage difference between a target price and its closest revision. Columns 3 and 4 report figures for the 'Ideal Strategy' (IS) accuracy control metric and variable respectively. Columns 5 and 6 report figures for the 'Feasible Strategy' (FS) accuracy control metric and variable respectively.

TABLE 5 HERE

Figures indicate that implicit returns are decreasing in recommendation classes, ranging between 38.18% for 'strong buy' recommendations to -31.22% for 'strong sell' recommendations. This result is consistent with a rational approach to forecasting: stocks that are less favourably recommended by qualitative measures are also expected to grow less. Intuitively, both implicit expected returns and TP changes should decrease the more unfavorable is the revision. Indeed, that is confirmed by our data which also show that negative recommendations are associated with larger and more skewed target price revisions.

Columns 3 and 4 report figures for the *IS* control metric and variable respectively. Data show that, assuming a "hold" recommendation as the pivotal point, an investment strategy driven by recommendations and target prices yield a monotonically positive return in the level of recommendation with a maximum average yield offered of 14.43%.[17] Yet overshooting[18] is statistically significant and large, ranging from slightly less than 0% for "hold" recommendations, to 22.39% and 9.77% respectively for "strong buy" and "strong sell".

IS metrics assume that investments in stocks are undertaken at the report issue date and liquidated once the price reaches its maximum level within the investment time-horizon. Most of the time, though, as shown by columns 3 and 4, prices never get reasonably close to the expected target price level,[19] calling into question the hypothesis that, on average, investors can discriminate between market prices and understand which price represents a "real" maximum. Less informed investors in high recommendation level stocks (strong buy/strong sell), still observing a large deal of implicit return not yet reflected by market prices, are keener to wait for the price to change.

To test for the predictive ability of market prices in a more realistic investment strategy we constructed the *FS* variables which assume an investor to open the position on any report issue date and close it at the end of the time horizon.[20]

FS data are reported in columns 5 and 6 and surprisingly, this strategy yields consistently negative average returns across all recommendation level classes. Overshooting is significantly larger with the same signs of *IS* variables. The highest overshooting is for the 'StrongBuy' class with 46.81%. These results indicate a smaller accuracy than those in Asquith et al. (2005) but are aligned with those in Bradshaw and Brown (2005) and suggest that when reports are issued there is a significant effect on

[17] Figures are non-annualized returns..
[18] In both directions: upwards and downwards according to the relevant recommendation.
[19] Furthermore, several times the maximum price empirically calculated ex-post, is exactly the issuing date market price That means that a particular share over the relevant time-horizon has shown a monotonically decreasing (or increasing) market price.
[20] If the end of the time horizon is a research update we consider the update release date minus three days as explained in section 4.1

market prices which allow positive *IS* returns expressed by variable δ_1.[21] Eventually though market prices reverse yielding a negative return on a buy-and-hold strategy position opened at the report issue date and closed either at the first update or after 12 months, whichever comes first.

V. Do firms try to avoid publishing?

Table 6 panel A documents research diffusion across banks. The most actively publishing firms are: Intermonte (815 reports), Euromobiliare (614), UBM (500) and Deutsche Bank (455). All these firms contribute less than 11% to the full sample. Preliminary analysis show the striking absence from the database of large, high status firms like Morgan Stanley, HSBC or Barclays. Given the European market composition, we classify firms into two groups Domestic and Foreign, assuming a firm to be foreign if its headquarter is not incorporated in Italy and it does not have a research team in Italy[22]. We then cross check the number of reports published by foreign firms with the same figure by Italian banks. Evidence shows that only slightly more than one quarter of research has been published by foreign banks. Yet, rankings data on underwriting and trading activity in Italy obtained from Bloomberg's "Equity Underwriting Rankings" for the period January 2000-December 2003, show that, the apparent lack of research activity has not prevented foreign banks to occupy the top places. We argue that this can be interpreted as an indication of the existence of a strategic behaviour in publishing research: underwriting and trading best practices generally require a reasonable amount of research to support the investment activity therefore the absence or limited amount of research shown by some banks suggests that research exists but has not been transmitted to the local authorities. To check in more detail this hypothesis we have sorted banks according to the absolute value of underwriting activity. In Table 6 Panel B, we have imposed three cutoffs (Top50%; Top80%; Top90%) to measure the relative contribution to the relevant group.

[21] This evidence can be interpreted as an indirect corroboration of previous studies on the effect on market prices of research publication.
[22] In our sample, the only foreign firm which ends up being classified as "Domestic" although being foreign is Deutsche Bank, since its Italian research team is based in Italy where research is issued.

TABLE 6 PANEL B HERE

Looking at the "Top50%" cutoff, we have striking evidence of the expected behaviour: foreign banks account for slightly less than 25% of the market, a figure very close to that of Domestic banks; their research activity though, accounts for only 1.35% of total publications, vis-à-vis a 17.68% figure for Domestic banks. Anecdotal evidence and unreported analysis[23] shows that, for many firms, research activity is indeed considerably larger than that available in our database, suggesting that a good deal of research has been published abroad and not transmitted to the Italian authorities. The pattern is consistent across all three groupings as shown in Figure 3.

FIGURE 3 HERE

Since foreign firms are not obliged to submit research to the Italian authorities, there is no breach of law in this behaviour but only a strong signal that avoiding public disclosure is strongly preferred by issuers.

A caveat is the potential country bias in our data given by the legal requirement to monitor and publish research on companies for which banks have been sponsors[24]: since domestic issuers may lean towards domestic advisors, this may generate an overrepresentation of domestic banks vis-à-vis foreign ones.

To control for this risk we inspect the database composition,[25] observing that the total number of reports issued on nine companies included in our sample that returned to the market[26] between 1999 and 2003 is 765 or 10.87% of our final sample, with each company representing 1,21% (1,08%) mean (median) reports out of the total sample. Two companies appointed a bank that we have defined as "Foreign" as Sponsor or

[23] We have checked Thomson Financial First Call database and required research statistics to banks to control for the existence of reports by firms showing small or null figures for research publication. Due to restrictions in data gathering we are still unable to fully disclose these information.
[24] See CONSOB rule 11971, art.48.
[25] These data are based on unreported analyses, available upon request from the authors.
[26] We have not considered companies that went public in this time window for avoiding sample biases documented by Michaely and Womack (2000), as specified in section III B.

Global Coordinator. The total amount of reports targeting these two companies is 268 or 3.81% of our sample. These figures are consistent with findings on the whole sample. The risk for a country bias is therefore limited, although the small size of this sub-sample suggests that the evidence may not be conclusive.

VI. How accurate are analysts?

To test accuracy we adopt a modified Asquith et al. (2005) approach, defining accurate a target price if the underlying share price reaches the target price with an accuracy tolerance of +/-5%, at the end of the forecasting period or anytime between the issuing date and the end of the forecasting period, respectively for our δ_2 and δ_4 metrics. We break down the analysis at three levels: the "Absolute" test measures the number of accurate forecasts by one analyst over the total number of reports issued; "RelativeIN" measures the ratio of accurate forecasts issued by one analyst over the total number of forecasts issued by the same analyst; "RelativeHits" measures the ratio of accurate forecasts by one analyst over the total number of accurate forecasts issued by any analyst.

TABLE 7 HERE

Results reported in Table 7 show a surprisingly limited prediction ability by analysts: only 23.05% of issued targets in our sample are eventually met by the underlying share price, when looking at the δ_2 metric; adopting the δ_4 metric this number drops to a tiny 12.06%. Looking at the RelativeIN variable, some firms seem to be performing better than others. Yet, when we look at the normalized RelativeHits figure this apparent superiority unravels: correlation between the two variables is negative and large across the two metrics, suggesting that a good internal performance is not a signal of general superior ability. Interpretation may more easily be that performing (and eventually publishing) less research drives smaller prediction errors. This phenomenon seem to contradict standard learning curve theory predictions. We try to further check this surprising evidence by testing the relation between research intensity measured as the absolute number of reports published by firm *i* on all companies and the magnitude and sign of prediction errors for the δ_2 and δ_4 average error measures. We model our test with in the following functional form:

$$Y_{i,j} = \alpha + \beta_{i,j} \text{ N° report}_j + \varepsilon_{i,j}$$

where $Y_{i,j}$ are the yearly averages of prediction errors for each firm *i* and *j*= (δ_2;δ_4) indicates the type prediction error.

TABLE 8 HERE

Regressions results are reported in Table 8. IS errors (δ_2) are reported in column one, *FS* errors (δ_4) in column two. Significance is high for both regression (F=22.192 and 192.122, one-tailed p<0.01) and coefficients and results indicate that a higher degree of research activity is associated with larger prediction errors. This result confirms the surprising intuition of the analysis reported in Table 7: there seem to be no learning curve in the analysts' target price forecasting activity. A possible interpretation is that adopting as the independent variable the 'overall coverage' measure (i.e. total reports published by one form over total amount of report published) leads to biased results. Standard learning curve theory suggests that a deeper coverage of one specific company should be negatively correlated with the size of prediction errors: the greater the knowledge of a company's activity the better the ability to correctly estimate value. With respect to our analysis, this could yield to a double-signed relationship: positive correlation between errors and <u>absolute</u> coverage by each firm (due to a "skills dispersion" effect) and negative correlation between prediction errors and <u>relative</u> coverage by each firm (due to a "knowledge effect"). Yet, unreported results fail to confirm this interpretation, not showing evidence that a measure of relative coverage has a negative effect on the size of prediction error. Furthermore, results significance is extremely low. We therefore interpret these results as a confirmation of our strategic behaviour hypothesis: if a firm cannot avoid to publish its research (thus preventing it from exploiting private information), then it has an incentive in overshooting in order to maximize the price effect associated with the publication of research.

If such a strategic behaviour exists and is reflected in increasing inaccuracy in the volume of reports published, we should also expect to observe dispersion of ex-ante implicit returns to be increasing in the amount of research published. The following test aims at cross-checking the previous results by regressing implicit returns volatility measured as standard deviation of the TP/P variable research intensity calculated as the absolute amount of reports published by each bank.

$$Y_i = \alpha + \beta_i \text{ N° report} + \varepsilon_i$$

where Y_i= standard deviation of TP/P for firm *i*.

Regression results reported in column three of Table 8 indicate that a lower amount of reports is associated with a lower variance in Target Prices implicit returns as expected. Signs are positive as expected and significance is large at 1% level.

Evidence then shows that when research is scarce, analyses are more conservative, while, conversely, an increasing number of reports is associated with larger prediction errors and greater dispersion of forecasts. These results seem to support the strategic use of reports hypothesis: the scattered publication of a few reports has, in fact, less chances of influencing market price. On the other hand, continuous coverage and reiteration of extreme valuations can build more confidence on one firm's ability thus driving investor behaviour.

VII. What determines forecasts accuracy?

A. Recommendation classes and revisions

Brav and Lehavy (2003) showed that the informativeness of qualitative recommendation is different among recommendation class. We test this effect relating the predictive power of target prices to the relative recommendation class and controlling for target price implicit return. Our goal is to understand whether accuracy is affected more by qualitative valuations as recommendations or by the point measure of expected return (or loss) expressed by the Target Price. The test regression takes the following form:

$$Y_{i,j} = \alpha + \beta_{i,j,1}TP/P_i + \beta_{i,j,2}\text{ Strong buy} + \beta_{i,j,3}\text{Buy} + \beta_{i,j,4}\text{Sell} + \beta_{i,j,5}\text{Strong sell} + \varepsilon_{i,j}$$

where $Y_{i,j}$ are the yearly prediction errors for each firm *i* and $j = (\delta_2;\delta_4)$, TP/P_i represents the implicit return expressed by target price at the time of report publication and the recommendation variables (Strongbuy; Buy; Sell; StrongSell) are dummies taking a value of 1 if the Target Price is associated with a specific recommendation and 0 otherwise. Overall significance for regressions is high (F=682.548 and 161.284, one-tailed $p<0.01$) with an adjusted R^2 for the δ_2 regression of 35.3% and 14.1% for the δ_4 regression. Results show that the largest effect on accuracy is given by the implicit return associated with each target price (0.541, t=39.271, one-tailed $p<0.01$): the greater is the return and the smaller is accuracy. Since we measure the prediction errors a positive sign indicates overshooting by the analyst. Furthermore, the more extreme is the recommendation class and the larger is the effect on accuracy. These results are consistent with Bradshaw and Brown (2005) which also documented a large and negative effect of target price implicit returns on analysts accuracy, although adopting a simpler metric.

TABLE 10 HERE

Francis and Soffer (1997) and Brav and Lehavy (2003) documented that recommendation revisions have a non negligible effect on market abnormal returns. If the market reacts to revisions, we should also expect prediction errors to be affected by the evolution of judgment by analysts. To test target price sensitivity to recommendation revisions, we regress prediction errors on two dummy variables indicating whether a recommendation is an upgrade or a downgrade of previous research on the same company by the same firm, controlling for target prices implicit returns. The ‘reitaration’ class is excluded and captured by the intercept. The regression takes the following form

$$Y_{i,j} = \alpha + \beta_{i,j,1} TP/P_i + \beta_{i,j,2} \text{ Upgrade} + \beta_{i,j,3} \text{ Downgrade} + \varepsilon_{i,j}$$

where $Y_{i,j}$ are the yearly are the prediction errors for each firm *i* and *j*= (δ_2;δ_4).

Regressions are significant (F=249.41 and 129.85, one tailed p<0.01) with adjusted R^2 of 12.8% and 8.6% for the δ_2 and δ_4 variables respectively. As expected the implicit return coefficient is positive and highly significant indicating that a large part of every target price forecast is systematically not met by eventual market prices. This result holds for both variables with similar significance. More interestingly, we document that recommendation revisions (on both sides, i.e. up and down) have a small positive impact on accuracy. We interpret this result as a consequence of the consistent overshooting by analysts: since an overwhelming majority of reports largely overshoots target prices and most revisions are to nearest recommendation class, a recommendation upgrade or downgrade strengthens the analyst indication expressed by the target price delivering a valuable additional information to investors. Yet, regression coefficient are small and non-significant for the second accuracy variable, thus making the absolute value of this additional piece of information limited.

TABLE 11 HERE

B. Market factors

Investors are generally more attracted by large, high growth, highly liquid stocks. To control for whether this attention is reflected in a different degree of predictive power by analyst recommendation we run the following regressions:

$$\delta_{2i} = \alpha + \beta MV + \gamma VOL + \delta MIB\_30 + \eta COV.RATIO + \theta MKT\_INDX + \varphi\ TP_{t0}/P_{t0} + \varepsilon_i$$

$$\delta_{4i} = \alpha + \beta MV + \gamma VOL + \delta MIB\_30 + \eta COV.RATIO + \theta MKT\_INDX + \varphi\ TP_{t0}/P_{t0} + \varepsilon_i$$

where:

MV: company market value

VOL: volume of share transaction in the recommendation issuing day

MIB_30: dummy variable with value of 1 if company is included in MIB30 index (index of 30 most capitalized Italian companies), 0 otherwise

COV.RATIO: number of reports issued on company *i* divided by total reports considered

MKT_INDEX: market momentum variable given by (relative level of the market index at any report issue date, divided by the average index value between 2000 and 2003.

TP_{t0}/P_{t0}: target price issued on company divided by price at date issuing

TABLE 12 HERE

Results, are statistically highly significant and confirm the predicted signs, but for the "MV" variable which appears to be somehow inconclusive across the two regressions. Table 12 column one reports results for δ_2. As expected, higher trading volumes as well as inclusion in the stock market index (MIB_30) are associated with higher prediction errors.

Market momentum (MKT_INDEX) influences prediction errors with the expected sign but its magnitude is somehow small. Coverage ratio affects positively analyst performance, i.e. reduces prediction errors, suggesting that a learning effect exists and analysts seem to be increasingly accurate in the amount of research published on one firm. Alternative explanations could also be given by the "herding" behaviour documented by Welch (2000) and Barucci et al. (2003), which shows that analysts concentrate not only on publication dates but also show increasingly converging estimates the larger the volume of research published. Finally, the size of the expected implicit return explains a large part of the prediction errors suggesting that overshooting is a consistent and repeated phenomenon in the research industry.

Not surprisingly, results reported in Table 12 column two, for the δ_4 variable are aligned with previous analysis. The greatest change in parameters is in the market index level variable which is consistent with previous evidence on the magnitude of prediction errors.

Unreported graphical analysis of regression residuals doesn't provide any indication of a misspecification, thus further confirming the conclusions drawn from previous results.

C. Recommendation class breakdown

Data and analysis' results, seem to suggest that prediction errors are not uniformly distributed across recommendation classes. This hypothesis seem to fit our "strategic behaviour" model: if a change is needed for, say, rebalancing portfolios, then it is reasonable to assume a recommendation to be issued as an upgrade (or downgrade) to higher(lower) classes and with increasing expected implicit returns.

To test this implication we have run the multivariate regressions and the industry and firms regression on two different sample groupings. We first sort recommendations into three classes (Strong buy/buy), (Hold), (Sell, Strong Sell) to understand whether positive, neutral or negative expectations have any differential effect on prediction errors. We then constructed a second grouping criteria based on the prediction errors realized sign, i.e. $\delta_i>0$ and $\delta_i<0$: since a positive sign in prediction errors represents overshooting, we expect, consistently with our "strategic behaviour" hypothesis, results to be more significant for positive prediction.

Results are presented in Table 12 and confirm our predictions: at any level of breakdown, reports' prediction errors are increasing in the recommendation class and are strongly, positively correlated with the sign of the prediction errors. Regressions results are stronger (F tests are all significant with one tailed $p<0.01$) and R^2 generally increase. Inspecting the 'StrongBuy-Buy' class we observe that significance results are aligned with those of the general regression presented in Table 11 which is consistent with the distribution of reports across classes presented in Table 2 Panel B. In particular the VOL and MKT_INDEX variable are not significant. Differently, the same parameters for the 'Hold' and 'StrongSell-Sell' classes show a high statistical significance ((0.134, t=6.881, $p<0.01$ and -0.212, t=-5.403, $p<0.01$) suggesting that accuracy for positive recommendation classes is not influenced by market movements.

Furthermore, ‘hold’ recommendation forecasts are generally upward biased and the size of the prediction error is positively correlated with market momentum while negative recommendation predictions are more accurate the stronger the market level. Implicit return plays the largest role in driving accuracy across all recommendation classes and also when breaking down the sample for error sign. The latter analysis show that when target prices are conservative, the relative level of the market index plays a different role in determining the absolute level of accuracy: the parameter is negative and significant for both the accuracy metrics.

TABLE 12 HERE

VIII. Conclusions and future research agenda

Using a large and uniquely developed database of analyst recommendations issued on companies listed on the Italian Stock Exchange, we examined the effectiveness of target prices published in research reports to anticipate future market prices efficiently. We expected target prices to be consistently biased predictions for a number of reasons: first, publishing research is costly and means disclosing information that is typically sold at a premium. Compulsory free publication, as mandated by Italian law, results in a loss of value for firms which have an incentive to either publish less or try to avoid compulsory publication by issuing research from overseas offices which fall out of the scope of the law. Second, target prices have been shown to have a consistent and significant short-term effect on market prices: since research issuers also have a large equity stake invested and research needs to be compulsory shared with the market, when a recommendation is issued, the target price effect on market prices is anticipated by analysts by overshooting extreme recommendations. Consistent with our predictions, we find that many firms apparently try to avoid publishing and that research intensity is associated with increasing prediction errors. Prediction errors are large and statistically significant, ranging from a minimum of 4% for the ‘sell’ recommendation class to 46.81% and 31.98% for the ‘strong buy’ and the ‘buy’ recommendation classes. We also document a significant positive relationship between prediction errors and the ex-ante implicit return expressed by target prices which suggests that strategic overshooting may be playing a role in target price issuing.

We further argue that, since big investors have sizeable positions in large, highly traded, high growth stocks, strategic report publication will result in prediction errors to be positively related to some explanatory variables like: Market capitalization, Inclusion in the Stock Market Index, Trading Volume and Size. Regressions results confirm our hypotheses both in sign and significance suggesting that, indeed research activity outputs are largely flawed and uninformative. Given the uniqueness of the Italian regulation and the resulting database we have collected, we believe our analysis to be a starting point for future research which will be addressing questions like: What is the cross-section of firms' predictive power? Are valuation techniques adopted by analysts a driver in minimizing prediction errors? What is the effectiveness of target prices issued by foreign firms and not disclosed according to the legal requirement? What is the relationship between target price update and market price evolution: are target prices lagged, are they "chasing" stock market prices or are they effectively anticipating a price pattern? What is the relationship between prediction errors and firms' "affiliation"? Are investors learning from analysts errors? IUs an investment strategy based on Target Price forecasts profitable? We believe these to be interesting questions for future research.

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TABLE 1 PANEL A
Descriptive statistic of companies

The table shows descriptive statistics for the 7036 report issued on 98 companies included in the sample. Companies industry classification is based on FTSE classification at level 3. Report N° is the number of reports included in the final sample.

Company	Industry	Report N. and %	Company	Industry	Report N. and %
Aedes	Financials	9 (0.13%)	Gewiss	General Industries	12 (0.17%)
Alitalia	Cyclical services	26 (0.37%)	Gruppo Coin	Cyclical services	76 (1.08%)
Alleanza	Financials	130 (1.85%)	Gr. E. L'espresso	Cyclical services	125 (1.78%)
Amga	Utilities	33 (0.47%)	Ifil	General Industries	20 (0.28%)
Autogrill	Cyclical services	128 (1.82%)	Irce	General Industries	13 (0.19%)
Autostrada To-Mi	Cyclical services	36 (0.51%)	It Holding	Cycl. cons. goods	33 (0.47%)
Autostrade	Cyclical services	170 (2.42%)	Italcementi	Basic Industries	105 (1.49%)
Banca Carige	Financials	6 (0.09%)	Italmobiliare	Basic Industries	17 (0.24%)
Banca Fideuram	Financials	107 (1.52%)	Jolly Hotels	Cyclical services	8 (0.11%)
Banca Intesa	Financials	184 (2.62%)	La Doria	Non-Cycl. cons. goods	23 (0.33%)
Banca Lombarda	Financials	37 (0.53%)	Marcolin	Cycl. cons. goods	10 (0.14%)
Banca Mps	Financials	118 (1.68%)	Marzotto	Cycl. cons. goods	127 (1.81%)
Bnl	Financials	143 (2.03%)	Mediaset	Cyclical services	219 (3.11%)
Bca.Ppo.Etruria	Financials	7 (0.10%)	Mediobanca	Financials	13 (0.19%)
Bca.Ppo.Intra	Financials	14 (0.20%)	Mediolanum	Financials	136 (1.93%)
Bca.Ppo.Lodi	Financials	23 (0.33%)	Merloni	Cycl. cons. goods	74 (1.05%)
Bca.Ppo.Milano	Financials	73 (1.04%)	Milano Assic.	Financials	20 (0.28%)
Benetton	Cycl. cons. goods	172 (2.45%)	Mirato	Non-Cycl. cons. goods	37 (0.53%)
Beni Stabili	Financials	58 (0.82%)	Mondadori Ed	Cyclical services	141 (2.00%)
Bonif.Ferraresi	Non-Cycl. cons. goods	4 (0.06%)	Navig. Montanari	Cyclical services	18 (0.26%)
Brembo	Cycl. cons. goods	87 (1.24%)	Parmalat	Non-Cycl. cons. goods	147 (2.09%)
Bulgari	Cycl. cons. goods	218 (3.10%)	Permasteelisa	Basic Industries	55 (0.78%)
Buzzi Unicem	Basic Industries	102 (1.45%)	Pininfarina	Cycl. cons. goods	43 (0.61%)
Capitalia	Financials	109 (1.55%)	Pirelli	General Industries	146 (2.08%)
Carraro	Cycl. Cons. goods	18 (0.26%)	Poligrafici Ed.	Cyclical services	13 (0.19%)
Cembre	General Industries	13 (0.19%)	Ras	Financials	135 (1.92%)
Cementir	Basic Industries	26 (0.37%)	Rcs Mediagroup	Cyclical services	68 (0.97%)
Class Editori	Cyclical services	50 (0.71%)	Recordati	Non-Cycl. cons. goods	108 (1.54%)
Credito Emiliano	Financials	61 (0.87%)	Reno De Medici	Basic Industries	20 (0.28%)
Cdt.Valtellines	Financials	2 (0.03%)	Rich. Ginori	Basic Industries	12 (0.17%)
Cremonini	Non-Cycl. cons. goods	57 (0.81%)	Risanamento	Financials	3 (0.04%)
Crespi	Basic Industries	2 (0.03%)	Sabaf	General Industries	42 (0.60%)
Csp Intern.	Cycl. cons. goods	13 (0.19%)	Saes Getters	General Industries	53 (0.75%)
Danieli	General Industries	4 (0.06%)	Saipem	Resources	124 (1.76%)
Ducati Motor Hold.	Cycl. cons. goods	92 (1.31%)	San Paolo Imi	Financials	168 (2.39%)
Edison	Utilities	39 (0.55%)	Sirti	Information Technology	10 (0.14%)
Enel	Utilities	210 (2.99%)	Snai	Cyclical services	10 (0.14%)
Enertad	Cyclical services	7 (0.10%)	Snia Ord	Non-Cycl. cons. goods	55 (0.78%)
Eni	Resources	225 (3.20%)	Sogefi	Cycl. cons. goods	23 (0.33%)
Erg	Resources	106 (1.51%)	Sol	Basic Industries	10 (0.14%)
Ergo Previd.	Financials	41 (0.58%)	Stefanel	Cycl. cons. goods	12 (0.17%)
Ericsson	Information Technology	10 (0.14%)	Stm	Information Technology	97 (1.38%)
Fiat	Cycl. cons. goods	204 (2.90%)	Targetti	General Industries	28 (0.40%)
Fin Part	Cycl. cons. goods	5 (0.07%)	Telecom Italia	Non-cyclical services	219 (3.11%)
Finecogroup	Financials	91 (1.29%)	Telecom It. M.	Information Technology	151 (2.15%)
Finmeccanica	General Industries	116 (1.65%)	Tim	Non-cyclical services	233 (3.31%)
Fondiaria-Sai	Financials	57 (0.81%)	Trevi	General Industries	17 (0.24%)
Gabetti	Financials	6 (0.09%)	Unicredito	Financials	161 (2.29%)
Generali	Financials	166 (2.36%)	Unipol	Financials	31 (0.44%)
Mean number or reports					71.8
Median					46.5
Standard deviation					66.1

TABLE 1 PANEL B
Summary statistics of reports by industry

This table presents reports' descriptive statistics of the final sample sorted by industry distribution. Mean coverage is the arithmetic mean coverage.

Industry	Reports	Companies	Mean coverage
Basic Industries	349	9	39
Cycl. Cons. Goods	1131	15	75
Cyclical services	1095	15	73
Financials	2109	29	73
General Industries	464	11	42
Information Technology	268	4	67
Non Cycl. cons. Goods	431	7	62
Non Cyclical services	452	2	226
Resources	455	3	152
Utilities	282	3	94
Average number of report per industry			703,6
Average number of companies per industry			9,8
Most represented Industry by number of report			Financials
Most represented Industry by number of companies			Financials

TABLE 2 PANEL A
Yearly and monthly report distribution

We report research distribution breakdown by months., quarters, half-year and years. Reports considered are all the reports included in the final database. The first three columns report absolute and percentage report distribution broken down by month, quarter and semester over the total number of reports issued in the four years sampling period. Columns four, five, six and seven report absolute distribution for each year. Percentages report the relative number of reports issued each month over the total number of reports issued the relevant year.

Month	Monthly	Quarterly	Semester	2000	2001	2002	2003
January	322 (4,58%)			43 (4,36%)	100 (5,62%)	43 (2,31%)	136 (5,65%)
February	565 (8,03%)			93 (9,42%)	128 (7,20%)	107 (5,74%)	237 (9,85%)
March	706 (10,03%)	1593 (22,64%)		104 (10,54%)	233 (13,10%)	77 (4,13%)	292 (12,14%)
April	406 (5,77%)			48 (4,86%)	132 (7,42%)	77 (4,13%)	149 (6,20%)
May	864 (12,28%)			152 (15,40%)	221 (12,42%)	156 (8,36%)	335 (13,93%)
June	328 (4,66%)	1598 (22,71%)	3191 (45,35%)	39 (3,95%)	83 (4,67%)	95 (5,09%)	111 (4,62%)
July	594 (8,44%)			64 (6,48%)	139 (7,81%)	212 (11,37%)	179 (7,44%)
August	372 (5,29%)			38 (3,85%)	88 (4,95%)	135 (7,24%)	111 (4,62%)
September	985 (14,00%)	1951 (27,73%)		130 (13,17%)	278 (15,63%)	310 (16,62%)	267 (11,10%)
October	565 (8,03%)			78 (7,90%)	167 (9,39%)	163 (8,74%)	157 (6,53%)
November	998 (14,18%)			126 (12,77%)	160 (8,99%)	373 (20,00%)	339 (14,10%)
December	331 (4,70%)	1894 (26,92%)	3845 (54,65%)	72 (7,29%)	50 (2,81%)	117 (6,27%)	92 (3,83%)
Total	7036 (100,00%)	7036 (100,00%)	7036 (100,00%)	987 (100,00%)	1779 (100,00%)	1865 (100,00%)	2405 (100,00%)

TABLE 2 PANEL B
Reports annual distribution per recommendation class

This table shows total recommendations' distribution and yearly recommendations' distribution. The first column reports absolute and percentage report distribution per recommendation class over the total number of reports issued. Columns two, three four and five report absolute distribution for each year. Percentages report the relative number of reports issued per recommendation class over the total number of reports issued each year.

	TOTAL	**2000**	**2001**	**2002**	**2003**
Strong buy	1075 (15,28%)	254 (25,73%)	327 (18,38%)	255 (13,67%)	239 (9,94%)
Buy	2803 (39,84%)	421 (42,65%)	644 (36,20%)	740 (39,68%)	998 (41,50%)
Hold	2430 (34,54%)	259 (26,24%)	618 (34,74%)	662 (35,50%)	891 (37,05%)
Sell	694 (9,86%)	51 (5,17%)	173 (9,72%)	204 (10,94%)	266 (11,06%)
Strong sell	34 (0,48%)	2 (0,20%)	17 (0,96%)	4 (0,21%)	11 (0,46%)
TOTAL	7036 (100,00%)	987 (100,00%)	1779 (100,00%)	1865 (100,00%)	2405 (100,00%)

TABLE 3
Stock recommendation conversion scale

We illustrate conversion criteria adopted for the database. If a recommendation has been issued according to a five-steps scale conversion has been performed by the upper table conversion rule. If recommendation adopted a three-step scale, conversion followed the rule presented in the lower table

FIVE STEPS SCALE CONVERSION CRITERION

Original Scale				Adopted Scale
Buy	Buy	Strong buy	→	Strong buy
Outperform	Accumulate/Add	Buy	→	Buy
Market perform	Neutral/Hold	Hold	→	Hold
Underperform	Reduce	Sell	→	Sell
Sell	Sell	Strong Sell	→	Strong Sell

THREE-STEPS SCALE CONVERSION CRITERION

Original Scale			Adopted Scale
Buy	$(Tp-p)/p>0.2$	→	Strong buy
	$(Tp-p)/p<0.2$	→	Buy
Hold		→	Hold
Sell	$(Tp-p)/p<-0.2$	→	Sell
	$(Tp-p)/p>-0.2$	→	Strong Sell

TABLE 4
Stock recommendations transition matrix

We present the absolute and relative stock recommendation transitions. For each initial recommendation class (FROM), we identified the revised recommendation (TO). Figures are then calculated as the ratio between the number of reports revised in the new recommendation class (TO) over the total number of reports of the initial recommendation class (FROM).

	TO					
FROM	**Strong buy**	**Buy**	**Hold**	**Sell**	**Strong sell**	**TOTAL**
Strong buy	567 (61,50%)	241 (26,14%)	96 (10,41%)	18 (1,95%)	0 (0,00%)	922 (100,00%)
Buy	182 (8,18%)	1574 (70,71%)	385 (17,30%)	85 (3,82%)	0 (0,00%)	2226 (100,00%)
Hold	56 (2,98%)	294 (15,66%)	1371 (73,04%)	152 (8,10%)	4 (0,21%)	1877 (100,00%)
Sell	7 (1,43%)	46 (9,41%)	115 (23,52%)	315 (64,42%)	6 (1,23%)	489 (100,00%)
Strong sell	0 (0,00%)	0 (0,00%)	1 (3,70%)	8 (29,63%)	18 (66,67%)	27 (100,00%)
TOTAL	812	2155	1968	578	28	5541 (100,00%)

FIGURE 1

Accuracy metrics

We graphically present the four accuracy measures we developed in this paper. δ_1 is defined as the 'Ideal Strategy' (IS) control variable which calculates the ideal return as the difference between the maximum/minimum price over the time horizon and the issue date share price. δ_2 measures the IS prediction error for any report as the difference between the issued target price at t0 and the maximum/(minimum) market price in the relevant prediction time-horizon. δ_3 is the second control variable measuring the 'Feasible Strategy' (FS) return as the difference between the price at the end of the time horizon and the report's issue date share price. δ_4 measures the FS prediction error for any report as the difference between the issued target price and the stock market price at the end of the investment time-horizon.

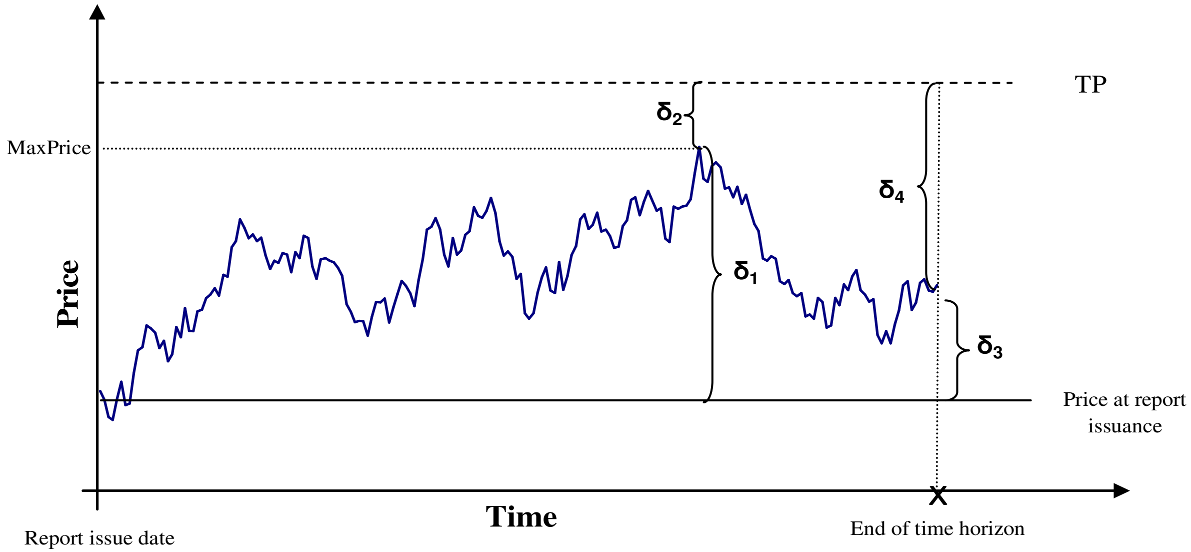

FIGURE 2
Variables' construction and sign interpretation

Variables are constructed as follows: if TP is greater than market price at t_0 (top side of the graph), a positive sign for variables δ_2 δ_4 means that TP has proved to be greater than the realized market price at the end of the time horizon. We name this event as "overshooting". A negative sign means that the realized market price has exceeded the issued TP: we define this recommendation to be "conservative". For the bottom part of the graph (when TP is lower than current market price at t0), overshooting occurs when we obtain a positive sign i.e.when the issued TP is lower than the realzied market price.

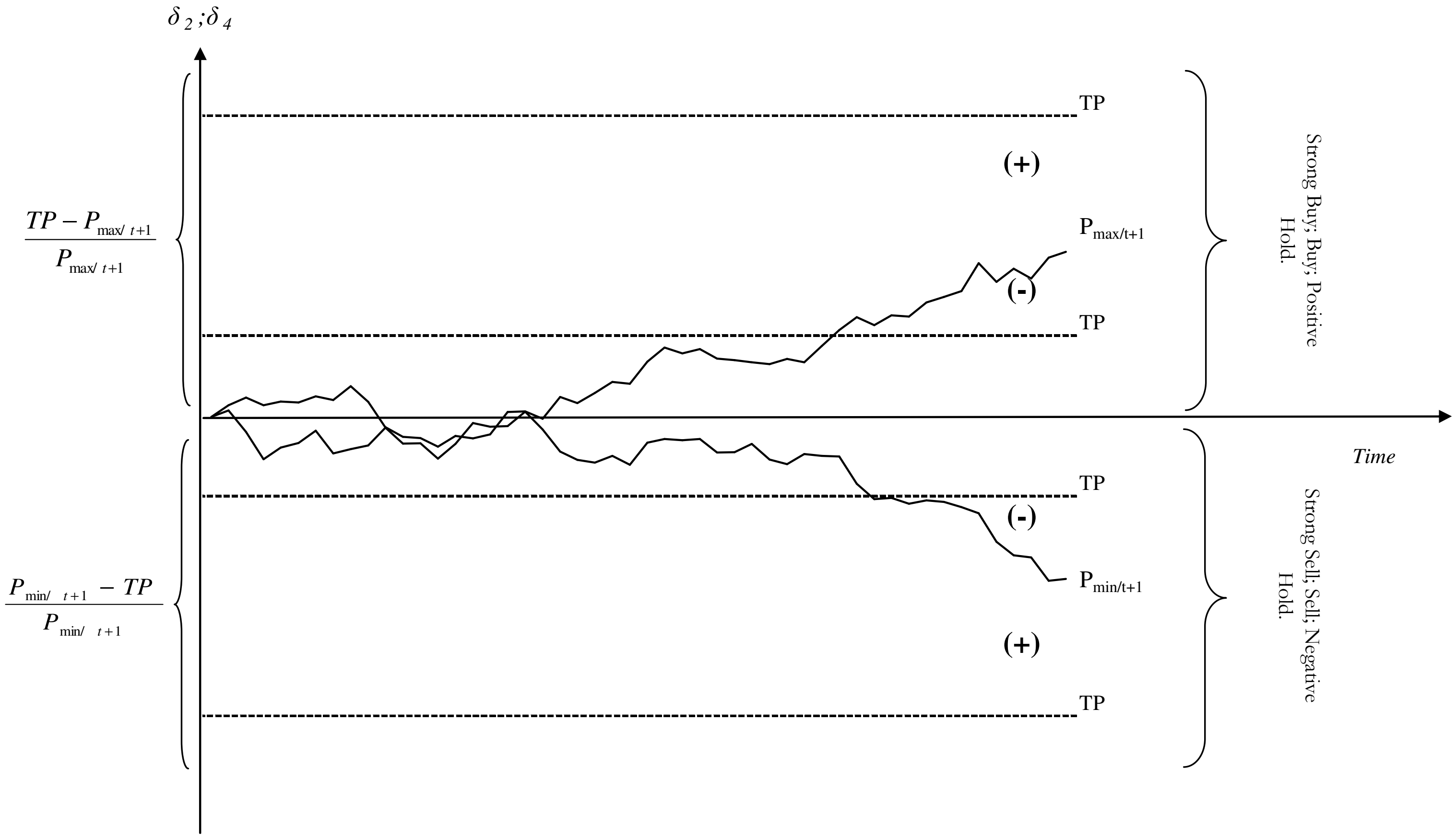

TABLE 5
Reports accuracy summary statistics

This table shows summary statistics for implicit returns, target price revisions and accuracy metrics. In columns 1 we report predicted implicit returns computed as the difference between target price and the market price at the issue date. In Column 2 we report the quantitative change in Target Price revisions measured as the percentage difference between a target price and its closest revision. Columns 3 and 4 report figures for the 'Ideal Strategy' (IS) accuracy control metric and variable respectively. Columns 5 and 6 report figures for the 'Feasible Strategy' (FS) accuracy control metric and variable respectively

	$[TP_{t0}/P_{t0}]$-1	$[TP_{t1}/TP_{t0}]$-1	δ_1	δ_2	δ_3	δ_4
Strong buy						
Mean	38,18%	1,23%	14,43%	22,39%	-0,26%	46,81%
Median	46,25%	0,00%	19,52%	32,68%	-0,71%	37,42%
Std. Dev.	22,03%	20,92%	17,63%	20,89%	22,89%	46,55%
Max	247,49%	127,27%	156,92%	115,38%	132,43%	488,52%
Min	-1,11%	-89,29%	0,00%	-51,46%	-79,51%	-46,34%
N° of obser.	1064	798	1064		913	
Buy						
Mean	22,63%	-0,70%	12,65%	10,09%	-1,61%	31,98%
Median	28,45%	0,00%	16,30%	18,18%	-0,36%	22,68%
Std. Dev.	15,05%	19,76%	15,91%	15,93%	21,13%	42,59%
Max	236,08%	166,67%	233,00%	198,53%	142,46%	462,43%
Min	-38,27%	-77,54%	-36,47%	-97,99%	-77,32%	-49,24%
N° of obser.	2595	1980	2595		1990	
Hold						
Mean	7,52%	-6,31%	9,69%	-0,63%	-4,53%	18,67%
Median	6,25%	0,00%	6,43%	-0,53%	-2,18%	11,34%
Std. Dev.	15,64%	22,36%	15,97%	17,50%	21,72%	43,26%
Max	180,00%	179,17%	98,34%	146,36%	96,52%	460,98%
Min	-48,85%	-85,78%	-59,93%	-99,51%	-79,62%	-173,90%
N° of obser.	2050	1618	2050		1547	
Sell						
Mean	-10,21%	-13,50%	-15,62%	-12,78%	-5,09%	4,08%
Median	-1,91%	-8,24%	-3,32%	-2,28%	-4,17%	9,20%
Std. Dev.	14,93%	26,53%	18,28%	36,74%	21,72%	32,69%
Max	52,49%	126,67%	57,61%	48,05%	83,45%	79,42%
Min	-63,33%	-87,83%	-84,02%	-218,58%	-74,49%	-178,40%
N° of obser.	568	463	568		391	
Strong Sell						
Mean	-31,22%	-17,17%	-16,85%	9,77%	-8,88%	17,06%
Median	-11,37%	-11,35%	-4,93%	18,77%	-1,48%	17,31%
Std. Dev.	20,69%	31,59%	18,91%	41,93%	19,92%	33,07%
Max	1,15%	76,00%	0,00%	61,31%	14,05%	66,91%
Min	-67,06%	-71,88%	-75,59%	-123,21%	-71,61%	-57,62%
N° of obser.	32	28	32		26	

TABLE 6 PANEL A
Descriptive statistic of firms

This table shows summary statistics for the 47 firms included in the sample and the absolute and relative number of report issued by these firms. We classify firms into two groups Domestic (D) and Foreign (F), assuming a firm to be foreign if its headquarter is not incorporated in Italy and it does not have a research team in Italy.

Firm	Nationality	Report N. and %	Firm	Nationality	Report N. and %
Abaxbank	D	24 (0.34%)	DKW	F	124 (1.76%)
ABN AMRO	F	95 (1.35%)	Eptasim	D	135 (1.92%)
Actinvest	D	263 (3.74%)	Euromobiliare	D	614 (8.73%)
Axia	D	1 (0.01%)	Fortis bank	F	24 (0.34%)
Banca Aletti	D	9 (0.13%)	Gestnord	D	2 (0.03%)
Banca Finnat	D	7 (0.10%)	Goldman Sachs	F	72 (1.02%)
Banca Leonardo	D	281 (4.00%)	Ideaglobal	D	140 (1.99%)
Banca Mediosim	D	5 (0.07%)	IMI	D	405 (5.76%)
Banca Sella	D	7 (0.10%)	ING	F	39 (0.55%)
Banknord	D	7 (0.10%)	Intermonte	D	815 (11.59%)
Bipielle/Santander	D	119 (1.69%)	Intesa	D	338 (4.81%)
BNP Paribas	F	121 (1.72%)	JP Morgan	F	3 (0.04%)
Borsaconsult	D	2 (0.03%)	Julius Baer	F	187 (2.66%)
BP Bari	D	6 (0.09%)	Lehman brothers	F	92 (1.31%)
BPM	D	258 (3.67%)	M. Mortari	D	58 (0.82%)
Cazenove	F	5 (0.07%)	Mediobanca	D	229 (3.26%)
Centrosim	D	198 (2.82%)	Merrill Lynch	F	325 (4.62%)
Cheuvreux	F	194 (2.76%)	Metzler	F	19 (0.27%)
Citigroup	F	19 (0.27%)	Rasfin	D	171 (2.43%)
Cofiri	D	41 (0.58%)	SG	F	133 (1.89%)
Consors	D	31 (0.44%)	UBM	D	500 (7.11%)
Credit Lyonnais	F	40 (0.57%)	UBS	F	304 (4.32%)
CSFB	F	90 (1.28%)	Uniprof	D	29 (0.41%)
Deutsche bank	D	455 (6.47%)			
Total Domestic Firms (D)					5150 (73.19%)
Total Foreign Firms (F)					1886 (26.81%)
Mean number of reports (full sample)					150
Median number of reports (full sample)					92
Max					815
Min					1

TABLE 6 PANEL B
Research intensity and nationality

This table reports for each bank the million dollar amount of underwritten securities (equity, debt, equity-linked) on the italian market between 1/1/2000 and 31/12/2003, and the relative frequency of research issued by the underwriter (report frequency) measured as the amount of report issued by the underwriter divided by the total amount of report issued by all researchfirms. Firms are sorted into Domestic and Foreign according to the nation of incorporation of the headquarter and the existance of a research team based in Italy.

	Firm	Amount	Frequency	Report frequency	Nationality
Top 50%	Unicredito Italiano	20172,61	10,62%	7,11%	D
	Gruppo Intesa	18014,68	9,48%	4,81%	D
	JP Morgan	17765,84	9,35%	0,04%	F
	Banca IMI	14724,33	7,75%	5,76%	D
	Morgan Stanley	14372,8	7,56%	0,00%	F
	Lehman Brothers	14090,46	7,42%	1,31%	F
Cumulated		**99140,72**	**52,18%**	**19,03%**	
Cumulated Domestic			*27,85%*	*17,68%*	
Cumulated Foreign			*24,33%*	*1,35%*	
Top 80%	Mediobanca	11320,24	5,96%	3,26%	D
	Merrill Lynch & Co	10490,79	5,52%	4,62%	F
	Citigroup	8048,09	4,24%	0,27%	F
	Deutsche Bank AG	6909,38	3,64%	6,47%	D
	Goldman Sachs & Co	5542,97	2,92%	1,02%	F
	UBS	5383,58	2,83%	4,32%	F
	BNP Paribas Group	4852,11	2,55%	1,72%	F
Cumulated		**151687,88**	**79,83%**	**40,71%**	
Cumulated Domestic			*41,68%*	*27,41%*	
Cumulated Foreign			*38,15%*	*13,30%*	
Top 90%	Credit Suisse First Boston	4219,29	2,22%	1,28%	F
	ABN Amro Bank NV	4010,13	2,11%	1,35%	F
	MPS Finance BM	2566,49	1,35%	11,91%	D
	Banca di Roma	2103,64	1,11%	0,58%	D
	Abaxbank	1779,39	0,94%	0,34%	D
	HSBC	1755,21	0,92%	0,00%	F
	Banca Nazionale del Lavoro	1569,65	0,83%	0,00%	D
	Credit Agricole Indosuez	1535,78	0,81%	2,76%	F
Cumulated		**171227,46**	**90,11%**	**58,93%**	
Cumulated Domestic			*45,90%*	*40,25%*	
Cumulated Foreign			*44,22%*	*17,34%*	

FIGURE 3
Research intensity and market activism

This figure exhibits the cumulative amount of research issued by firms paired with the same firms' level of investment activity measured as the dollar value of securities underwritten in the 2000-2003 time horizon. We sort data by three cutoffs: Top 50% compares the amount of research issued by firms representing 50% of the total underwriting in the time horizon; Top 80% and Top 90% are analogously defined.

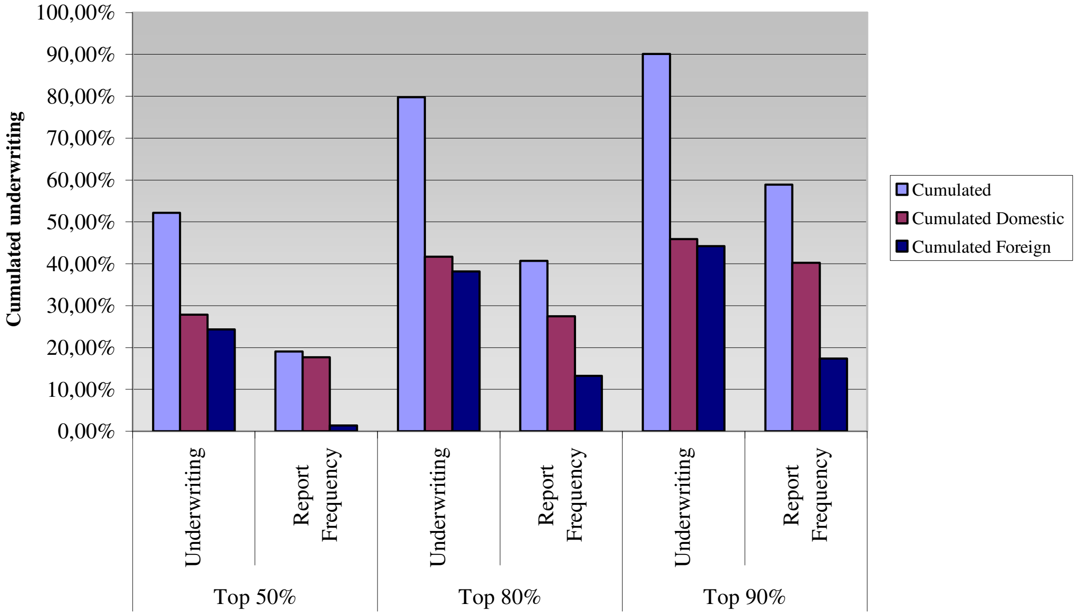

Table 7
Analysts comparative accuracy

We show descriptive statistics of the accuracy of target price predictions. A target price is considered to be accurate if the underlying share price reaches the target price (with an accuracy tolerance of +/-5%) at the end of the forecasting period (δ_4) or anytime between the issuing date and the end of the forecasting period (δ_2). RelativeIN is the ratio of accurate reports over total reports issued by the bank; Absolute accuracy is the ratio between accurate reports over total reports issued by all banks; Relative Hits is the ratio between accurate reports over total accurate reports issued by all banks. Missing data are due to lack of stock market data on the last issued report.

	δ_2 Accuracy			δ_4 Accuracy		
Company	Absolute	RelativeIN	Relative Hits	Absolute	RelativeIN	Relative Hits
Abaxbank	0,11%	31,82%	0,49%	0,08%	30,77%	0,68%
ABN AMRO	0,27%	23,94%	1,18%	0,08%	9,76%	0,68%
Actinvest	1,04%	26,64%	4,53%	0,41%	10,64%	3,42%
Banca Aletti	0,02%	16,67%	0,07%	-	-	-
Banca Finnat	0,02%	14,29%	0,07%	-	-	-
Banca Leonardo	1,06%	23,57%	4,60%	0,68%	13,81%	5,65%
Banca Sella	0,06%	57,14%	0,28%	-	-	-
Bipielle/Santander	0,30%	16,24%	1,32%	0,10%	6,49%	0,86%
BNP Paribas	0,50%	26,27%	2,16%	0,25%	14,46%	2,05%
BP Bari	0,02%	50,00%	0,07%	-	-	-
BPM	0,95%	26,34%	4,11%	0,37%	10,91%	3,08%
Centrosim	0,48%	20,41%	2,09%	0,23%	10,58%	1,88%
Cheuvreux	0,63%	21,43%	2,72%	0,23%	8,73%	1,88%
Citigroup	0,05%	15,79%	0,21%	0,02%	33,33%	0,17%
Cofiri	0,22%	36,84%	0,97%	0,06%	12,00%	0,51%
Consors	0,14%	29,03%	0,63%	-	-	-
Credit Lyonnais	0,10%	16,67%	0,42%	0,02%	6,25%	0,17%
CSFB	0,47%	34,94%	2,02%	0,19%	17,65%	1,54%
Deutsche bank	1,27%	21,88%	5,50%	0,91%	14,24%	7,53%
DKW	0,37%	23,96%	1,60%	0,10%	7,46%	0,86%
Eptasim	0,39%	18,90%	1,67%	0,17%	9,09%	1,37%
Euromobiliare	1,75%	18,08%	7,59%	1,01%	9,11%	8,39%
Fortis bank	0,13%	33,33%	0,56%	0,02%	7,69%	0,17%
Gestnord	0,02%	50,00%	0,07%	-	-	-
Goldman Sachs	0,06%	15,38%	0,28%	0,04%	16,67%	0,34%
Ideaglobal	0,75%	34,81%	3,27%	0,39%	21,11%	3,25%
IMI	1,20%	23,01%	5,22%	0,68%	12,55%	5,65%
ING	0,16%	25,64%	0,70%	0,08%	12,50%	0,68%
Intermonte	3,07%	23,61%	13,30%	2,23%	14,79%	18,49%
Intesa	1,03%	21,19%	4,46%	0,50%	9,96%	4,11%
JP Morgan	0,02%	50,00%	0,07%	-	-	-
Julius Baer	0,72%	25,14%	3,13%	0,23%	9,48%	1,88%
Lehman brothers	0,24%	16,48%	1,04%	0,25%	17,14%	2,05%
M. Mortari	0,24%	27,78%	1,04%	0,14%	16,28%	1,20%
Mediobanca	0,91%	28,08%	3,97%	0,50%	16,00%	4,11%
Merrill Lynch	0,72%	21,74%	3,13%	0,33%	9,64%	2,74%
Metzler	0,03%	14,29%	0,14%	-	-	-
Rasfin	0,45%	18,18%	1,95%	0,12%	6,00%	1,03%
SG	0,30%	18,45%	1,32%	0,12%	9,38%	1,03%
UBM	1,65%	23,90%	7,17%	0,76%	9,97%	6,34%
UBS	1,04%	21,74%	4,53%	0,72%	14,17%	5,99%
Uniprof	0,08%	55,56%	0,35%	0,02%	50,00%	0,17%
Overall Accuracy	23,05%			12,06%		
Mean	0,55%	26,65%	2,38%	0,35%	14,08%	2,94%
Median	0,34%	23,75%	1,46%	0,23%	11,45%	1,88%
Correlation In-Hits		-22,41%			-10,74%	

TABLE 8
Accuracy and research intensity

We test the effect of research intensity on analysts' accuracy. Column 1 and 2 show estimates obtained by regressing each firm yearly average δ_2 and δ_4 accuracy measure on the total amount of reports published by the firm in every sample year. Column 3 shows estimates obtained by regressing the average volatility of implicit returns (TP_{t0} / P_{t0}) embedded in target prices issued by each firm on the number of reports published by each bank. Significance at 10%,5% and 1% level is denoted by *,**,*** respectively.

Dependent Variable	δ_2		δ_4		Implicit return volatility	
	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Intercept	-0.005	-0.573	0.027***	5,975	0.167	12.974
N° report	0.579 ***	4.711	0,910 ***	13,854	0.320**	2.192
Adj R^2	0.320		0.823		0.081	
Std. Error of Estimate	0.047		0.021		0.064	
F-Statistic	22.192***		191.922***		4.807**	

TABLE 9

Accuracy measures and recommendation classes

This table provides evidence on the effect on prediction errors of each recommendation class controlling for the Implicit return effect. We regress δ_2 and δ_4 on 4 dummy variables representing the recommendation classes 'Strong Buy, 'Buy', 'Sell', 'Strong Sell' and on one variable representing the implicit return (TP_{t0}/P_{t0}) expressed by target price at the time of report publication. We exclude the “hold” class which is our control class. Significance at 10%,5% and 1% level is denoted by *,**,*** respectively.

	δ_2		δ_4	
Dependent Variable	Coefficient	T-stat	Coefficient	T-stat
Intercept	-0.588***	-38.30	-0.559***	-14.184
TP/P	0.541***	39.271	0.691***	19.632
Strong buy	0.064***	7.957	0.070***	3.427
Buy	0.025***	4.345	0.300**	2.035
Sell	-0.026***	-2.938	-0.023	-0.947
strong sell	0.314***	9.582	0.240***	2.903
Adj R^2	0.353		0.141	
Std. Error of Estimate	0.181		0.412	
F-Statistic (Significance Level)	682.548***		161.284***	

TABLE 10

Accuracy measures and recommendation revisions

In this table we test the effect on accurcay by recommendation revisions controlling for the implicit return effect. We regress δ_2 and δ_4 on 2 dummy variables representing the recommendation revision types 'upgrade' and 'downgrade' and on one variable representing the implicit return (TP_{t0}/P_{t0}) expressed by target price at the time of report publication. We exclude the 'reiteration' class which is our control class. Significance at 10%,5% and 1% level is denoted by *,**,*** respectively.

	δ_2		δ_4	
Dependent Variable	Coefficient	T-stat	Coefficient	T-stat
Intercept	-0.490***	-20.962	-0.628***	-13.144
TP/P	0.504***	26.078	0.764***	19.540
Upgrade	-0.027**	-2.177	-0.027	-1.059
Downgrade	-0.035***	-3.038	0.026	1.121
Adj R^2	0.128		0.086	
Std. Error of Estimate	0.296		0.545	
F-Statistic (Significance Level)	249.41***		129.85***	

TABLE 11

Accuracy and market factors

This table provides results from regressing δ2 and δ4 errors on 6 variables related to: company status, market momentum and research intensity. Regressors interpretation goes as follows: company market value (MV) is measured at each report issuing date as the stock market capitalization in million euro,volume of share transaction (VOL) is calculated at each recommendation issuing day as the average turnaround volume measured in million euro; inclusion in the stock market index (MIB30) is treated as a dummy variable taking a value of 1 if, at the report issue date, the company is included in the index; research intensity (COV: RATIO) is measured by the company coverage ratio given by the number of reports issued on company *i* divided by total number of reports issued, market momentum (MKT_INDEX) is measured as the relative level of the market index at any report issuing date, divided by the average index value between 2000 and 2003; expected implicit return is measured as the ratio between the target price and the share market price at t_0 (TP_{t0}/P_{t0}). Significance at 10%,5% and 1% level is denoted by *,**,*** respectively.

	δ_2		δ_4	
Dependent Variable	Coefficient	T-stat	Coefficient	T-stat
Intercept	-0.640***	-36.042	-0.858***	-18.886
MV	0.070***	4877	-0.060***	-3.238
VOL	0.004	0.302	0.039**	2.456
MIB30	0.025*	1.751	0.090***	5.024
COV: RATIO	-0.047***	-3.169	-0.034*	-1.810
MKT_INDEX	0.006	0.559	0.122***	8982
TP_{t0}/P_{t0}	0.580***	55.681	0.380***	28.381
Adj R^2	0.342		0.157	
Std. Error of Estimate	0.183		0.410	
F-Statistic (Significance Level)	533.032***		149.731***	

TABLE 12
Partial prediction error regression

This table provides results from regressing δ_2 and δ_4 partial errors previously sorted by 3 stock recommendations groups: Strong buy-Buy, Hold, Sell-Strong Sell and by 2 groups of sign of errors: positive δ_2,δ_4 and negative δ_2,δ_4. Regressors are calculated as follows: company market value (MV) is measured at each report issuing date as the stock market capitalization in million euro,volume of share transaction (VOL) is calculated at each recommendation issue date as the average turnaround volume measured in million euro; inclusion in the stock market index (MIB30) is treated as a dummy variable taking a value of 1 if, at the report issue date, the company is included in the index; research intensity (COV: RATIO) is measured by the company coverage ratio given by the number of reports issued on company *i* divided by total number of reports issued, market momentum (MKT_INDEX) is measured as the relative level of the market index at any report issuing date, divided by the average index value between 2000 and 2003; expected implicit return is measured as the ratio between the target price and the share market price at t_0 (TP_{t0}/P_{t0}). Panel A and B reports results for the δ_2 and δ_4 accuracy metric respectively. Significance at 10%,5% and 1% level is denoted by *,**,*** respectively.

PANEL A

	(StrongBuy-Buy)		(Hold)		(StrongSell-Sell)		$\delta_2>0$		$\delta_2<0$	
Dependent Variable	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Intercept	-0.754***	-38.358	-0.759***	-25.229	0.900***	7.863	-0.272***	-20.451	-0.491***	-10.164
MV	0.119***	7.188	0.039	1.488	0.062	1.061	0.039**	2.265	0.109***	3.430
VOL	0.006	0.421	0.012	0.515	-0.033	-0.616	0.016	1.195	0.008	0.285
MIB30	0.047***	2.822	0.055**	2.255	-0.153***	2.914	0.060***	3.642	-0.073**	-2.335
COV: RATIO	0.068***	-3.900	-0.053**	-2.116	0.125**	2.362	-0.080***	-4.501	0.050*	1.654
MKT_INDEX	0.005	0.393	0.134***	6.881	-0.212***	-5.403	-0.011	-0.866	-0.079***	-3.245
TP_{t0}/P_{t0}	0.711***	59.399	0.545***	28.739	-0.326***	-8.221	0.593***	49.215	0.233***	9.774
Adj R^2	0.506		0.053		0.141		0.359		0.073	
Std. Error of Estimate	0.130		0.168		0.346		0.120		0.211	
F-Statistic (Significance Level)	610.566***		19.639***		17.285***		418.524***		22.881***	

PANEL B

	(StrongBuy-Buy)		(Hold)		(StrongSell-Sell)		$\delta_4>0$		$\delta_4<0$	
Dependent Variable	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Intercept	-0.938***	-13.386	-0.966***	10.075	0.707***	5.749	-0.628***	-13.021	-0.419***	-5.599
MV	-0.053**	-2.160	-0.062**	-1.811	-0.016	-0.226	-0.099***	-4.786	0.064	1.369
VOL	0.072**	3.497	-0.023	-0.762	-0.034	-0.515	0.047***	2.634	-0.029	-0.726
MIB30	0.095**	3.962	0.110***	3.495	-0.011	-0.167	0.097***	4.803	0.024	0.535
COV: RATIO	-0.062	-2.424	-0.006	-0.177	0.080	1.208	-0.043**	-2.026	0.049	1.131
MKT_INDEX	0.169***	9.594	0.108***	4.265	-0.277***	-5.668	0.181***	12-062	-0.246***	-6.871
TP_{t0}/P_{t0}	0.338***	19.158	0.319***	12.923	-0.154***	-3.171	0.300***	20.166	0.255***	7.379
Adj R^2	0.144		0.104		0.096		0.124		0.126	
Std. Error of Estimate	0.412		0.412		0.312		0.397		0.219	
F-Statistic (Significance Level)	80.973***		30.361***		8.305***		95.834***		19.425***	