Essays on Sell-Side Analyst Industry

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CHAPTER 1

Introduction

Financial analysts play a key role in the proper functioning of markets and the maintenance of market liquidity and price efficiency. The ready availability of various types of financial information ensures appropriate pricing and helps issuers to raise capital in primary markets, and ensures deep and liquid secondary markets for financial instruments.

Research produced by financial analysts provides investors with interpretation of financial and economic data on traded securities. Analysts synthesise raw information into readily accessible research. This research is used in turn by investors to help make their investment decisions or by intermediaries to produce investment research, advice or marketing communications. Commonly, there are three categories of financial analyst: sell-side, buy-side and independent. The first group typically work on behalf of brokerage firms, brokers or dealers, and their work consists of driving the investment decisions of customers. The second group work on behalf of institutional money managers, i.e. people who are responsible for asset management and buying their own financial instruments, such as investment funds, hedge funds and so on. Their activity is aimed at orienting the portfolio choices of their clients. Finally, the so-called independent analysts act on their own behalf or on that of people who cannot be attributed to groups. Given that the their research is often directly provided to retail investors, sell-side analysts are usually the most common type of analyst to be investigated in research.

There is no legal description of financial analysts, as indicated by the EU Forum Group: "s/he provides third parties (i.e. an analyst's employer or its clients) with verbal and written analyses based on established financial analytical techniques. S/he is primarily responsible for, contributes to, or is connected with, the interpretation of economic, strategic, accounting, financial and non-financial data relating to securities issued by companies and/or public sector issuers, and/or industry sectors, in order to forecast their results and assess the securities' value for use in taking investment decisions." Therefore, an analyst's report is the final product of a process which includes the collection and valuation of information related to the future performance of a specific company. The process starts with a company's disclosure of public information, such as its strategies, the competitive landscape, financial data and other non-financial factors like the quality of its management. Based on this information, analysts use their skills to process (through one or more valuation methods) heterogeneous data into valuations of the firms, which, when compared to the current trading price, result in a justifiable stock recommendation which is released to investors.

This complex process of collecting and valuing information results in a written report, which usually contains a minimum content, including at least three summary measures on its front page: the actual recommendation level (i.e., buy, hold, or sell), the earnings forecast and the target price forecast. In addition, sometimes the full text of the report provides quantitative and qualitative analyses supporting the three summary measures, and the extra information disclosed here in can be rich and extensive. In these cases, the analysts show in a quite transparent way the valuation method(s) which were used to reach their final recommendation and, thus, provide the investors with details which help them to determine how the company valuation has been conducted.

Finally, the investment bank which employs the analysts disseminates the report to its clients and thus to the market. Therefore, financial analysts act as intermediaries between portfolio managers and the companies which they evaluate.

The importance of the activity of financial analysts is evidenced by the big investments which the financial services industry make each year in the formal analysis of stock prices and the production of investment recommendations. Furthermore, investors pay great attention to these recommendations in order to gain information about the prospective value of securities.

The growing influence of this 'secondary information' in determining the investment decisions of investors and, more generally, market trends has motivated the legislatures of different countries to act to ensure that such research is reliable and objective, and, as a result of the corporate scandals of recent years, attention has focused on the preparation and dissemination of studies on securities (both simple and complex) carried out by financial analysts.

The main concerns relating to how financial analysts respond to the obligation of information disclosure relate to the fact that their research, in many cases, is not entirely independent as they may face a complex mix of conflicts of interest. In fact, as demonstrated by many different studies, the reliability of the recommendations made by financial analysts often appear to be compromised by their personal interest in the securities which they are researching, due to their relationships with the companies involved or the banks responsible for the placement of the securities.

In response, regulators have increased the amount of regulatory disclosure in this area. In the US, two major regulatory changes are worth highlighting. One is the introduction in 2000 of 'Regulation Fair Disclosure' (RegFD), which prohibits US firms from making selective disclosures. The other is the Sarbanes-Oxley Act (SOX) of 2002. Title V of SOX, entitled 'Analyst Conflicts of Interest', requires analysts to disclose the existence of a financial interest in or association with the firms which they review, reinforcing investor protection against analysts' conflicts of interest.

In 2003, the European Parliament adopted Directive 2003/6/EC[1], known as the Market Abuse Directive (MAD), which is the European counterpart of the US regulations. In the EU, as in the US, financial institutions are required to erect a 'Chinese Wall' between research and other investment banking departments, disclose their interests (e.g. brokerage and investment banking ties) in the firms which they recommend and provide investors with statistics concerning their recommendations.

Most previous literature on financial analysts has focused upon the US. The European context has been rather less studied. However, it is an interesting area of research both for its unique characteristics and for its differences from the American market.

Regarding conflicts of interest, for instance, in Europe the regulations may be, to a large extent, ineffective. Firstly, conflicts due to investment banking ties are less acute in the EU than in the US as the number of European financial institutions active in both financial analysis and investment banking activities is fairly small. In addition, these financial institutions are mainly universal banks, meaning that they are more diversified in terms of revenue than their US counterparts. They are, therefore, expected to exert less pressure on sell-side analysts to make them issue overoptimistic recommendations. Secondly, European analysts differ in many respects from their US counterparts. Jegadeesh and Kim (2006) find that optimism in recommendations is lower in Europe than in the US or Canada, probably because, as shown by Clement, Rees and Swanson (2003) and Bolliger (2004), forecast accuracy is not a major concern in terms of their career progression.

This thesis focuses on the European setting and aims to analyse unexplored issues of the equity analysis industry. Given the crucial importance of a high standard of analyst research on financial markets, the extremely negative effects which low quality oversights can produce (see, for example, the recent financial scandals) and the big efforts and resources put towards regulating financial analyst activity, we decided to focus our research interests specifically on the analysis of issues related to financial analyst activity in Europe.

Beyond the large number of studies about financial analysts, the focus of most of the extant research is on theoretical issues relating to the creation and dissemination of value or the use of

[1]See http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2003:096:0016:0016:EN:PDF.

quantitative methods, often leaving out the practical dimension of the specific valuation processes employed by European analysts. In other words, the numerous empirical studies on financial analyst forecasts have rarely studied the actual valuation processes followed by financial analysts.

The academic research on the topic of financial analysts can be roughly divided into three main streams: the value of their information, the accuracy of their forecasts and conflicts of interest.
Prior research focused on the issue of the value analysts' information sought to analyse market reaction following the release of a new report, especially when the report contains a revision of an earnings forecast, target price or recommendation. Attention is usually focused on the price impact, but some studies also explore the impact on the volume which is traded.

The pioneer works of Givoly and Lakonishok (1980) and Griffin (1976) documented significant abnormal returns at the same time as earning forecast revisions were released. Lys and Sohn (1990) found that each analyst forecast is informative regarding price, though they are preceded by other types of disclosure, including the forecast revisions of other analysts. Stickel (1992) highlighted that analyst members of II-All America research team issue more accurate forecasts, which have a more significant impact on short-term pricing. Gleason and Lee (2000) analysed not only the immediate impact of the forecast changes on prices, but also extended the time horizon of their monitoring to up to two years after the time of the revision, and detected a persistent price drift in each of the two monitored years. Womack (1996) documented a strong short-term abnormal return associated with upgrading recommendations and an even stronger impact from downgrading recommendations, plus a longer-term price drift in the direction forecast by the analyst. Various subsequent works have confirmed the short- and longer-term impact generated by a new report release, while exploring in more depth the combined and independent value of the information of different features of the report: earnings forecasts and recommendations (Francis and Soffer, 2003), target prices (Brav and Lehavy, 2003), the strengths of the arguments proposed by the analyst (Asquith et al., 2005), the expected accuracy and timing of forecasts, the analyst experience, broker size and forecast frequency (see Stickel (1992), Abarbanell et al. (1995), Mikhail et al. (1997), Clement (1999), Jacob et al. (1999), Park and Stice (2000), and Clement and Tse (2003)). Further details of this stream of literature are provided in Chapter 3.

Papers focused on the issue of the accuracy of forecasts seek to measure and compare the forecasting ability of different analysts, exploring the main drivers of this ability (or inability) and its consistency over time. Stickel (1992) and Shina et al. (1997), for instance, documented systematically different levels of accuracy in earnings forecasts. Many studies have looked for a relationship between the accuracy of forecasts and the characteristics of individual analysts. In particular, with reference to a model of 'learning by doing', some have focused on the relationship between accuracy and the experience accumulated by an analyst who follows a specific company. Mikhail et al. (1997) found that accuracy improves with the experience of the analyst, either in general or in a specific industry. However, in failing to separate the effects of 'learning by doing' from those which are a result of better access to information provided by company management, the authors did not explain how this improvement in accuracy actually occurs.

Lys and Soo (1996) evaluated accuracy in relation to some cost- and revenue-related variables. In particular, they showed that accuracy is positively related to public company information and the number of analysts covering the stock, but it is negatively correlated to the predictability of earnings, trading volume and the forecasting horizon since it increases when the release date of profits approaches. Mikhail et al. (1997) demonstrated that accuracy is negatively related to the forecasting horizon and positively related to the available company information. Jacob (1997) noted that accuracy is a sum of subsequent improvements, some of which are attributable to a 'learning by doing' process; but other factors must be added. Specifically, he considers those elements which affect analysts' performance, such as, for instance, the increased availability of historical information, the environment in which they operate or the interests of the brokers for whom they work. Clement (1999) found evidence that the accuracy of earnings forecasts is positively associated to analysts' experience and the size of their firm (seen as a proxy of the resources available), while it is negatively affected by the scope of coverage, measured by the number of companies and industries which are followed. Hong et al. (2000) and Jacob et al. (1999) do not support the 'learning by doing' hypothesis. Hong et al. (2000) claimed that the model based on 'learning by doing' is insufficient to explain the different levels of accuracy and that a wider understanding of the phenomenon must be based on theories related to analysts' reputation and their herding behaviour.

Jacob et al. (1999) mentioned the work of some researchers of psychology, who believe that learning by experience is a difficult task and that the opportunity to make forecasts is not sufficient to learn how to do it. On the contrary, there is the possibility of learning the wrong things. For these authors, understanding the relationships between factors is crucial for the learning process.
Consistent with earlier research, Jacob et al. (1999) demonstrated that different levels of aptitude or natural skills for difficult tasks, affiliation to bigger brokers or specific association with a company can be a source of advantage in issuing more accurate forecasts.

Brown (2001) proposed a model which evaluates the accuracy of analysts only in the light of their past accuracy and showed that it works as well as that used by Clement (1999) by combining five characteristics related to analysts: generic experience, specific experience related to a company, the number of companies and industries followed, and the size of the broker. Furthermore, some of the literature has analysed the link between the accuracy of forecasts and their boldness, by indicating how much the estimates are above or below either the previous individual forecast or the most recent consensus. Trueman (1994) found that analysts tend to produce estimates similar to those previously issued by others (herding behaviour), even though it is not always justified by the available information, and that they also tend to produce estimates closer to previous expectations, even though the information justifies more extreme predictions. Hong et al. (2000)'s study confirmed the tendency towards herding behaviour. Clement and Tse (2005) extend the earlier research and find that the forecasts of analysts who herd are better correlated to errors in forecasts and, therefore, less accurate. This confirms the fact that analysts who make bold estimates incorporate more information into their new forecasts, while analysts who follow the herd simply review their forecasts using the limited information they held.

Furthermore, Clement and Tse (2005) showed that the probability of bold predictions increases with the time horizon, the accuracy track of the analyst, the size of broker and the frequency of forecasts, while it decreases with the number of industries followed. With regard to the relationship between boldness and the level of accuracy, the authors show that bold forecasts are also more accurate on average than those which follow the herd, which is probably due to the incorporation of important private information. Duru and Reeb (2002), dealing with accuracy in an international context, recognised that the international diversification of firms leads to less accurate and more optimistic estimates than those made in the domestic context. In these international cases, the forecast activity is made more difficult by lack of knowledge of the country in question. Hope (2003) took into account the corporate information which analysts use to make their forecasts and showed that the amount of disclosure is positively associated with the accuracy of their forecasts since it is a considerable help to understand better those corporate events not reflected in either the usual budget tables or accounting practices. Enforcement is also associated with a high level of forecast accuracy. Its importance is even greater when the companies are allowed to choose from an extensive set of valuation methods, which supports the assumption that encouraging or, in some cases, forcing managers to follow the accounting and disclosure rules reduces the analysts' uncertainty and the complexity of their estimates. Several studies have analysed the accuracy of target prices and its determinants. However, for the time being, the literature on this subject is fairly inadequate. In fact, only recently has the issue of target price accuracy found the same interest as earnings forecasts or changes in recommendations.

Papers dealing with the conflict of interest issue try to test whether analysts who are more exposed to distorting incentives do actually provide overoptimistic and biased forecasts. Several studies have documented a disproportionate number of buy (relative to sell) recommendations (e.g. Elton, Gruber and Grossman (1986), Stickel (1995), and Malmendier and Shanthikumar (2004)) and others have shown that affiliated analysts make optimistic forecasts for current or potential clients (Michaely and Womack (1999), Dugar and Nathan (1995), and Lin and McNichols (1998)). Specifically, Michaely and Womack (1999) documented a significant underperformance of the buy recommendations issued by affiliated brokers in case of IPOs, confirming the bias suspicion. Jackson (2005) and Cowen et al. (2006) found that trading incentives are as strong as or even stronger than investment banking incentives in determining research optimism. They also documented the important role of reputation building as a counterbalance to analysts' opportunistic behaviour. Ljungqvist et al. (2007) found that analyst firms are more accurate and less optimistic when covering stocks which are largely owned by institutional investors. Barber et al. (2007) documented a significant lower abnormal return of the buy recommendations issued by investment banks compared to other types of analyst firm (brokerage houses or pure research firms). Counter-evidence emerges for hold and sell recommendations, suggesting reluctance on the part of the investment banks to downgrade stocks whose prospects are deteriorating. Ertimur et al. (2007) documented a strong positive correlation between the accuracy of earning forecasts and the profitability of the recommendations. Nevertheless, this correlation does not hold when considering the buy recommendations issued by the analysts who are more exposed to conflicting incentives. The authors argued that, in these cases, the issue of rosy recommendations can be seen as a good revenue-boosting device with low reputation costs, compared to the provision of inaccurate earnings forecasts.

Therefore, as discussed earlier, one of the major aims of the analyst is to provide an assessment of the investment value of a particular stock; earnings forecasts are just one input into this decision process. As mentioned above, financial analysts need many more information inputs, which they insert into one or more valuation methods which summarise this information and return outputs in the form of investment recommendations and target prices.

These considerations motivate the first two papers of this thesis since they analyse, on one hand, whether the investors fully recognise and appreciate the different levels of information disclosure from the analysts, and, on the other, whether the different ways to process the input, i.e. the information set, can affect the accuracy of the final output, i.e. the target prices.

Moreover, as already noted, the inputs which make up the financial analysis are drawn from a wide field. Financial statements represent an important source, though financial analysts themselves usually recognise that they do not constitute their most important source of information. Instead, direct contact with the managers of the company being evaluated appears to be a predominant source of information. Financial analysts must know the firms they are covering. They must know what these firms do and know and evaluate their managers, strategies and the likely consequences. In order to do so, they must be experts in the industry in which these firms compete, as well as being knowledgeable about the position of the firms in their sector.

These latter considerations motivate the last paper of this thesis since it aims to explore the role of proximity of financial analysts to what we named industrial 'hubs of expertise' to explain the performance of financial analysts.

Therefore, this thesis is structured as three different empirical contributions to the literature on financial analysts.

The first empirical paper is entitled 'Financial analysts' accuracy: do valuation methods matter?' Here we analyse equity research reports as evidence of how analysts carry out their valuation tasks. The aim of the research is to find more evidence on the performance of an observable outcome of the equity research report: the target price.

As reported above, the literature has already demonstrated that there are some variables affecting the accuracy of the output of the reports, but just a handful number of prior studies have analysed the impact of 'structural' variables, such as valuation methods. For the most part, earlier research on financial analysts was based on commercial financial databases (e.g. *I/B/E/S* or First Call), collecting just a small proportion of the overall information which is potentially included in a report. Usually, these datasets catalogue only the most basic elements of a report, such as earnings forecasts, target prices and analysts' recommendations, but they do not provide other additional elements which supporting the valuation procedure. However, the full body of a report, at least in some cases, could be more exhaustive and include details of the additional information used by the analysts, such as accounting forecasts, valuation methods, qualitative analysis, actualisation rates or market risk premium or other justifications. The only way to find this information is to read the text of the reports and code the content by hand. The expectation is that the hypotheses and assumptions on which many methods are based could lead analysts to greater discretion in the choice of parameters for their models and, therefore, lead them to different levels of accuracy.

With this in mind, we downloaded about 2,200 reports from the Investext database, collecting the full text of the financial analysts' reports. We examined the European market, looking at reports over a three-year period (from January 2007 to April 2009) for the 50 companies included in the EuroStoxx50 Index. We carefully read the full text of all of the reports and coded by hand the information about the valuation methods used by the analysts to evaluate the companies.

In order to analyse the effects of different valuation methods on the predictive performance of the reports, we examine in detail and catalogue the methods (named and unnamed) used by analysts. Furthermore, since analysts often use two or more methods simultaneously, whenever possible, we try to identify the primary one, that is, the valuation method upon which the final recommendation relies more heavily. All of the methods not explicitly defined or indicated as 'primary' have been classified as 'secondary'.

We run fixed effect regressions where we assume that the dependent variable is the accuracy of the target price and include as independent variables both the respective valuation methods and a group of control variables suggested by the existing literature.

The main results are interesting and can be summarised as follows. First, consistent with expectation, the target prices supported by the disclosure of the valuation methods are as accurate as those issued without contemporaneous disclosure of the valuation method upon which they are based.

Second, the accuracy of the target price decreases when the target price is based on a primary method. In other words, this result suggests that analysts can obtain accurate performance by simply combining a few selected techniques, instead of using only one method to assess company value.

Third, we focus on primary methods and define as 'absolute' methods those which include financial, income-based, net assets-based and hybrid methods (such as the EVA approach). On the contrary, we define the 'relative' approach as those methods which require an active market making fair prices (the market is always right), and including market ratio methods. The results suggest that there are no differences between the accuracy associated with the 'relative' or 'absolute' methods.

Lastly, analysis of the different classes of valuation method shows that they lead to the same level of accuracy, apart from the net asset method which is visibly poorer. This result is consistent with the theories which argue that this kind of method is 'inferior' since it is static and, therefore, does not capture both future opportunities and the different levels of risk of the evaluated company.

The second empirical paper is entitled 'Transparency and Market Impact of Security Analyst Recommendations' and it investigates whether the level of transparency in financial analyst disclosure, conditional on the release of other information, is value-relevant for capital markets. As illustrated above, much of the prior research has focused on whether analyst reports contain useful information and affect market efficiency. However, the majority of these studies are only based on the minimum content of the reports (recommendations and target prices) or on the forecasts of earnings, which are usually collected from commercial datasets (e.g. Womack (1996), Gleason and Lee (2000), Mikhail et al. (1997)). Generally, these studies have not measured the value of analyst recommendations when the recommendations are released concurrently with other report information, i.e. the methods of valuation. Asquith et al. (2005) represent a noticeable exception in this context. They investigated the association between market returns and the content of analyst reports using a set of about 1,100 reports issued by members of the *Institutional Investor* All-American Research Team from 1997 to 1999. Their findings show that there is no correlation between specific types of valuation methodology used by analysts and market reaction.

Although this paper is strongly related to Asquith et al. (2005), it proposes a new and original approach by extending the analysis and providing new empirical evidence. The degree of transparency is not a straightforward measure: we define it assuming that a report is *transparent* when the valuation methods used to perform the analysis are clearly disclosed by the analyst. Conversely, a report is *opaque* when the valuation methods are not disclosed or are unclear.

Financial analysts' reports are not usually freely available to the market. Although Investext is a very comprehensive database, some investment brokerage houses do not make their research publicly available and do not provide reports to this database. Therefore, the analysis could be jeopardised by this selection bias. We focus on the Italian setting as, in this respect, Italy represents a uniquely advantageous research setting. The Italian market has a mandatory rule requiring all investment banks, both domestic and international, issuing research reports on Italian-listed firms to deposit them with the Italian Stock Exchange. Thus, all of these reports are available to investors.

We have taken advantage of this regulation and analysed 4,603 research reports issued by 50 different investment banks in relation to 28 Italian-listed firms over a four-year period (2000-2003). The full text of the reports has been carefully examined and the different report information - both the summary measures and, whenever possible, the valuation methods used - catalogued by hand. The report sample was then divided into two different categories: low (*opaque*) and high (*transparent*) disclosure level reports.

In order to test the transparency of the reports, an event study was performed. This methodology allows for the verification of market efficiency by incorporating new information, such as measuring the effects on the stock return of the event in correspondence to the event date, that is, the date on which the report was issued. In Italy, this corresponds, by definition, to the date on which the information is made available to the clients of brokerage firms.

Overall, the results partially replicate the findings of previous research, showing that changes of recommendation are significantly associated with the market reaction to the release of an analyst's report. The results also show that the target prices may contain important information for the market, depending on how bold and unconventional the forecasts (target prices) are. In particular, we find that the market reaction to analysts' change of recommendation is stronger (greater R^2) when the target prices move away from the consensus price than when they move towards the consensus target price for that stock. This result may indicate that the change of recommendation effect is partly driven by analysts' tendencies to herd. In fact, a convincing explanation for the relevance of the target price boldness proxy can be shown by behavioural herding models. In these models, observable actions by agents act as signals of the quality of an agent's private information. Thus, everything else being equal, actions which differ markedly from what many other agents (analysts) do lead the market to assess the agent with the unconventional action as more likely to be 'smarter' than the others.

However, our findings add new information about the source and nature of market reaction to the release of analysts' reports. Our results, in fact, indicate that market reaction is not symmetric and the cause of this asymmetry is the level of transparent disclosure in the report. This means that, in general, markets react consistently to the signals provided by recommendations and target prices, but they also modify their reaction depending on the additional information provided. Interestingly, positive investor reaction to good news is unrelated to the level of information disclosed by analysts. On the contrary, they only trust negative news when they are provided with the supporting elements which enable the understanding of the valuation procedures underlying the estimates.

We then investigate whether the results are affected by other variables, such as the reputation of the broker or when other information is released contemporaneously with the analyst report (the confounding effect). However, neither of these variables is found to be statistically significant.

The third empirical paper is entitled 'Proximity to hubs of expertise in financial analyst forecast accuracy'. In this paper, we assert that the research on analysts' accuracy should be shifted towards analysis of the set of information which is available to analysts and, furthermore, we argue that the location of the analysts is a fundamental affecting factor.

Only a handful of papers investigate, either directly or indirectly, the relationship between the location of analysts and their performance. Although the literature argues that local analysts issue more accurate forecasts since they have an informational advantage over analysts who are located elsewhere, the results are still inconclusive.

The purpose of this study is related to this latter idea but it introduces and proposes a new concept of proximity. Drawing on international industrial economics-based research, network analysis and cluster theories, this work aims to explore the roles of proximity, industrial hubs of expertise and country-specific knowledge in explaining financial analysts' performance.

Industrial clusters constitute important knowledge spillovers, creating formal or informal networks amongst firms, higher education and research institutions. In such a hub, information can easily flow and propagate. I propose that physical proximity to these hubs is an advantage for many economic and financial agents, as well as financial analysts.

We hypothesise that previously unstudied aspects of analysts' characteristics, specifically, their geographical location with respect to the hubs of expertise around countries, could be the reason for the inconclusive findings in prior literature.

We test our hypothesis by collecting both macroeconomic data, in order to identify the hubs of expertise, and financial analysts' data, specifically earnings forecasts, research dates and details about the analysts' location. The final filtered sample of 205 matched observations relates to 33 firms across seven countries and ten sectors over four years (2004 to 2008).

Specifically, we first establish the location of the hubs of expertise over the country and industry of the sample and then test whether the accuracy in the financial analyst forecasts depends on the location of analysts with respect to the hubs of expertise identified.

The results obtained are consistent with the hypothesis. In order to establish the robustness of this approach, we employed different measures of both earnings forecast accuracy and proxies of proximity. Even though they are preliminary and possibly in part biased by sample selection issues until additional industrial and time data can be collected, overall, these results are interesting in that they confirm the benefit of being part of a network, whether formal or informal, where information, knowledge and expertise can be easily shared.

CHAPTER 2

Paper 1

Financial Analyst Accuracy: Do valuation methods matter?

1. Introduction

In this paper we examine how different ways to evaluate a company influence the accuracy of the valuation output, the target price. Our aim is to investigate the task of valuation by sell-side analysts by examining the valuation methods actually used and testing whether different methods have different impacts on the accuracy of the target price.

We know that finance theory and professional practice propose alternative approaches to the evaluation of a company. The traditional distinction is between valuation methods based on the fundamentals of the company (future cash flows, earnings and so on) and the market ratios approach, which is based on the company's market multiples. Furthermore, within each class of method, there are different ways to apply it. Analysts also frequently use some low-cost simplifications of the traditional methods, leading to quick and less accurate value estimates than would have been arrived at with the full implementation of the original models. There are, therefore, a variety of methods for company valuation used by practitioners. Different methods may be applied at the same time in the same report in order to arrive at a target price which is the average result of the various estimation techniques used, while in other cases, the target price is the result of the application of just one method, sometimes checked with other control methods. We try to detect whether different choices of valuation process and technique bring the same final result and this is measured in terms of the accuracy of the target prices.

Through hand coding the valuation content of a sample of 1,650 reports, issued by 53 different international investment brokerage houses and covering a total of 48 companies across 20 different sectors, we find that the accuracy of target prices decreases when the target price is based solely on a main method. Thus, we argue that the analysts can obtain better accuracy performance by simply combining a few selected techniques, instead of using just one method to evaluate a company. Furthermore, we show that methods based on company fundamentals and those based on market multiples lead to similar levels of accuracy. Among the different classes of evaluation method, there are no superior methods in terms of output performance, the one standout being the net asset method as it gives a visibly poorer accuracy level. This latter evidence is consistent with those theories arguing that this method is 'inferior' since it is static and does not capture future opportunities and the different levels of risk of the evaluated company.

Therefore, in summary, we argue that in order to improve forecast accuracy, analysts need to assess company value by choosing and applying a set of different methods, combining them and getting the average value, but regardless of the specific technique chosen.

This paper is mainly related to the literature on target prices and the determinants of their accuracy, providing new empirical evidence. Prior literature has shown that analysts differ in their ability to forecast. However, the empirical research has focused mainly on market reaction to analysts' earnings, recommendations and revisions. Analysis of the accuracy of target prices and the relevance of valuation models in the valuation process are relatively unexplored areas of accounting and finance research. Only a small number of studies have focused on the relationship between the valuation methods used by sell-side analysts in their reports and target price accuracy (e.g. Demirakos et al. (2004), Demirakos (2009) and Asquith et al. (2005)), and the results are still inconclusive and contradictory.

By looking at an extended sample of international analysts' reports covering European companies, this study assesses the performance of different company valuation methodologies and helps to fill a gap in the literature by proposing a new approach for analysing and classifying the valuation methods used in financial analysts' reports.

The importance of equity research is well known. Brokerage houses and investment banks issue thousands of reports on a yearly basis, providing trading advice to investors and forecasts concerning the future market price of listed stocks. The figures on equity research spending are impressive. Johnson (2006) showed that equity research by investment banks has reached over US $20 billion in 2006. Furthermore, both *The Wall Street Journal* and the Institutional Investor (II) annually award an 'oscar' to the best financial analyst on the basis of the performance of the reports issued.

Accuracy is, therefore, the key feature of the output of equity research. However, since the reports are not freely available, studies analysing how the valuation methods used influence the target price accuracy are rare. Consequently, this study may help fill an important gap in the literature.

The paper is organised as follows: Section 2 discusses the main results obtained by prior literature; Section 3 describes the theoretical framework; Section 4 reports the data and data classification criteria; Section 5 presents the research design; Sections 6 and 7 report the empirical results, their discussion and interpretation; and Section 8 concludes the paper.

2. Literature review

Sell-side analysts issue reports about the equity valuation of companies. The more verifiable elements of these reports are earnings forecasts, stock recommendations and target prices.

Earlier studies have mainly focused on the market reaction to analysts' earnings, recommendations and revisions (see also Chapter 1). Despite the empirical evidence which shows the relevance of target prices to the market (see, for instance, Asquith et al. (2005) or Brav and Lehavy (2003)), the research on the accuracy of target prices is still scant and inconclusive. This paper is mainly related to the literature on target prices and the determinants of their accuracy, providing new empirical evidence.

A possible reason for the poor attention given to the target price is that earnings forecasts, recommendations and target price revisions convey homogeneous information to investors, leading to the same market reaction. However, Francis and Soffer (1997), Brav and Lehavy (2003) and Asquith et al. (2005) do not confirm this evidence. They report that target prices convey new information to the market, independent from recommendations and earnings forecasts. For instance, Brav and Leavy (2003) show market reaction to target prices which is both unconditional and conditional on stock recommendations and earning forecast revisions. Similarly, Asquith et al. (2005) demonstrate that the market reacts to target price revisions regardless of earnings forecasts revisions. Furthermore, target price revisions cause a market reaction which is greater than that determined by an equivalent revision in the earnings forecast.

Since target prices are relevant for the market, part of the academic interest in them has focused on the drivers of their accuracy. The empirical evidence shows a certain variability in target price accuracy. For instance, Asquith et al. (2005) and Bradshaw and Brown (2006) report a good level of target price accuracy over a time horizon of 12 months (in at least 50% of cases the target prices are then reached by the market stock prices are, while De Vincentiis (2010) shows a poor level of accuracy (above the 30% of cases are successful). There are multiple factors which have the potential to affect this variability and the empirical results are controversial.

Part of the literature has focused on the features of forecasts, such as the well-documented bias in estimates and the level of analysts' optimism. The main empirical results show that forecasts which are highly inflated with respect to the current market price are more difficult to achieve (Asquith et al. (2005), Bradshaw and Brown (2006), Bonini et al. (2009), Demirakos et al. (2009) and De Vincentiis (2010)).

Another part of the literature has focused on firm, stock and analyst characteristics which affect target price accuracy. Specifically, company size, loss-making firms and company coverage are positively associated with target accuracy, while stock momentum is negatively related (Bonini et al. (2009) and De Vincentis (2010)).

Finally, only a few studies have analysed how the tools used by analysts to reach the target price, i.e. the valuation models, can affect the accuracy of the forecast.

Financial analysts can adopt several different valuation methods to evaluate companies, which are usually categorised into two different macro-classes: single-period valuation methods, i.e. market multiples, and multi-period valuation methods, such as discounted cash flow (DCF) and residual income methods (RIM). Empirical research has shown that financial analysts prefer single-period earnings models, such as market multiples (Barker (1999), Block (1999), Bradshaw (2002), Demirakos et al. (2004) and Asquith et al. (2005)) as they are simple to apply. Analysts adopt more complex and time-consuming multi-period models to value companies which are characterised by high level of uncertainty due to their highly volatile earnings or unstable growth (Demirakos et al., 2004). Imam et al. (2008) reported that sell-side analysts increased their preference for DCF models only in recent years, probably influenced by their clients and their valuation preferences.

Corporate finance theory and the main financial analysis textbooks suggest estimating a company's value using, whenever possible, multi-period valuation methods, the reason being that they should better capture its fair value (Penman (2003) and Koller et al. (2005)). Using 'superior' valuation methods should, therefore, lead to more accurate target prices. This theory is only partially confirmed in practice. Bradshaw (2004) shows that the analysts who issue more accurate earnings forecasts and who employ rigorous valuation methods such as RIM get better target prices. Similarly, Gleason, Johnson, and Li (2007) followed Bradshaw (2004) and inputted analyst earnings forecasts into price-to-earnings-growth (PEG) and RIM in order to generate pseudo target prices, and found that RIM is a superior method in terms of target prices accuracy. Gleason et al. (2006, 2008) found evidence which suggests that market ratio methods produce less accurate and more unreliable target prices than DCF. On the other hand, Demirakos et al. (2009) compared the DCF and the price-to-earnings (PE) ratio approaches and found that it is more likely to arrive at the target price by using the PE ratio (69.88%) rather than the DCF method (56.28%). However, this result holds only for a very short time horizon. Measuring accuracy over a period of 12 months shows, in fact, that the market ratios approach is no longer the most accurate. Asquith et al. (2005) do not find any significant correlation between valuation methods and target accuracy. Specifically, they fail to demonstrate the superiority of the DCF method with respect to other methods. The probability of getting the target price within 12 months is almost the same, regardless of the specific method used (48.8% used the market ratio approach and 52.3% DCF). Even less successful are those analysts who employ the Economic Value Added approach. Finally, Liu, Nissim and Thomas (2002) tested the valuation accuracy of several market ratios and found that the PE approach based on forecast earnings has the greatest accuracy.

The results of this stream of research remain inconclusive and, therefore, the topic needs further investigation. This paper tries to produce new empirical evidence on this relevant issue and aims to enrich the existing literature by investigating how different unexplored features of the procedures followed by analysts to assess the company value can affect target price accuracy.

3. Theoretical framework

The task of sell-side analyst evaluation is a complex process. It starts with the collection of economic and company information, followed by the processing of this qualitative and quantitative data, and it ends with the production of forecasts to be inputted into one or more valuation methods, giving the target prices. Finally, depending on the comparison between the company valuation and the market price, the analyst issues an investment recommendation (buy, hold, sell and so on).

Finance theory and professional practice propose alternative approaches to the evaluation of a company. The traditional distinction is between valuation based on the fundamentals of the company (future cash flows, earnings and so on) and the market ratios approach, which is based on the market multiples of a company. Penman (2001) gives a definition of the fundamental analysis as a five-step process consisting of: 1) knowing the business through the strategic analysis; 2) analysing the accounting and non-accounting information; 3) specifying, measuring and forecasting the value relevant payoffs; 4) converting the forecast to a valuation; and 5) trading on the valuation. In contrast to fundamental analysis, the market multiple approach requires an active market of fair stock prices. A fundamental valuation can be done without reference to a market.[2]

[2] In reality, the discount rate and the market risk premium, the basic elements for the fundamental analysis, do require an active market.

With respect to the quality of the different methods, finance theory considers the company fundamentals-based valuation methods to be superior tools for the evaluation of a company in comparison to the market multiples approaches. Therefore, finance textbooks recommend their use whenever possible as they bring a more reasonable and well-grounded estimation of company value. Thus, market multiples are indicated as control methods, to be used as a second step in estimating a range of control company values.

Given this theoretical difference between the methods, this paper aims to investigate better whether different approaches to valuation can have a different impact on the output of the valuation process conducted by practitioners. Specifically, we test whether different valuation practices affect the accuracy of target prices.

In order to do this, we analyse the distribution of valuation methods adopted by financial analysts amongst different industries and the differences in valuation practices over the years. Then, we test whether there is a link between the method of valuation method and the final output.

Asquith et al. (2005), for instance, found no correlation between valuation methods and their accuracy in predicting target prices. However, this study suffers from a selection bias issue as it only focuses on celebrity analysts, excluding others. Demirakos et al. (2009) did not find significant differences in target price performance depending on the specific model used. However, this research was based on a small sample of sell-side analyst reports only covering UK companies. Furthermore, they did distinguish between DCF and PE methods and did not consider the wide range of methods which analysts use and personalise.

If a relationship exists, it would be of great interest because it would show that target prices, and thus investment recommendations, are linked to the specific criteria chosen for the analysis. Even if there is only a partial relationship or indeed no relationship at all, it would, nevertheless, be an interesting result. On one hand, for example, the lack of a relationship should rationally mean that every method employed by analysts should achieve the same result, as expressed by the recommendation or target price. However, this lack of relationship could also indicate that valuation methods are regarded as 'tools' for achieving a predetermined result, which is consistent with the conflict of interest hypothesis. Bradshaw (2002), for example, finds that valuations based on price earnings multiples and expected growth are more likely to be used to support favourable recommendations, while qualitative analysis (which is less verifiable) of a firm is more likely to be associated with less favourable recommendations. In other words, the analyst evaluates firms regardless of the best criteria which could be used and only afterwards does he or she select the method which better argues and supports the expected result.

First, in line with Bradshaw (2002), we test whether analysts' reticence in disclosing the methods used for company valuation is related to the accuracy of their estimates. Our expectation is to find no significant relationship as, in the absence of opportunistic behaviour, the analyst should disclose the valuation method used, regardless of the level of boldness of the estimate. The first hypothesis tested is, therefore, the following:

H1: Analysts who make explicit the valuation methods which they use are more accurate than those who do not disclose the specific tools which they use to arrive at their estimate of companies..

Then, we verify whether the different valuation practices which go towards the estimation of the final target price can produce more or less accurate target prices. By analysing the actual reports of the financial analysts, it is possible to distinguish between the target prices which have been obtained as a result of the linear combination of different methods and those which have been obtained by applying a 'primary' method and then checked by the implementation of other control methods. Since the valuation methods require subjective estimations and assumptions about a company's future, our expectation is that target prices which have been obtained as the result of an average of different techniques are more accurate than those based on a primary method considered as superior and a set of control methods.

The specification of the second hypothesis is therefore:

H2: Target prices derived from an average of different valuation methods are more accurate than those obtained with one primary method which is then checked by other valuation techniques.

The third hypothesis follows on from H2. Specifically, we test whether the accuracy level of the sub-sample of target prices based on just one primary method can change if this method is the only one implemented by the analyst or if it is considered to be superior amongst a set of different methods used as controls. The specification of the third hypothesis is:

H3: Target prices based on only one valuation method have a different accuracy level depending on the analyst's choice of method.

We then focus on the type of valuation method used in the report. Our aim is to test whether a hierarchy exists amongst different valuation criteria. According to finance theory, our expectations should be that alternative fundamental valuation methods should yield the same results when applied to the same set of data. At the same time, market multiple approaches should be inferior to fundamental valuation methods and thus perform worse. However, among the fundamental valuation methods, some of them could be more appropriate for the evaluation of specific companies than others. For instance, insurance and utility stocks are often considered to be ‘nearly bond’ because the future cash flows that such stocks generate are usually positive and easy to predict, and the payout ratio is high and constant. Therefore, the discounted cash flow or dividend discounted models, which are close to those usually used for bond valuation, could be preferable for company valuations. Conversely, banking and especially manufacturing stocks are more similar to dynamic companies which operate in a much more competitive environment and exposed to higher technological risk. It is much more difficult for an analyst to forecast the future cash flow, profits and dividends of these types of stock by applying methods belonging to fundamental analysis; it is much easier to collect data from the market using the growth rate of future cash flows, profits and dividends implied in the market ratios.

The set of hypotheses for testing different levels of analysis is therefore:

H4: The specific types of valuation method (DCF, DE, NAV and so on) used in the report overall have different impacts on target price accuracy. In other words, we test whether some methods are better than others in obtaining more accurate estimates.

H5: At the macro category level, target prices resulting from fundamentals-based methods are more accurate than those derived from market multiple-based methods.

H6: The latter hypothesis is also verified in correspondence to primary valuation methods. In other words, we investigate whether the general finance textbook suggestion of using fundamentals-based methods instead of market multiple methods make sense in terms of estimate performance.

4. Sample selection & description

4.1. Sample selection

Most of the earlier research on financial analysts is based on commercial financial databases (e.g. *I/B/E/S* or First Call), collecting only a small proportion of the overall information which is potentially included in a report. Usually, these datasets catalogue the basic elements of a report, such as earnings forecasts, target prices and analyst recommendations, but do not provide any other additional elements which support the valuation procedure. The full body of the report, at least in some cases, could be much more exhaustive than this and include the additional information used by the analysts, such as accounting forecasts, valuation methods, qualitative analysis, actualisation rates, market risk premium or other justifications. The only way to discover this information is to read the text of the reports and to code their content by hand.

For our purposes, we downloaded approximately 2,200 reports from Investext, a database which contains the full text of financial analyst reports. We examined the European market, collecting reports over a three-year period (from January 2007 to April 2009) for the 50 companies and 20 industries included in the EuroStoxx50 Index.

Some of the reports have been excluded from the analysis because they were too short or did not contain any relevant information for this analysis. Therefore, the final sample consists of 1,650 reports issued by 53 international investment brokerage houses, covering a total of 48 companies across 20 sectors. Each report was read in its entirety and its content coded by hand. The aim was to identify the valuation models employed by the analysts and, in particular, which of them was chosen to be the main one used in the valuation task.

Some of the variables were easy to classify (e.g. report date, analyst's name, target prices and so on), while others (e.g. valuation methods) needed more attention in order to be successfully classified.

With regard to the recommendations issued, since we refer to the original ones issued by the analysts, caution needed to be used in their classification. Most analysts use a three-level scale (i.e., 'buy', 'hold' and 'sell'), while others use a larger scale, which also includes 'strong buy' or 'strong sell'. Furthermore, some analysts use different terminology, such as 'market perform' or 'market outperform', 'reduce', 'add' and so on. We reduced all of the recommendations to three different categories, classifying them depending on their meaning, that is, good, bad or neutral.

For firm-level data, such as company market capitalisation, P/BV ratios, the industry code and the time series of stock prices, we used Datastream.

4.2. A structured analysis of the evaluation methods used in the reports

The identification and classification of the valuation methods used by analysts was a complex procedure. Differently from Asquith et al. (2005), in the reports which we analysed, the analysts seldom explained the specific valuation methods used for the company.

Furthermore, the analysts often combine different methods and approaches, creating new ones or personalising valuation procedures, probably in order to fit them to the firm-specific characteristics of the companies analysed better. This forced us to deduce, whenever possible, the methods from the reports by building a structured framework to capture their variety and reduce the different (and more or less sophisticated) procedures to some known evaluation methods.

Initially, we started from the theoretical ranking proposed for valuation methods by most of the finance books which identifies the following five classes of method: net assets-based methods, cash flow-based methods, earnings-based methods, hybrid methods and market ratios methods. However, during our empirical work, several valuation methods emerged to a more significant extent than expected and we needed to add some specifications about each class. Analysts frequently use low cost simplifications of the traditional techniques leading to quick and less complex value estimates than those which would be achieved by fully implementing the original models. For instance, within the net asset methods, we included the net asset value approach (*NAV*) and the embedded value (*EV*) and appraisal value (*AV*) methods.[3] We classified as 'earnings-based methods' discounted shareholder profit (*DSP*) and discounted earnings (*DE*), but also other heuristic methods.[4] Among these heuristic methods, one is based on the *ROIC* index, another one named Warranty Equity Valuation (*WEV*) and finally, one called Required *ROE* (*RR*).[5] We included in 'financial methods' the dividend discounted model (*DDM*), discounted cash flows (*DCF*), the Gordon growth model (*GGM*), the adjusted present value (*APV*) and a particular model based on the actualisation of cash flow which is used by a small number of brokers called *HOLT-CFROI*.[6] We named as 'hybrid models' the economic value added (*EVA)* and regulatory asset based methods

[3] The *NAV* approach considers the underlying value of the company assets net of its liabilities. In this approach, the book value is adjusted by substituting the market value of individual assets and liabilities for their carrying value on the balance sheet. This approach is most applicable in the context of asset holding companies, real estate holding companies or natural resources companies. *EV* is the valuation of a company's current in-force value without taking into account its capacity to generate new business. It is then a minimum value for the company. The embedded value can then be adjusted by adding the estimated value of future new sales in order to obtain the *AV* of the company. Both the *EV* and the *AV* approaches are particularly appropriate for the evaluation of the insurance industry.
[4] According to both *DSP* and *DE*, the value of a company's stock is calculated on an accounting basis and is equal to the present value of all of the expected future profits or earnings, discounted at the shareholders' required rate of return.
[5] The warranty equity evaluation method establishes that the value of equity (*E*) is given by this formula: $E = (ROE - g) / (COE - g) . P/BV$, where ROE is the return on equity, g is long term growth rate, *COE* is the cost of equity and *P/BV* is price to book value. *ROE* required is the same as *WEV*, but g is equal to zero.
[6] The financial method category is a multi-criteria framework including cash flow-based methods. *DDM* considers cash flow as company dividends, *DCF* free cash flow, *GGM* is a specification of *DDM* which assumes a constant dividend growth rate and *APV* first estimates the value of an unlevered firm to consider the net effect on value of both the benefits and costs of borrowing. *HOLT-CFROI* is the acronym of Cash Flows Return on Investment and is a model originally developed in 2002 by *HOLT* Value Associates, based in Chicago. Basically, it is an inflation-adjusted indicator for measuring a company's ability to generate cash flows.

(*RAB*)[7] which are particularly used by the energy companies to estimate the value of net invested capital. With regard to market ratio methods, we included the approaches of both comparable companies and trades.[8]

Table 1 summarises the classification of these methods.

Insert Table 1

Furthermore, since analysts often adopt two or more methods to evaluate a firm simultaneously, whenever possible we tried to identify the main one, that is, the valuation method upon which the final recommendation relies on most. All of the methods not explicitly defined or indicated as 'primary' have been classified as 'secondary.

5. The research design

In order to analyse the effects on the predictive performance of the reports of the different valuation methods, we run some industry fixed effects regressions. We assumed target price accuracy as the dependent variable and, as independent variables, both of the alternative variable specifications related to the valuation method issue and a group of control variables, as the main literature suggests. By including industry fixed effects in our regressions, we control for average differences across industries.

With regard to the dependent variable, in order to control for the possibility that the results could be biased by the accuracy measure, we repeated the analysis using two alternative proxies of the target prices performance from those proposed by the main literature.[9] The first (*FE1*), derived from De Vincentiis [2010], is calculated as:

$$FE1 = \begin{Bmatrix} \dfrac{TP - P_{\max 12m}}{P_t} \text{ upward} \\ \dfrac{TP - P_{\min 12m}}{P_t} \text{ downward} \end{Bmatrix} \qquad (1)$$

[7] Both the *EVA* and *RAB* methods are approaches which adjust the *NAV* approach with the present value of future company performances.

[8] The market multiple approaches consider the market value of companies similar to the company being valued, as observed either in the trading prices of publicly traded companies or the purchase prices in business sales, with respect to earnings, cash flow or the book value of those businesses.

[9] We also used a naive measure of target price accuracy (*ACC*) used in Bradshaw and Brown (2006]). According to their definition, a target price can be assumed to be accurate if it is achieved by the market price 365 days after the forecast. However, since the results were not robust, we did not report this analysis.

where *FE* represent the forecast error, *TP* is the target price, P_{max12m} (P_{min12m}) is the maximum (minimum) market stock price recorded during the 12 months following the report date and P_t is the current market stock price.

The second accuracy measure (*FE2*), derived from Bradshaw and Brown (2006]), Bonini et al. (2009) and De Vincentiis (2010) is instead:

$$FE2 = \left| \frac{TP - P_{+365}}{P_t} \right| \tag{2}$$

where *FE* is the forecast error, *TP* is again the target price, P_t is the current market price and P_{365} is the stock price registered in the market 365 days after the forecast date.

We report and discuss only the results based on *FE1* because of their comparability with those obtained with *FE2*.

With regard to the independent variables, in order to test the first hypothesis, that is, whether analysts' disclosure of their valuation methods is related to the accuracy of their estimates, we distinguish between the reports which disclose the valuation methodology used and those which do not. So, the variable *DISCLOSED_NOTDISCLOSED* is equal to 1 if a valuation method is disclosed in the report, 0 otherwise. Our expectation is that, because of the conflicts of interest which beset financial analysts, their accuracy level is greater whether the valuation methodology used is made explicit. Hiding the valuation procedure could be a tool to justify, for instance, a price decided a priori by the broker and not supported by any of the valuation techniques.

Secondly, we focus on the hierarchy among the methods in order to test whether the target prices which are derived as an average of different valuation methods are more accurate than those obtained by the use of one main method and then checked by other secondary valuation techniques. So, we distinguish between primary and secondary methods through the *PRIMARY_SECONDARY* dummy variable, which is equal to 1 if there is a primary valuation method, 0 otherwise. Furthermore, we focus only on those reports which contain an explicit main valuation method. We define the *PRIMARY* dummy variable as equal to 1 if the analyst uses only that main method to evaluate the company and 0 if the method is selected as primary in a group of other, secondary methods.

We then investigate the effect of the type of valuation method used on the accuracy achieved more specifically. In order to test the fourth hypothesis, we include the different method categories (financial, income-based, net asset, hybrid and market ratios methods) in the regression specification.[10] We define five dummy variables, each representing one specific method category, respectively: *M_FIN*, *M_INC*, *M_NAV*, *M_HYB* and *M_MRATIO*. Each dummy gives the value of 1 to the category it represents, 0 otherwise. Conceptually, all of the five dummies can be inserted simultaneously into the model since the analyst can theoretically use all of the methods at the same time, so all of the dummies can assume value equal to 1.

In order to test the fifth hypothesis, we only focus on the primary methods, we distinguish between the methods based on company fundamentals (such as financial, income-based, hybrid and net asset) and those based on company market multiples. Thus, the regression includes the dummy *FUNDAMENTAL_MULTIPLE*, which is equal to 1, if the analyst uses a fundamentals-based method, 0 if he or she uses a market ratios approach. Then, we include the dummy of each method category again in the model specification, this time equal to 1, if the analyst uses that specific method as the main valuation method (*MM_FIN*, *MM_INC*, *MM_NAV*, *MM_HYB* and *MM_MRATIO*). As we just focus on the primary methods, only one dummy per report can assume the value of 1, i.e. a report has only one primary valuation method. Hence, in this case, we insert only four out of five dummies as the others residually define the last one.

With regard to the control variables, we first insert the boldness of the target price (*BOLDNESS*). This is the absolute value of the difference between the target price and the current stock price, scaled by the current stock price. We expect that the larger the absolute difference between the target price and the current price, the more difficult it is to meet the target price. Consistent with the literature, we expect a negative association between target price accuracy and boldness.

The second control variable included in the regressions is price volatility (*VOL*), which is a proxy for the difficulty in predicting the company value. This is measured as the standard deviation of company prices for each of the three years considered. Based on option pricing theory, Bradshaw and Brown (2006) predicted that target price accuracy is higher for stocks with higher price volatility. However, consistent with Demirakos et al. (2009), we expect a negative association between a firm's risk and the accuracy of the forecast. This is because, although it is easier for the target price of a highly volatile stock to be met at some point during a 12- month forecast horizon, it is more challenging for the analyst to predict the price of a volatile stock at the end of that period.

SIZE is another control variable which we use in the various regression specifications. This is the natural logarithm of the firm's market capitalisation on the report's date of issue. We expect a positive association between target price accuracy and firm size and a negative association between

[10] For the method classification, see section 4.

forecast error measures and size, based on the argument that it is easier for an analyst to value a large, mature and well-established firm, which has readily available information about its future prospects. On the other hand, small firms are less complicated in structure but usually operate in niche markets and their future performance is more uncertain. For these reasons, we expect that *SIZE* is positively related to accuracy and negatively correlated to forecast error.

The *GROWTH* variable, measured by the price-to-book-value ratio, represents the growth associated with the firm. As more stable companies are also more predictable than those with greater growth opportunities, we expect a negative association between this variable and target price accuracy.

Then, we include the accuracy of earnings forecasts in the model. Consistent with the results obtained by Loh and Mian (2006), Gleason et al. (2006) and Ertimur et al. (2007), our expectation is that we will find a positive relationship between the accuracy of the earnings forecasts and the target price. The prediction is that a more accurate input forecast (earnings forecast) should provide a better output forecast (target price) in terms of accuracy. In order to measure the accuracy of earnings forecasts, we use two measures proposed by the main literature. Specifically, we calculate both the *Absolute Forecast Error* (*AFE*) and *Proportional Mean Absolute Forecast Error* (*PMAFE*) measured as the following ratios:

$$PMAFE_{ijt} = \frac{AFE_{ijt} - AAFE_{jt}}{AAFE_{jt}}(\text{-}1) \tag{3}$$

where EPS_{ijt} is the actual earnings per share of company j, in year t, $AVG(EPS_{ijt})$ the average earnings per share forecast issued by analyst i in relation to company j during year t and P_j the mean price of the stock during year t.

$$AFE_{ijt} = \frac{ACTUAL_{jt} - FORECAST_{ijt}}{ACTUAL_{jt}} \tag{4}$$

where AFE_{ijt} is defined above and $MAFE_{jt}$ is the mean absolute error of all of the analysts of company j during year t.

We also include three other control variables. The first (*FORAGE*) is strictly related to earnings forecast accuracy and the forecast horizon and is measured as the time interval between the forecast date and the end of the fiscal year. This variable should capture the effects of factors which impact upon the accuracy of earnings forecasts, but which are unexplained by earnings forecast errors. Our expectation, in line with the literature, is to find that this variable has a negative impact on target price accuracy.

The second control variable is year dummies to distinguish between the different years when reports are issued (*D_2007, D_2008* and *D_2009*). This variable aims to capture the unexplained effects of time-related factors which have the potential to modify the dependent variable, but which are not revealed by the regressions.

The third and final control variable is the analyst's nationality (*NAZ*), which controls for the effect of nationality. The aim of this is to understand whether a coincidence of analyst and company nationality can improve the level of target price accuracy. It is a dummy variable that is equal to 1 when the analyst's nationality coincides with that of the company, 0 otherwise. We expect a positive correlation between price accuracy and the nationality variable as we assume that there is less information available to analysts on foreign companies than there is on domestic firms.

Table 2 summarises the definition of the variables used in the analysis.

Insert Table 2

6. Results

6.1. Descriptive results

This section reports the main descriptive statistics of the variables of the model.

Table 3 reports the main descriptives with regard to the dependent variable of the regression models, the measures of forecast accuracy, distinguishing by year and recommendation type (Panel A) and by valuation method features (Panels B to F).

Insert Table 3

First, consistent with prior empirical evidence, Panel A and B show that, on average, forecast errors fluctuate, but maintain a constant positive sign, indicating a general excess of optimism through all of the years, regardless of the specific recommendation issued.

Panel C focuses on the relationship between forecast errors and disclosure of the valuation method. As illustrated, the mean forecast errors (both *FE1* and *FE2*) do not change substantially between the reports which disclose their valuation method(s) and those which do not.

Similarly, Panels D shows that there is no significant evidence of the superior performance of those forecasts which were obtained as a result of an average of different valuation methods rather than those made with only one primary method.

Focusing on the different method categories, and consistent with prior literature, both the methods based on company fundamentals and those based on market multiples perform in a similar way in terms of forecast accuracy (see Panel E). Furthermore, we cannot clearly discriminate whether some specific methods outperform the others from the simple descriptive analysis as the forecast errors grouped by method depend on the specific forecast error measure used (Panels F and G). For instance, the hybrid methods are the most accurate, according to *FE1* but, according to *FE2*, they are ranked third. However, this consideration does not apply to *NAV*-based methods. The mean forecast errors based on these methods are in fact higher according to both measures (*FE1*=45% and *FE2*=64%).

An analysis of forecast errors by sector is reported in Graph 1.

Insert Graph 1

Overall, the different sectors are ranged around a mean forecast error of 20-30% according to *FE1*, and 30-45% according to *FE2*. The top value is 60%, by the automobile sector. Other sectors which are quite difficult to predict seem to be the banking and the insurance industries.

Graph 2 shows different boldness classes with respect to target price accuracy. In the lowest boldness class (between 0% and 10%), the forecast error is approximately 30% (28% with *FE1* and 33% with *FE2*). The difference between *FE1* and *FE2* increases in the intermediate boldness classes but returns to a similar level for very high boldness (>70%). In the latter class, the means of both *FE1* and *FE2* are very high (approximately 65% of the stock value at the time of the issue of the report).

Insert Graph 2

With regard to the independent variables in the regression models, Table 4 reports the main descriptive statistics of the control variables by year, while Table 5 summarises the main statistical features of the different valuation method variables.

Insert Table 4

Insert Table 5

As indicated in Table 5, in our sample only 39% of reports express the valuation method(s) used for analysis, meaning that in about 60% of cases, the investor does not know how the target price has been estimated. This means that, in these latter cases, the valuation procedure is just a black box for investors. With regard to the group of 'transparent' reports, in approximately 40% of cases the analysts are explicit about the main valuation methodology adopted. Approximately 38% of cases are in line with the finance textbooks which suggest checking the estimate of company value with just one method (the main one) with a set of control methods (secondary ones). In the other 62% of cases, there is no main method and the target price is a simple average of the application of different techniques. Furthermore, at odds with the theory, in about 67% of cases, the analysts obtain the target price by applying only one method, without any further checks (see Table 5).

In relation to the choice of valuation method made by the financial analyst, Graphs 3, 4 and 5 show a breakdown of the methods across different years and industries.

Insert Graph 3

Insert Graph 4

Insert Graph 5

As illustrated above, the trend of the methods used over the three years examined changed. Specifically, in 2007 the proportions of the market ratios approach and the other valuation procedures based on the fundamentals of a company were clearly unbalanced. In that year, analysts reduced the market ratios approach considerably and favoured the other methods. In 2009, the proportions of the two approaches were more balanced. Generally, the analysts used market ratios as the 'control' secondary method in the majority of cases (53.33% in 2007, 69.39% in 2008 and 67.36% in 2009).

Graph 4 shows that among the fundamentals-based methods, the most frequently used by analysts to justify their target prices are financial methods (from 63.6% in 2007 to 98.3% in 2009). The hybrid method (27.3%) and the income-based methods (9.1%) are frequent in 2007, but decrease in the following two years.

Graph 5 reports the different valuation methods across different industries. In line with other studies (see, for instance, Abrosetti Stern Stewart Italia (2008) and Bertinetti et al. (2006)), market ratios are the most used amongst all of the sectors overall. There are some exceptions, however. For instance, analysts evaluating the banking sector prefer the market ratios approach (80%), whilst in other sectors, such as technology hardware and equipment, utilities and electricity, and energy and oil, they prefer fundamental analysis. Net asset value methods are preferred for the evaluation of the insurance sector, while the automotive sector is characterised by financial methods.

To conclude the descriptive analysis, Tables 6 and 7 report the Pearson and Spearman correlations among the variables, respectively. No multicollinearity issues seem to arise.

Insert Table 6

Insert Table 7

6.2. Inferential analysis

In this section, we test our research hypothesis. Specifically, we investigate whether the accuracy of target prices depends on the financial analyst's choice of valuation method, controlling for variables at both firm and analyst level.

The results, obtained using a naïve accuracy measure (*ACC*) did not show any systematic relationship between the variables, and the determination coefficient was close to zero. Therefore, we decided not to report this set of results, focusing only on the other two measures of accuracy, used alternatively (*FE1* and *FE2*).[11]

In order to test the first research hypothesis, we run the following fixed-effect regression model:

$$ACCURACY_{ijt} = \alpha + \beta 1 DISCLOSED\_NOTDISCLOSED_{ijt} + \beta 2 CONTROL\_VARIABLESi_{jt} + \varepsilon_{ijt} \quad (5)$$

where *i*, the fixed effect, represents the sector, *t* the year and *j* the single analyst. With respect to the variables, the dependent variable is forecast error while the independent variables are *DISCLOSED_NOTDISCLOSED*, indicating whether or not the report discloses the valuation method(s) used, and the set of control variables specified and defined above.

Table 8 provides the results of different specifications of the model, obtained with a bottom-up procedure. Specifically, the columns show that that *VOL*, *PMAFE* and *FORAGE* are not significant, while the other control variables are significant at 5%. In particular, *BOLDNESS* and *GROWTH* are positively (negatively) related with forecast error (accuracy), while *SIZE* has a negative (positive) impact. The *DISCLOSED_NOTDISCLOSED* variable is statistically insignificant in all of the model specifications, meaning that the presence of a valuation method does not affect the level of accuracy.

Insert Table 8

[11] As mentioned earlier, we only report the results based on *FE1* as comparable to those obtained with *FE2* in this paper.

We then test the second hypothesis, investigating the relationship between target price accuracy (*FE1*) and the ranking of the primary and secondary valuation models, represented by the *PRIMARY_SECONDARY* variable. As control, we add the chosen set of control variables.

Therefore, the tested equation is:

$$ACCURACY_{ijt} = \alpha + \beta 1 PRIMARY\_SECONDARY_{ijt} + \beta 2 CONTROL\_VARIABLESi_{jt} + \varepsilon_{ijt} \quad (6)$$

Table 9 reports the results.

Insert Table 9

The different model specifications show evidence that *VOL*, *PMAFE* and *FORAGE* are insignificant, but *PRIMARY_SECONDARY* is significantly positive, indicating that target prices based on a main valuation method are systematically less accurate than those based on a group of methods.

We then substitute in equation (6) the *PRIMARY_SECONDARY* variable with the *PRIMARY* variable, capturing whether the primary valuation technique is also the only one used in the report (*PRIMARY*=1) or whether it is chosen from amongst others considered to be superior by the analyst (*PRIMARY*=0). In other words, we test the following equation and report the results in Table 10:

$$ACCURACY_{ijt} = \alpha + \beta_1 PRIMARY_{ijt} + \beta_2 CONTROL\_VARIABLES_{ijt} + \varepsilon_{ijt} \quad (7)$$

The columns confirm the prior evidence and specify the previous results. In fact, the set of control variables is consistent with the previous signs, while the *PRIMARY* variable is not statistically significant.

Insert Table 10

This means that the forecasts based on only one primary valuation method are in general less accurate, regardless of whether it is chosen from amongst others or used as uniquely.

Furthermore, we focus on the specific valuation methods used and examine whether or not target price accuracy is dependent on the specific technique used, regardless of the ranking between the consideration of primary or secondary methods. Hence, the model that we test is the following:

$$ACCURACY_{ijt} = \alpha + \beta_1 VALUATION\_METHODS_{ijt} + \beta_2 CONTROL\_VARIABLES_{ijt} + \varepsilon_{ijt} \quad (8)$$

where *VALUATION METHOD/S* is a matrix of the five dummy variables defined above and represents the different evaluation methods categories. Table 11 reports the findings.

Insert Table 11

The control variables confirm the results of the previous regressions (Columns (2), (3) and (4)), while the evaluation method dummies are insignificant (Columns (1) and (4)), with the exception of the *M_NAV* variable, which has a positive and statistically significant coefficient.

This means that, in general, the accuracy of target prices is independent of the different valuation techniques, with the exception of *NAV*-based prices which are systematically less accurate than those based on the other methods.

In the following regressions, the analysis focused only on methods considered as primary by analysts in their reports. The reason is that the target prices often are the output of a main valuation method, sometimes accompanied by other control methods. In these cases, if the valuation methods were different in terms of forecasting power, then they should affect the accuracy of the target price in a clearer way. Hence, we first aggregate the various methods in two macro-categories of methods: those based on company fundamentals and those on the comparison with market prices, that is, market multiple approaches. We define the *FUNDAMENTAL_MULTIPLE* dummy variable by this distinction. Table 12 reports the results of the following regression:

$$ACCURACY_{ijt} = \alpha + \beta_1 FUNDAMENTAL\_MULTIPLE_{ijt} + \beta_2 CONTROL\_VARIABLES_{ijt} + \varepsilon_{ijt} \quad (9)$$

Insert Table 12

The variable *FUNDAMENTAL_MULTIPLE* is not significant, indicating that, with regard to the accuracy of price forecasts, valuation techniques based on market multiples are the equivalent of more conceptually sophisticated methods, such as, for instance, *DCF*.

Secondly, we disaggregate the primary methods and test the following regression:

$$ACCURACY_{ijt} = \alpha + \beta_1 TYPE\_OF\_PRIMARY\_METHOD_{ijt} + \beta_2 CONTROL\_VARIABLES_{ijt} + \varepsilon_{ijt} \quad (10)$$

where *TYPE OF PRIMARY METHOD* is a matrix of vector variables (dummies), each representing the specific type of method used as a main valuation technique.

As already discussed, we only insert four out of five dummy variables in the model because of the problem of over-identification. For this reason, we run five different regressions, excluding one of the dummies in turn. Table 13 reports the results of this model.

Insert Table 13

Overall, the empirical findings document that financial, income-based, hybrid and market ratios methods lead to similar levels of accuracy, but perform better than the net asset value method.

A significance test run on the difference between the coefficients confirms this latter result.

7. Discussion of the results

The regression outputs allow the comparison of the results obtained using the two different accuracy measures.

The determination coefficient (R^2 *adj*) is always not very high. However, this evidence is consistent with prior literature. The factors influencing the accuracy of target prices can be various and each study aims to analyse the relationship between the dependent variable and a specific small group of independent variables.

With regard to the signs of the control variables, when significant they are consistent with our expectations: *BOLD*, *VOL*, *GROWTH* and *PMAFE* are negatively correlated with accuracy, while *SIZE* is positively correlated. Specifically, with regard to forecast-related variables, these results indicate that the greater the difference between the forecast and the current stock price (greater boldness), the lower the probability that the forecast will be achieved (less accuracy)., Focusing on the accuracy of earnings forecasts, the results show that less precise earnings forecasts lead to less accurate target prices, which is consistent with prior literature and expectations.

With regard to firm-specific variables, the findings suggest that stable companies are easier to predict. Furthermore, the stock volatility coefficient confirms that the more volatile stock prices are, the more difficult it is to forecast a value 12 months ahead.

At odds with our expectations, the nationality of analysts (*NAZ*) is not statistically significant in any of our model specifications, indicating that this variable does not add any useful information to our analysis.

The age of the forecast is not significant in any of the model specifications. This result is partially in line with expectations as this variable mainly refers to the age of the earnings forecast. However, we decided to include it in the analysis since we did not find any significant correlation between this and *PMAFE*. It had the potential to affect the accuracy of the prediction as an individual element.

Focusing on the main variables of interest in this study, that is, the variables related to valuation methods, as expected, *DISCLOSED_NOTDISCLOSED* is not significant with both the dependent variables. This means that the disclosure of the valuation method used in a report is not related to the level of target price accuracy (Table 8). This result is in line with the descriptive analysis: with both the accuracy measures, the mean forecast error is similar regardless of the disclosure of the valuation method. Therefore, there is no evidence to support the initial hypothesis that a hidden valuation is worst than a disclosed one. We argue that analysts can base their estimations on very rigorous and precise procedures, but they can decide not to disclose them as they prefer to keep the data and procedure used private. Another explanation can be derived from the reputation effect, which assures analysts strong credibility even when they issue black-box reports.

In the second level analysis, introducing ranking among the valuation methods (primary and secondary), the results are consistent with our expectations and theory (see Section 3) overall. They show that the target prices only based on one method are systematically inferior to others (see Table 9). This result holds regardless of whether the main method is the only one used or it is chosen as primary from a set of others (Table 10). The message of these results is that in order to obtain a more accurate forecast, it is better to choose the right combination of different methods. Hence, the problem can be shifted as it is worth not choosing the right model, but taking advantage of the benefits and merits of different methods.

In the analysis of the different method categories, the only method which is different from the others in terms of target price accuracy is the net asset value method. This method leads to significantly less accurate estimates than those obtained with others (Tables 11 and 12). Therefore, divergent from both our expectations and finance theory, diverse valuation approaches (fundamental valuation methods vs market multiple approaches) do not exhibit different performance in the forecast of target prices. On the contrary, as expected, different fundamental valuation methods yield the same results when applied to the same sets of data. The exception of the *NAV* method can be explained by its features, which are backward oriented and do not capture the future profitability of the company, the main driver of value. However, this latter consideration cannot be generalised out of this sample because of the few observations related to net asset value methods (only 5% of the sample presents this valuation technique).

8. Conclusions

This study analyses the full text of financial analyst reports and aims to understand whether the choice of a specific evaluation method affects target price accuracy.

The diffusion of numerous, often personalised, techniques and the frequent use of the market ratios approach to estimate the future value of a company lead the author to speculate whether different methods should be considered as equivalent to each other or whether there are factors which differentiate them in terms of final result.

After the recent financial scandals, which have highlighted the poor reliability of the forecasts issued by financial analysts, the issue of target price accuracy is very timely and bears investigation, particularly the variable of valuation methods, which has so far been neglected.

The expectation is that both the hypothesis and the assumptions of methods could lead analysts to greater discretion in their choice of model parameters and, therefore, lead them to different levels of accuracy.

The literature has already demonstrated that there are some variables which affect the output of the reports, but only a handful number of prior studies have analysed the impact of 'structural' elements of a company valuation, such as valuation methods. Furthermore, prior results are scant and inconclusive. Some of these studies do not find any evidence to support the notion that different methods display varying abilities in the forecast of company value, while others show that a superior forecasting performance is associated with more rigorous techniques. This study provides new empirical evidence on this issue as it adopts a wider perspective and considers different features of the actual valuation procedure followed by financial analysts.

We use a sample of 1,650 reports, issued between 1 January 2007 and 30 April 2009, and two measures of target price accuracy, based on forecast errors.

In relation to our research hypothesis, we find that target prices supported by the disclosure of the valuation methods used are as accurate as those issued without contemporaneous disclosure. Moreover, the accuracy of the target price decreases when the target price is based on a main method. We argue that this result suggests that analysts evaluating companies can obtain more accurate performances by simply combining a few wisely chosen techniques, instead of using only one method.

Furthermore, when considering primary methods only, there are no significant differences in the accuracy associated with methods based on company fundamentals and those on market multiples.

Lastly, our analysis of the different types of valuation method shows that they lead to the same level of accuracy. This is a relevant result since it indicates that the development of a complex and time-consuming company fundamental analysis in the hope of achieving better company evaluation is not enough. The market and fundamental approaches do not differ significantly in the accuracy levels of their results, apart from the net asset method, which leads to a visibly poorer accuracy level. This result is consistent with those theories which have labelled this method 'inferior' since it is static and does not capture either potential future opportunities or the different levels of risk of the evaluated company.

Overall, this research indicates that target price accuracy does not depend on the choice of specific valuation method, but on the valuation procedure adopted by the analysts. In other words, our empirical evidence suggests that in order to improve the accuracy of their forecasts, analysts need to assess company value by choosing and applying a set of different methods, combining them and obtaining an average value, regardless of the specific technique chosen. Therefore, as we find no differences in the performance ability of the methods, we do not confirm the finance textbooks' theory of a hierarchy amongst methods, promoting the multi-period valuation models as superior. If the method is not so important for accuracy, this rationale may also justify the widespread use among analysts of market ratios approaches or other low-cost techniques in order to achieve their conclusions on company value.

Furthermore, this research, although with some limitations, provides results which could be a starting point for future analysis. For instance, since the literature has only been focused on the contraposition between financial and market ratios methods, it could be interesting to extend this field of research to all of the valuation methodologies and, in particular, to analyse the forecasting ability of the net assets-based methods, which are often used to evaluate insurance companies.

It could also be interesting to re-analyse the numerous reports which do not explicitly disclose the valuation methods adopted in them. These reports could be without an explicit valuation method merely because they are an update of a recent report, in which case the target prices would be estimated starting from the previous valuation procedure. For this reason, the econometric analysis should be repeated following a new reports classification, whereby the reports without an explicit valuation procedure could be associated with the last available method(s) disclosed by the same analyst.

Tables

Table 1. The method classification.

Method class	Method technique
Net Assets based Methods (NAV)	Embedded Value (*EV*) and Appraisal Value (*AV*).
Earnings-based Methods	Discounted Shareholder Profit (DSP), Discounted Earnings (DE), heuristic methods (WEV, RR).
Cash flows-based Methods	Dividend Discounted Model (DDM), Discounted Cash Flows (DCF), Gordon Growth Model (GGM), Adjusted Present Value (APV), *HOLT-CFROI.*
"Hybrid" Methods"	Economic Value Added (EVA), Regulatory Asset Based methods. (RAB).
Market ratios Methods	Comparables companies and comparable trades

Notes. This table summarizes the method classification criteria followed. The *NAV* approach considers the underlying value of the company assets net of its liabilities. In this approach, the book value is adjusted by substituting the market value of individual assets and liabilities for their carrying value on the balance sheet. This approach is most applicable in context of asset holding companies, real estate holding companies or natural resources companies. The Embedded Value is the valuation of a company's current in-force value without taking into account its capacity to generate new business. it is then a minimum value for the company. The Embedded Value can be then adjusted by adding the estimated value of future new sales to obtain the Appraisal Value of the company. Both the *EV* and the *AV* approaches are particularly indicated to evaluate the insurance industry.

According to both the *DSP* and the *DE*, the value of a company stock is calculated on a n accounting basis and it is equal to the present value of all expected future profits or earnings, discounted at the shareholders required rate of return. Warranty equity evaluation method establishes that the value of equity (*E*) is given by this formula: $E = (ROE - g) / (COE - g) \cdot P/BV$, where *ROE* is return on equity, g is long term growth rate, *COE* is the cost of equity and *P/BV* is price to book value. *ROE* required is the same of *WEV*, but g is equal to zero.

The financial method category is a multicriteria framework including cash flows-based methods. The *DDM* considers as cash flows company dividends, the *DCF* the free cash flows, the *GGM* is a specification of the *DDM* model, assuming a constant dividend growth rate; the *APV* estimates first the value o fan unlevered firm to consider the net effect on value of both the benefits and the costs of borrowing. The *HOLT-CFROI* is the acronym for Cash Flows Return on Investment and it is a model originally developed in 2002 by *HOLT* Value Associates, based in Chicago. Basically it is an indicator inflation-adjusted to measure the company ability to generate cash flows.

Both *EVA* and *RAB* methods are approaches that adjust the *NAV* approach with the present value of future company performances.

The market multiple approaches consider the market value of business companies similar to the company being valued, as observed either in trading prices of publicly traded companies or the purchase prices in the business sales, with respect to earnings or cash flows or book value of those business.

Table 2. Summary of variable definitions.

Variable name	Description	Measure
FE1	First proxy for the forecast error	$FE1 = \begin{cases} \dfrac{TP - P_{\max 12m}}{P_t} & \text{upward} \\ \dfrac{TP - P_{\min 12m}}{P_t} & \text{downward} \end{cases}$
FE2	Second proxy for the forecast error	$FE2 = \left\lvert \dfrac{TP - P_{+365}}{P_t} \right\rvert$
DISCLOSED_NOTDISCLOSED	Indicating those reports disclosing the valuation methodology from those without any explanation of the methods used	Dummy variable equal to 1 if in the report a valuation method is disclosed, 0 otherwise.
PRIMARY_SECONDARY	Indicating the method hierarchy (primary vs secondary) in the report.	Dummy variable equal to 1 if there is a primary valuation method, 0 otherwise.
PRIMARY	Indicating those reports using just a primary valuation method to get the target price.	Dummy variable equal to 1 if the analyst uses just a main method to evaluate the company, 0 if the method is selected as primary in a group of other, secondary, methods.
M_FIN, M_INC, M_NAV, M_HYB, M_MRATIO	Set of variables indicating the different kinds of valuation methodologies used in the report	Set of dummy variables representing the kind of method/s used in the report (*M_FIN* is the financial method, *M_INC* is an earnings-based method, *M_NAV* a NAV-based method, *M_HYB* represent the hybrid methods, *M_RATIO* indicates the market ratios methods). Each dummy gives value 1 to the category it represents, 0 otherwise.
FUNDAMENTAL_MULTIPLE	Variable indicating methods based on company fundamentals and methods based on company market multiples	Dummy variable equal to 1 if the analyst uses a fundamentals-based method, 0 if he/she uses a market ratios approach.
MM_FIN, MM_INC, MM_NAV, MM_HYB, MM_MRATIO	Set of variables indicating the different kinds of valuation methodologies used in the report as main method.	Set of dummy variables representing the kind of main method used in the report. Each dummy gives value 1 to the category it represents, 0 otherwise. *(MM_FIN* is the financial method, *MM_INC* is an earnings-based method, *MM_NAV* a NAV-based method, *MM_HYB* represent the hybrid methods, *MM_RATIO* indicates the market ratios methods)
BOLDNESS	Indicating the analyst boldness with respect to the prices.	It is measured as the absolute value of the difference between the target price and the current stock price scaled by the current stock price
VOL	Indicating the price volatility.	It is the standard deviation of company prices for each of the three years considered
SIZE	Indicating the company size.	It is the natural logarithm of the firm's market capitalization at the report issuing date
GROWTH	Indicating the company growth.	It is the price-to-book-value ratio
PMAFE	First proxy for earnings forecasts.	$PMAFE_{ijt} = \dfrac{AFE_{ijt} - AAFE_{jt}}{AAFE_{jt}}$
AFE	Second proxy for earnings forecasts.	$AFE_{ijt} = \dfrac{ACTUAL_{jt} - FORECAST_{ijt}}{ACTUAL_{jt}}$
FORAGE	It is a proxy for the forecast age.	It is measured as the time interval between the forecast date and the fiscal year end
NAZ	It is a proxy for the analyst nationality.	It is a dummy variable It is a dummy variable that is equal to 1 when the analyst nationality coincides with the company one, 0 otherwise.

Notes. This table summarizes the definition of the variables used in the regression models.

Table 3. Descriptive statistics on target price accuracy

Panel A. Descriptive statistics on target price accuracy – by analyst's recommendation type								
Recommendation Type	**Positive Reccomendation**		**Neutral Reccomendation**		**Negative Reccomendation**		**Total**	
	FE1	**FE2**	**FE1**	**FE2**	**FE1**	**FE2**	**FE1**	**FE2**
No.	945	945	356	356	223	223	1524	1524
Mean	0.317	0.404	0.329	0.363	0.294	0.401	0.317	0.394
Std. Dev.	0.353	0.299	0.486	0.309	0.304	0.338	0.382	0.308
Median	0.24	0.36	0.2	0.29	0.19	0.3	0.23	0.34
Max	6	2.38	6.75	2.29	1.89	1.72	6.75	2.38
Min	0	0	0	0	0	0	0	0
Skewness	7.321	1.822	7.334	2.027	1.817	1.375	7.234	1.773
Kurtosis	100.288	9.803	89.124	9.514	6.914	4.823	100.195	8.638

Panel B. Descriptive statistics on target price accuracy – by year								
Year	**2007**		**2008**		**2009**		**Total**	
	FE1	**FE2**	**FE1**	**FE2**	**FE1**	**FE2**	**FE1**	**FE2**
No.	162	162	753	753	614	614	1524	1524
Mean	0.247	0.461	0.288	0.410	0.372	0.358	0.317	0.394
Std. Dev.	0.296	0.366	0.260	0.304	0.502	0.292	0.382	0.308
Median	0.16	0.4	0.22	0.36	0.25	0.29	0.23	0.34
Max	1.48	1.99	2.37	2.33	6.75	2.38	6.75	2.38
Min	0.01	0.01	0	0	0	0	0	0
Skewness	2.736	1.618	2.349	1.752	7.160	1.813	7.234	1.773
Kurtosis	10.655	6.278	12.515	9.331	79.195	8.590	100.195	8.638

Notes. Table 3 reports the main descriptives on forecast accuracy measures. Panel A and B report some descriptive statistics on the target price accuracy measures, distinguished by recommendation type and report year. The variable definitions are reported in Table 2.

Panel C. Descriptive statistics on target price accuracy – by level of disclosure of the valuation method used

	DISCLOSED_NOTDISCLOSED=0						DISCLOSED_NOTDISCLOSED =1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	840	0.321	0.328	0.24	4.74	0	584	0.310	0.457	0.21	6.75	0	1424	0.316	0.386	0.23	6.75	0
FE2	840	0.405	0.324	0.35	2.38	0	584	0.371	0.276	0.315	2.29	0	1424	0.391	0.306	0.34	2.38	0

Panel D. Descriptive statistics on target price accuracy – by hierarchy of valuation methods

	PRIMARY_SECONDARY =0						PRIMARY_SECONDARY =1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	361	0.285	0.256	0.21	1.49	0	231	0.345	0.651	0.21	6.75	0	592	0.308	0.454	0.21	6.75	0
FE2	361	0.370	0.250	0.33	1.27	0.01	231	0.372	0.309	0.3	2.29	0	592	0.371	0.274	0.32	2.29	0

	PRIMARY=0						PRIMARY=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	78	0.287	0.275	0.205	1.46	0.01	154	0.372	0.773	0.215	6.75	0	232	0.344	0.650	0.21	6.75	0
FE2	78	0.412	0.301	0.375	1.59	0.01	154	0.354	0.313	0.285	2.29	0	232	0.373	0.309	0.305	2.29	0

Panel E. Descriptive statistics on target price accuracy – by fundamental-based and multiple-based valuation methods

	FUNDAMENTAL_MULTIPLE =0						FUNDAMENTAL_MULTIPLE =1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	110	0.398	0.860	0.22	6.75	0	123	0.293	0.367	0.2	2.53	0.01	233	0.343	0.649	0.21	6.75	0
FE2	110	0.393	0.282	0.345	1.59	0.01	123	0.356	0.331	0.28	2.29	0	233	0.373	0.309	0.31	2.29	0

Panel F. Descriptive statistics on target price accuracy – by type of valuation method

	M_FIN=0						M_FIN=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	315	0.343	0.563	0.22	6.75	0	269	0.271	0.281	0.2	2.53	0	584	0.310	0.457	0.21	6.75	0
FE2	315	0.393	0.270	0.35	2.29	0.01	269	0.345	0.282	0.28	1.82	0	584	0.371	0.276	0.315	2.29	0

	M_INC=0						M_INC=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	577	0.310	0.459	0.21	6.75	0	7	0.267	0.227	0.21	0.76	0.1	584	0.310	0.457	0.21	6.75	0
FE2	577	0.370	0.276	0.31	2.29	0	7	0.489	0.249	0.56	0.76	0.13	584	0.371	0.276	0.315	2.29	0

	M_NAV=0						M_NAV=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	559	0.303	0.452	0.21	6.75	0	25	0.448	0.551	0.26	2.37	0.04	584	0.310	0.457	0.21	6.75	0
FE2	559	0.359	0.261	0.31	1.82	0	25	0.641	0.426	0.51	2.29	0.15	584	0.371	0.276	0.315	2.29	0

	M_HYB=0						M_HYB=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	570	0.312	0.461	0.21	6.75	0	14	0.198	0.184	0.13	0.53	0.02	584	0.310	0.457	0.21	6.75	0
FE2	570	0.370	0.277	0.31	2.29	0	14	0.416	0.213	0.385	0.8	0.07	584	0.371	0.276	0.315	2.29	0

	M_MUL=0						M_MUL=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	96	0.311	0.395	0.23	2.53	0.01	488	0.309	0.468	0.21	6.75	0	584	0.310	0.457	0.21	6.75	0
FE2	96	0.358	0.351	0.285	2.29	0	488	0.374	0.259	0.33	1.59	0.01	584	0.371	0.276	0.315	2.29	0

Panel G. Descriptive statistics on target price accuracy – by type of main valuation method

	MM_FIN=0						MM_FIN=1						TOTAL					
	No.	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**	**No.**	**Mean**	**Std. Dev.**	**Median**	**Max**	**Min**
FE1	118	0.404	0.852	0.22	6.75	0	114	0.281	0.324	0.2	2.53	0.01	232	0.344	0.650	0.21	6.75	0
FE2	118	0.414	0.330	0.35	2.29	0.01	114	0.331	0.282	0.275	1.82	0	232	0.373	0.309	0.305	2.29	0

	MM_INC=0						MM_INC=1						TOTAL					

	No.	Mean	Std. Dev.	Median	Max	Min	No.	Mean	Std. Dev.	Median	Max	Min	No.	Mean	Std. Dev.	Median	Max	Min
FE1	230	0.345	0.653	0.21	6.75	0	2	0.170	0.085	0.17	0.23	0.11	232	0.344	0.650	0.21	6.75	0
FE2	230	0.373	0.310	0.305	2.29	0	2	0.365	0.332	0.365	0.6	0.13	232	0.373	0.309	0.305	2.29	0
	MM_HYB=0						MM_HYB=1						TOTAL					
	No.	Mean	Std. Dev.	Median	Max	Min	No.	Mean	Std. Dev.	Median	Max	Min	No.	Mean	Std. Dev.	Median	Max	Min
FE1	227	0.346	0.656	0.21	6.75	0	5	0.234	0.220	0.08	0.48	0.07	232	0.344	0.650	0.21	6.75	0
FE2	227	0.370	0.310	0.3	2.29	0	5	0.512	0.293	0.65	0.8	0.07	232	0.373	0.309	0.305	2.29	0
	MM_MUL=0						MM_MUL=1						TOTAL					
	No.	Mean	Std. Dev.	Median	Max	Min	No.	Mean	Std. Dev.	Median	Max	Min	No.	Mean	Std. Dev.	Median	Max	Min
FE1	122	0.294	0.368	0.2	2.53	0.01	110	0.398	0.860	0.22	6.75	0	232	0.344	0.650	0.21	6.75	0
FE2	122	0.355	0.332	0.28	2.29	0	110	0.393	0.282	0.345	1.59	0.01	232	0.373	0.309	0.305	2.29	0
	MM_NAV=0						MM_NAV=1						TOTAL					
	No.	Mean	Std. Dev.	Median	Max	Min	No.	Mean	Std. Dev.	Median	Max	Min	No.	Mean	Std. Dev.	Median	Max	Min
FE1	231	0.335	0.638	0.21	6.75	0	1	2.370	.	2.37	2.37	2.37	232	0.344	0.650	0.21	6.75	0
FE2	231	0.365	0.283	0.3	1.82	0	1	2.290	.	2.29	2.29	2.29	232	0.373	0.309	0.305	2.29	0

Notes. This table (Panel B to G) report the main descriptive statistics on the target price accuracy measures, grouped by the valuation method characteristics of the report used in this study. The variable definitions are reported in Table 2.

Panel H. Other descriptive statistics on target price accuracy – by report valuation method features

	DISCLOSED_NOTDISCLOSED =0								DISCLOSED_NOTDISCLOSED =1							
	skewness	kurtosis	p1	p5	p25	p75	p95	p99	skewness	kurtosis	p1	p5	p25	p75	p95	p99
FE1	4.209998	43.776	0	0.02	0.11	0.41	0.945	1.41	8.741532	111.675	0.01	0.03	0.1	0.38	0.86	1.46
FE2	1.903732	9.137	0.01	0.04	0.17	0.53	1.02	1.65	1.611262	8.403	0.01	0.04	0.16	0.51	0.89	1.24
	PRIMARY_SECONDARY =0								PRIMARY_SECONDARY =1							
	skewness	kurtosis	p1	p5	p25	p75	p95	p99	skewness	kurtosis	p1	p5	p25	p75	p95	p99
FE1	1.606958	5.931	0.01	0.03	0.1	0.39	0.8	1.22	7.358732	66.769	0.01	0.02	0.1	0.36	0.98	2.53
FE2	0.85305	3.328	0.02	0.05	0.17	0.51	0.89	1.07	2.200216	11.304	0.01	0.04	0.16	0.5	0.85	1.59
	PRIMARY=0								PRIMARY=1							
	skewness	kurtosis	p1	p5	p25	p75	p95	p99	skewness	kurtosis	p1	p5	p25	p75	p95	p99
FE1	2.25932	8.787	0.01	0.05	0.11	0.35	0.96	1.46	6.477379	49.678	0.01	0.02	0.1	0.36	1.01	6
FE2	1.08061	4.675	0.01	0.03	0.17	0.6	1.02	1.59	2.725243	14.640	0.01	0.04	0.15	0.46	0.83	1.82
	FUNDAMENTAL_MULTIPLE=0								FUNDAMENTAL_MULTIPLE =1							
	skewness	kurtosis	p1	p5	p25	p75	p95	p99	skewness	kurtosis	p1	p5	p25	p75	p95	p99
FE1	6.281608	44.299	0.01	0.02	0.11	0.36	0.98	6	3.809336	21.152	0.01	0.02	0.1	0.35	0.96	2.37
FE2	1.351354	5.5780	0.02	0.06	0.18	0.54	0.95	1.3	2.674807	14.001	0.01	0.03	0.13	0.45	0.83	1.82
	M_FIN=0								M_FIN=1							
	skewness	kurtosis	p1	p5	p25	p75	p95	p99	skewness	kurtosis	p1	p5	p25	p75	p95	p99
FE1	8.186869	86.807	0.01	0.03	0.11	0.42	0.86	1.49	3.166292	19.812	0.01	0.02	0.09	0.34	0.87	1.33
FE2	1.682951	10.181	0.03	0.07	0.2	0.56	0.85	1.08	1.594552	6.823	0.01	0.03	0.14	0.46	0.9	1.24
	M_INC=0								M_INC=1							
	skewness	kurtosis	p1	p5	p25	p75	p95	p99	skewness	kurtosis	p1	p5	p25	p75	p95	p99
FE1	8.719091	110.884	0.01	0.02	0.1	0.38	0.87	1.46	1.685403	4.402	0.1	0.1	0.11	0.29	0.76	0.76
FE2	1.635258	8.5016	0.01	0.04	0.16	0.5	0.9	1.24	-0.5852587	1.801	0.13	0.13	0.16	0.7	0.76	0.76
	M_NAV=0								M_NAV=1							

	skewness	kurtosis	p1	p5	p25	p75	p95	p99	skewness	kurtosis	p1	p5	p25	p75	p95	p99
FE1	9.255953	121.626	0.01	0.02	0.1	0.38	0.84	1.26	2.234125	7.470	0.04	0.09	0.12	0.4	1.49	2.37
FE2	1.282099	5.634	0.01	0.04	0.16	0.5	0.85	1.17	2.373052	9.999	0.15	0.24	0.39	0.84	1.04	2.29
	M_HYB=0								**M_HYB=1**							
	skewness	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**	**skewness**	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**
FE1	8.68665	109.91	0.01	0.03	0.1	0.38	0.87	1.46	0.7789851	2.034	0.02	0.02	0.07	0.36	0.53	0.53
FE2	1.630386	8.442	0.01	0.04	0.16	0.51	0.9	1.24	0.0693842	2.229	0.07	0.07	0.27	0.57	0.8	0.8
	M_MUL=0								**M_MUL=1**							
	skewness	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**	**skewness**	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**
FE1	3.599761	19.076	0.01	0.02	0.075	0.38	0.97	2.53	9.293103	119.2	0.01	0.03	0.1	0.38	0.84	1.43
FE2	2.823189	14.014	0	0.02	0.14	0.445	0.97	2.29	0.9911456	4.035	0.02	0.05	0.17	0.535	0.88	1.08
	MM_FIN=0								**MM_FIN=1**							
	skewness	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**	**skewness**	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**
FE1	6.099276	42.883	0.01	0.02	0.1	0.39	1.02	6	3.774152	23.224	0.01	0.02	0.1	0.34	0.96	1.33
FE2	2.245488	11.664	0.02	0.06	0.18	0.57	1.02	1.59	2.021524	9.552	0.01	0.02	0.13	0.44	0.83	1.24
	MM_INC=0								**MM_INC=1**							
	skewness	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**	**skewness**	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**
FE1	7.34038	66.456	0.01	0.02	0.1	0.36	0.98	2.53	0	1	0.11	0.11	0.11	0.23	0.23	0.23
FE2	2.189838	11.2405	0.01	0.04	0.16	0.5	0.85	1.59	0	1	0.13	0.13	0.13	0.6	0.6	0.6
	MM_HYB=0								**MM_HYB=1**							
	skewness	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**	**skewness**	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**
FE1	7.309883	65.801	0.01	0.02	0.11	0.35	0.98	2.53	0.4079907	1.168	0.07	0.07	0.07	0.47	0.48	0.48
FE2	2.240929	11.501	0.01	0.04	0.16	0.49	0.85	1.59	-0.6554944	1.979	0.07	0.07	0.37	0.67	0.8	0.8
	MM_NAV=0								**MM_NAV=1**							
	skewness	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**	**skewness**	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**
FE1	7.748807	72.716	0.01	0.02	0.1	0.35	0.97	2.53	.	.	2.37	2.37	2.37	2.37	2.37	2.37
FE2	1.598129	7.093	0.01	0.04	0.16	0.5	0.85	1.3	.	.	2.29	2.29	2.29	2.29	2.29	2.29
	MM_MUL=0								**MM_MUL=1**							
	skewness	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**	**skewness**	**kurtosis**	**p1**	**p5**	**p25**	**p75**	**p95**	**p99**
FE1	3.791858	20.984	0.01	0.02	0.1	0.35	0.96	2.37	6.281608	44.299	0.01	0.02	0.11	0.36	0.98	6
FE2	2.669866	13.913	0.01	0.03	0.13	0.45	0.83	1.82	1.351354	5.578	0.02	0.06	0.18	0.54	0.95	1.3

Notes. Panel G reports other descriptive statistics on the target price accuracy measures, grouped by the valuation method characteristics of the report used in this study. The variable definitions are reported in Table 2.

Table 4. Descriptive statistics of the control variables of the models

	BOLDNESS	FORAGE	PMAFE	VOL	GROWTH	SIZE	NAZ
2007							
No.	168	132	132	171	171	171	147
Mean	0.22	190.90	0.02	4.31	2.71	10.81	0.69
Std. Dev.	0.34	95.55	0.54	3.53	1.69	0.45	0.46
Median	0.14	192	0	3.45	2.18	10.87	-
Max	1.61	354	1.72	13.69	7.69	11.6	1
Min	-0.16	21	-0.97	0.12	1.18	9.45	0
Skewness	2.67	0.01	0.67	0.79	1.69	-0.93	-0.84
Kurtosis	10.34	1.85	3.34	2.48	4.80	4.03	1.71
p1	-0.13	24	-0.95	0.12	1.29	9.45	0
p5	-0.06	46	-0.83	0.76	1.34	9.91	0
p25	0.03	103.5	-0.4	1.31	1.51	10.6	0
p75	0.29	257	0.295	7.04	3.15	11.12	1
p95	1.2	340	0.97	11.42	7.06	11.45	1
p99	1.6	353	1.46	12.88	7.66	11.57	1
2008							
	BOLDNESS	**FORAGE**	**PMAFE**	**VOL**	**GROWTH**	**SIZE**	**NAZ**
No.	753	671	681	813	805	805	774
Mean	0.36	100.97	0.01	6.10	1.85	10.33	0.39
Std. Dev.	0.33	71.00	0.52	5.77	1.27	0.64	0.49
Median	0.3	85	0.02	4.43	1.38	10.4	-
Max	2.95	358	4.41	24.29	6.55	11.67	1
Min	-0.37	0	-1	0.33	0.26	7.63	0
Skewness	1.993	1.440	2.359	1.734	1.443	-1.075	0.450
Kurtosis	12.627	5.413	17.081	5.663	4.681	4.687	1.203
p1	-0.18	8	-0.95	0.33	0.35	8.24	0
p5	-0.07	16	-0.77	0.62	0.51	9.2	0
p25	0.16	52	-0.24	2.08	0.93	10.01	0
p75	0.5	146	0.17	8.46	2.36	10.79	1
p95	0.89	272	0.63	20.4	4.58	11.17	1
p99	1.45	342	2.13	24.29	6.12	11.37	1
2009							
	BOLDNESS	**FORAGE**	**PMAFE**	**VOL**	**GROWTH**	**SIZE**	**NAZ**
No.	614	557	550	666	663	663	643
Mean	0.31	306.29	0.00	3.97	1.30	9.99	0.35
Std. Dev.	0.34	30.06	0.54	3.33	0.87	0.75	0.48
Median	0.27	308	-0.01	2.495	1.12	10.04	-
Max	3.12	359	6.46	11.32	4.16	11.51	1
Min	-0.55	160	-1	0.09	0.03	5.71	0
Skewness	1.782	-0.774	3.522	0.861	1.284	-1.511	0.622
Kurtosis	12.188	5.020	39.603	2.547	4.418	8.666	1.387
p1	-0.3	208	-0.95	0.09	0.2	7.87	0
p5	-0.12	259	-0.77	0.38	0.35	8.55	0
p25	0.1	287	-0.3	1.27	0.68	9.68	0
p75	0.47	328	0.25	5.91	1.73	10.39	1
p95	0.93	353	0.74	11.24	3.2	11.04	1
p99	1.33	358	1.58	11.32	3.9	11.46	1
Total							
	BOLDNESS	**FORAGE**	**PMAFE**	**VOL**	**GROWTH**	**SIZE**	**NAZ**
No.	1535	1360	1363	1650	1639	1639	1564
Mean	0.32	193.79	0.01	5.05	1.72	10.24	0.40
Std. Dev.	0.34	114.79	0.53	4.82	1.26	0.71	0.49
Median	0.27	170	0	3.81	1.36	10.3	-
Max	3.12	359	6.46	24.29	7.69	11.67	1
Min	-0.55	0	-1	0.09	0.03	5.71	0
Skewness	1.924	-0.092	2.690	39.751	1.781	-1.292	0.396
Kurtosis	11.816	1.411	25.619	1603.309	6.787	7.018	1.157
p1	-0.24	12	-0.95	0.12	0.29	8.11	0
p5	-0.09	26.5	-0.77	0.47	0.395	8.96	0
p25	0.11	78	-0.28	1.76	0.87	9.91	0
p75	0.46	307	0.21	7.04	2.135	10.75	1
p95	0.92	343	0.74	12.88	4.33	11.18	1
p99	1.45	356	1.82	24.29	6.47	11.47	1

Notes. This table reports the descriptive statistics (grouped by year and reported in total) of the control variables used in the different model specifications. Specifically, as reported in Table 2, *BOLDNESS* is the target price boldness and is measured as the absolute value of the difference between the target price and the current price scaled by current price;

VOL indicates the market price volatility measured as the standard deviation of company prices for each of the three years considered; *SIZE* indicates the natural logarithm of the firm's market capitalization at the report issuing date; *GROWTH* is the company price-to-book-value ratio; *PMAFE* is the Proportional Mean Absolute Forecast Error and is the earnings forecast accuracy measure. It is computed as:

$$PMAFE_{ijt} = \frac{AFE_{ijt} - AAFE_{jt}}{AAFE_{jt}} \ (-1)$$

It measures the difference between the absolute forecast error (*AFE*) of analyst *i* forecasting earnings for firm *j* in the fiscal year *t* and the average absolute forecast error across all analyst forecasts of firm *j*'s fiscal year *t* earnings, expressed as a fraction of the average absolute forecast error across all analyst forecasts of firm *j*'s fiscal year *t* earnings. *PMAFE* controls for firm-year effects by subtracting the mean absolute forecast error, *AAFE* , from the analyst's absolute forecast error. Deflating by *AAFE* reduces heteroskedasticity in forecast error distributions across firms (Clement (1999)). Multiplying by -1 ensures that higher values for *PMAFE* correspond to higher levels of accuracy.
FORAGE is the time interval (in number of days) between the forecast date and the fiscal year end, while *NAZ* is a dummy variable equal to 1 whether the analyst's nationality coincides with the company nationality, 0 otherwise.

Table 5. Descriptive statistics on the main independent variables of the models

Year		DISCLOSED_NOTDISCLOSED	PRIMARY_SECONDARY	PRIMARY	FUNDAMENTAL_MULTIPLE	MM_FIN	MM_INC	MM_HYB
2007	**No.**	166	85	33	33	33	33	33
	% (=1)	51.20%	38.82%	39.39%	33.33%	21.21%	3.03%	9.09%
2008	**No.**	746	258	90	91	90	90	90
	% (=1)	34.18%	34.50%	68.89%	60.44%	55.56%	0.00%	3.33%
2009	**No.**	612	262	111	111	111	111	111
	% (=1)	41.99%	42.37%	72.97%	52.25%	51.35%	0.90%	0.00%
Total	**No.**	1524	605	234	235	234	234	234
	% (=1)	39.17%	38.51%	66.67%	52.77%	48.72%	0.85%	2.56%
Year		**MM_NAV**	**MM_MRATIO**	**M_FIN**	**M_INC**	**M_NAV**	**M_HYB**	**M_MRATIO**
2007	**No.**	33	33	85	85	85	85	85
	% (=1)	0.00%	66.67%	50.59%	2.35%	12.94%	4.71%	91.76%
2008	**No.**	90	90	255	255	255	255	255
	% (=1)	1.11%	40.00%	43.53%	1.18%	3.14%	2.75%	80.78%
2009	**No.**	111	111	257	257	257	257	257
	% (=1)	0.00%	47.75%	46.30%	0.78%	3.50%	2.33%	83.27%
Total	**No.**	234	234	597	597	597	597	597
	% (=1)	0.43%	47.44%	45.73%	1.17%	4.69%	2.85%	83.42%

Notes. This table reports the descriptive statistics (grouped by year and reported in total) of the main independent variables of the models. They synthesize the report valuation methods features. Specifically, as reported in Table 2, *DISCLOSED_NOTDISCLOSED* is a dummy variable assuming value equal to 1 whether in the report has a distinguishable valuation method, 0 otherwise. *PRIMARY_SECONDARY* is equal to 1 if there's a primary valuation method, 0 otherwise; the *PRIMARY* variable is equal to 1 if the analyst uses just that method to evaluate the company, 0 if the method is chosen as primary in a group of other secondary methods; *M_FIN, M_INC, M_NAV, M_HYB, M_MRATIO indicate* different methods categories, respectively financial methods, income-based ones, net asset methods, hybrid and market ratios methods. Each variable is a dummy assuming value 1 in correspondence to the category it represents, 0 otherwise; *FUNDAMENTAL_MULTIPLE* is a variable assuming value equal to 1 if the analyst uses an absolute method (such as a financial method, an income based method, a hybrid or a net asset method, 0 if he/she uses a market ratios approach).;*MM_FIN, MM_INC, MM_NAV, MM_HYB, MM_MRATIO* are dummy variables representing the main valuation method used by the analyst. Each one is equal to 1 whether the analyst uses that specific method as main valuation method.

Table 6. The correlation matrix among variables.

Panel A - The Pearson's correlation.

	FE1	FE2	DISCLOSED_ NOTDISCLOSED	PRIMARY_ SECONDARY	PRIMARY	M_FIN	M_INC	M_NAV	M_MRATIO	M_HYB
FE1	1									
FE2	0.4617*	1								
DISCLOSED _NOTDISCLOSED	-0,0148	-0.0551*	1							
PRIMARY _SECONDARY	0,064	0,0034	0.1026*	1						
PRIMARY	0,0624	-0,0883			1					
M_FIN	-0.0785*	-0.0857*		0.1665*	-0.3348*	1				
M_INC	-0,0102	0,047		-0,0237	-0.1313*	-0.0687*	1			
M_NAV	0,0644	0.2069*		0,0494	-0.3185*	-0.0923*	0.1230*	1		
M_MRATIO	-0,0017	0,0217		-0.3165*	-0.4761*	-0.4315*	0,0486	0,035	1	
M_HYB	-0,0384	0,0258		-0,0057	-0,0887	-0,0359	-0,0186	0.1526*	-0.0861*	1
FUNDAMENTAL _MULTIPLE	-0,0814	-0,0606			-0.1634*	0.7701*	0,0877	-0.1940*	-0.6351*	0.1658*
MM_FIN	-0,0953	-0.1338*			-0.1270*	0.8643*	-0,0905	-0.2098*	-0.6170*	-0,121
MM_INC	-0,0249	-0,0025			-0.1313*	-0,1047	1.0000*	-0,0234	0,0625	-0,0163
MM_MRATIO	0,0804	0,0614			0.1634*	-0.7782*	-0,0882	0.1934*	0.6397*	-0.1668*
MM_HYB	-0,0251	0,0667			-0,0574	-0.1829*	-0,0151	-0,0409	-0,0658	0.9238*
BOLD	0.3770*	0.3416*	-0.1293*	-0,0341	0,0248	-0,0541	-0,0493	0,0657	0,0245	0,0629
FORAGE	0.0921*	-0,0162	0.0888*	0.0758*	-0,0155	0,0075	0,0326	0,0188	0,0491	0,0496
PMAFE	0,0262	0.1035*	-0.0492*	0	0,0479	0,0117	-0,0187	-0,0199	-0,0485	-0.0582
VOL	0.0569*	0.1883*	-0,028	0,0581	-0,0813	-0.1411*	-0,0119	0,0607	0,0495	-0.0462
GROWTH	-0.2277*	-0.1749*	0.0886*	0,0666	-0,0469	0.1488*	0,0012	-0.0904*	-0,0519	-0.0697*
SIZE	-0.3878*	-0.1898*	-0,0288	-0,0016	-0.1333*	0,0619	0.0696*	-0,0379	0,0341	0,0226
NAZ	0,021	0.0830*	-0.1279*	-0.0797*	-0.1698*	-0,0036	-0,0001	0.0973*	0.0842*	0,0319

Panel B - The Pearson's correlation.

	FUNDAMENTAL _MULTIPLE	MM_FIN	MM_INC	MM_MRATIO	MM_HYB	BOLD	FORAGE	PMAFE	VOL	GROWTH	SIZE	NAZ
FUNDAMENTAL _MULTIPLE	1											
MM_FIN	0.9259*	1										
MM_INC	0,0882	-0,0905	1									
MM_MRATIO	-1	-0.9259*	-0,0882	1								
MM_HYB	0.1541*	-0.1581*	-0,0151	-0.1541*	1							
BOLD	0,0066	0,0058	-0,0429	-0,0074	0,008	1						
FORAGE	-0,0599	-0,0584	-0,046	0,0576	0,0659	-0.0916*	1					
PMAFE	0,0799	0,1059	-0,0783	-0,0799	-0,0489	0,0311	0.1270*	1				
VOL	-0.1253*	-0.1270*	-0,0749	0.1257*	0,043	0.0460*	-0.1249*	0,0109	1			
GROWTH	0,0968	0.1240*	-0,0085	-0,0945	-0,052	-0.2329*	-0.1227*	0.0471*	-0.0992*	1		
SIZE	0,0171	-0,0117	0,0322	-0,0175	0.1627*	-0.1479*	-0.1472*	0.0742*	0,022	0.3878*	1	
NAZ	-0,1027	-0.1670*	0,0427	0,1027	0.1814*	0.1060*	-0,0027	0,0297	0.0898*	-0.0542*	0.0569*	1

Notes. These panels (A and B – Table 6) report the correlation matrix of the different model specification variables. It is based on the Pearson's correlation definition. Some of the correlations are missing because of the variables definition. All the variables have been defined above.
* denotes significance at the 10%

Table 7. The correlation matrix among variables.

Panel A - The Spearman's correlation.

	FE1	FE2	DISCLOSED_ NOTDISCLOSED	PRIMARY _SECONDARY	PRIMARY	M_FIN	M_INC	M_NAV	M_MRATIO	M_HYB
FE1	1									
FE2	0.4955*	1								
DISCLOSED_ NOTDISCLOSED	-0.0569*	-0,0403	1							
PRIMARY _SECONDARY	-0,0014	-0,0298	0.1026*	1						
PRIMARY	-0,0125	-0.1155*	.	.	1					
M_FIN	-0.0721*	-0.1164*	.	0.1665*	-0.3348*	1				
M_INC	0,0001	0,061	.	-0,0237	-0.1313*	-0.0687*	1			
M_NAV	0,0551	0.1770*	.	0,0494	-0.3185*	-0.0923*	0.1230*	1		
M_MRATIO	0,0128	0,0651	.	-0.3165*	-0.4761*	-0.4315*	0,0486	0,035	1	
M_HYB	-0,0572	0,0476	.	-0,0057	-0,0887	-0,0359	-0,0186	0.1526*	-0.0861*	1
FUNDAMENTAL _MULTIPLE	-0,0613	-0,1056	.	.	-0.1634*	0.7701*	0,0877	-0.1940*	-0.6351*	0.1658*
MM_FIN	-0,0611	-0.1505*	.	.	-0.1270*	0.8643*	-0,0905	-0.2098*	-0.6170*	-0.1210*
MM_INC	-0,0321	0,0041	.	.	-0.1313*	-0,1047	1.0000*	-0,0234	0,0625	-0,0163
MM_MRATIO	0,0594	0,108	.	.	0.1634*	-0.7782*	-0,0882	0.1934*	0.6397*	-0.1668*
MM_HYB	-0,0282	0,0896	.	.	-0,0574	-0.1829*	-0,0151	-0,0409	-0,0658	0.9238*
BOLD	0.3102*	0.1991*	-0.1515*	-0,0356	-0,0018	-0,0623	-0,0605	0.0691*	0,0311	0,0577
FORAGE	0.0779*	0,0007	0.0730*	0,057	-0,009	-0,006	0,0264	0,0157	0,044	0,0518
PMAFE	0,0095	0.0926*	-0.0544*	-0,0287	0,0547	-0,0156	-0,0023	-0,0204	-0,0198	-0,0648
VOL	0.0527*	0.1335*	-0,0081	0.0791*	-0.1091*	-0.1276*	-0,0157	0,0243	0,0578	-0,0548
GROWTH	-0.2836*	-0.1905*	0.1166*	0.1231*	-0.1242*	0.2087*	0,0374	-0.0799*	-0.0699*	-0,0456
SIZE	-0.2034*	-0.0690*	-0,0379	0,012	-0.1256*	0,0394	0.0797*	0,0309	0,0349	0,0438
NAZ	0,0274	0.0960*	-0.1279*	-0.0797*	-0.1698*	-0,0036	-0,0001	0.0973*	0.0842*	0,0319

Panel B - The Spearman's correlation.

	FUNDAMENTAL _MULTIPLE	MM_FIN	MM_INC	MM_MRATIO	MM_HYB	BOLD	FORAGE	PMAFE	VOL	GROWTH	SIZE	NAZ
FUNDAMENTAL _MULTIPLE	1											
MM_FIN	0.9259*	1										
MM_INC	0,0882	-0,0905	1									
MM_MRATIO	-1	-0.9259*	-0,0882	1								
MM_HYB	0.1541*	-0.1581*	-0.0151	-0.1541*	1							
BOLD	0,0364	0,0321	-0,0592	-0,0372	0,0163	1						
FORAGE	-0,0429	-0,0528	-0,0554	0,0419	0,0988	-0.0950*	1					
PMAFE	0,0838	0,1013	-0,0694	-0,0839	-0,0411	0.0596*	0.1731*	1				
VOL	-0.1451*	-0.1572*	-0,095	0.1473*	0,0696	-0,0152	-0.0644*	0,0442	1			
GROWTH	0,1052	0.1183*	0,0219	-0,1019	-0,0099	-0.2847*	-0.1018*	0.0954*	0,02	1		
SIZE	-0,0077	-0,0613	0,0275	0,0064	0.2028*	-0.0782*	-0.1435*	0.1324*	0,0377	0.4842*	1	
NAZ	-0,1027	-0.1670*	0,0427	0,1027	0.1814*	0.1249*	0,0002	0,0086	0.0971*	-0.0666*	0.0827*	1

Notes. These panels (A and B – Table 7) report the correlation matrix among of the different model specification variables. It is based on the Spearman's correlation definition. Some of the correlations are missing because of the variables definition. All the variables have been defined above.
* denotes significance at the 10%

Table 8. The effect on the target price accuracy of the valuation methods disclosure

	(1)	(2)	(3)	(4)
VARIABLES	FE1	FE1	FE1	FE1
BOLD		0.364***	0.394***	0.386***
		(0)	(0)	(0)
FORAGE		0.000255	0.000280*	
		(0.109)	(0.0907)	
PMAFE		0.0267	0.0155	
		(0.125)	(0.440)	
VOL		0.00294	0.00376	
		(0.238)	(0.152)	
GROWTH		0.0917***	0.0996***	0.0898***
		(9.43e-08)	(1.26e-08)	(2.31e-10)
SIZE		-0.346***	-0.348***	-0.311***
		(0)	(0)	(0)
D_2008		-0.109***	-0.0973**	
		(0.00358)	(0.0118)	
D_2009		-0.103**	-0.0823*	
		(0.0250)	(0.0816)	
NAZ		-0.00682	0.00402	
		(0.736)	(0.849)	
DISCLOSED_NOTDISCLOSED	-0.0109		0.0277	0.0270
	(0.599)		(0.165)	(0.129)
Constant	0.321***	3.623***	3.578***	3.209***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	1,424	1,275	1,213	1,424
R-squared	0.000	0.287	0.298	0.281
Number of sector	20	20	20	20

pval in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes. This table reports the main results of equation (5), testing the effect on the target price accuracy of the valuation methods disclosure. Table 2 defines all the variables used.

Table 9. The effect on the target price accuracy of the valuation method hierarchy disclosure

	(1)	(2)	(3)	(4)
VARIABLES	FE1	FE1	FE1	FE1
BOLD		0.364***	0.384***	0.371***
		(0)	(5.15e-10)	(2.02e-10)
FORAGE		0.000255	0.000294	
		(0.109)	(0.265)	
PMAFE		0.0267	-0.00885	
		(0.125)	(0.794)	
VOL		0.00294	0.0107**	
		(0.238)	(0.0231)	
GROWTH		0.0917***	0.129***	0.117***
		(9.43e-08)	(1.71e-05)	(2.50e-06)
SIZE		-0.346***	-0.464***	-0.427***
		(0.0000)	(0.0000)	(0.0000)
D_2008		-0.109***	-0.109*	
		(0.00358)	(0.0702)	
D_2009		-0.103**	-0.110	
		(0.0250)	(0.141)	
NAZ		-0.00682	-0.00534	
		(0.736)	(0.888)	
PRIMARY_SECONDARY	0.110***		0.104***	0.116***
	(0.00635)		(0.00300)	(0.000514)
Constant	0.266***	3.623***	4.656***	4.305***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	592	1,275	541	592
R-squared	0.013	0.287	0.360	0.334
Number of sector	20	20	20	20

pval in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes. This table reports the main results of equation (6), testing the effect on the target price accuracy of the valuation methods hierarchy disclosure. Table 2 defines all the variables used.

Table 10. The effect on the target price accuracy of the main and unique valuation method disclosure

VARIABLES	(1) FE1	(2) FE1	(3) FE1	(4) FE1
BOLD		0.364***	0.805***	0.821***
		(0)	(0)	(0)
FORAGE		0.000255	6.51e-06	
		(0.109)	(0.988)	
PMAFE		0.0267	0.0133	
		(0.125)	(0.815)	
VOL		0.00294	0.00405	
		(0.238)	(0.655)	
GROWTH		0.0917***	0.235***	0.178***
		(9.43e-08)	(1.90e-05)	(2.38e-05)
SIZE		-0.346***	-0.747***	-0.684***
		(0)	(0)	(0)
D_2008		-0.109***	-0.193*	
		(0.00358)	(0.0622)	
D_2009		-0.103**	-0.0654	
		(0.0250)	(0.580)	
NAZ		-0.00682	0.184***	
		(0.736)	(0.00839)	
PRIMARY	0.101		-0.0723	-0.0543
	(0.289)		(0.237)	(0.343)
Constant	0.277***	3.623***	7.400***	6.805***
	(0.000285)	(0)	(0)	(0)
Observations	232	1,275	210	232
R-squared	0.005	0.287	0.694	0.650
Number of sector	20	20	20	20

pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes. This table reports the main results of equation (7), testing the effect on the target price accuracy of the main and unique valuation method disclosure. Table 2 defines all the variables used.

Table 11. The effect on the target price accuracy of different valuation methods

	(1)	(2)	(3)	(4)
VARIABLES	FE1	FE1	FE1	FE1
BOLD		0.364***	0.396***	0.382***
		(0)	(4.66e-10)	(1.55e-10)
FORAGE		0.000255	0.000292	
		(0.109)	(0.282)	
PMAFE		0.0267	-0.0114	
		(0.125)	(0.745)	
VOL		0.00294	0.0111**	
		(0.238)	(0.0227)	
GROWTH		0.0917***	0.127***	0.108***
		(9.43e-08)	(3.35e-05)	(1.87e-05)
SIZE		-0.346***	-0.459***	-0.418***
		(0)	(0)	(0)
D_2008		-0.109***	-0.119*	
		(0.00358)	(0.0561)	
D_2009		-0.103**	-0.104	
		(0.0250)	(0.185)	
NAZ		-0.00682	-0.0132	
		(0.736)	(0.737)	
M_FIN	-0.0198		-0.00885	-0.0163
	(0.678)		(0.839)	(0.681)
M_INC	-0.157		0.0214	0.00813
	(0.363)		(0.892)	(0.955)
M_NAV	0.174*		0.112	0.190**
	(0.0961)		(0.249)	(0.0290)
M_MRATIO	-0.0657		-0.0534	-0.0503
	(0.257)		(0.301)	(0.295)
M_HYB	-0.311**		-0.0594	-0.106
	(0.0161)		(0.636)	(0.328)
Constant	0.375***	3.623***	4.690***	4.319***
	(4.62e-09)	(0)	(0)	(0)
Observations	584	1,275	531	584
R-squared	0.016	0.287	0.353	0.329
Number of sector	20	20	20	20

pval in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes. This table reports the main results of equation (8), testing the effect on the target price accuracy of different valuation methods used. Table 2 defines all the variables used.

Table 12. The effect on the target price accuracy of the "absolute" and "relative" valuation methods

	(1)	(2)	(3)	(4)
VARIABLES	FE1	FE1	FE1	FE1
BOLD		0.364***	0.807***	0.826***
		(0)	(0)	(0)
FORAGE		0.000255	-3.09e-05	
		(0.109)	(0.944)	
PMAFE		0.0267	0.0220	
		(0.125)	(0.704)	
VOL		0.00294	0.00452	
		(0.238)	(0.618)	
GROWTH		0.0917***	0.228***	0.175***
		(9.43e-08)	(2.96e-05)	(2.52e-05)
SIZE		-0.346***	-0.739***	-0.678***
		(0)	(0)	(0)
D_2008		-0.109***	-0.203**	
		(0.00358)	(0.0488)	
D_2009		-0.103**	-0.0641	
		(0.0250)	(0.589)	
NAZ		-0.00682	0.185***	
		(0.736)	(0.00812)	
FUNDAMENTAL _MULTIPLE	-0.0607		-0.0631	-0.0954
	(0.549)		(0.360)	(0.115)
Constant	0.375***	3.623***	7.328***	6.756***
	(7.45e-08)	(0)	(0)	(0)
Observations	233	1,275	210	233
R-squared	0.002	0.287	0.693	0.653
Number of sector	20	20	20	20

pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes. This table reports the main results of equation (9), testing the effect on the target price accuracy of "absolute" and "relative" valuation methods. Table 2 defines all the variables used.

Table 13. The effect on the target price accuracy of different kinds of main valuation methods

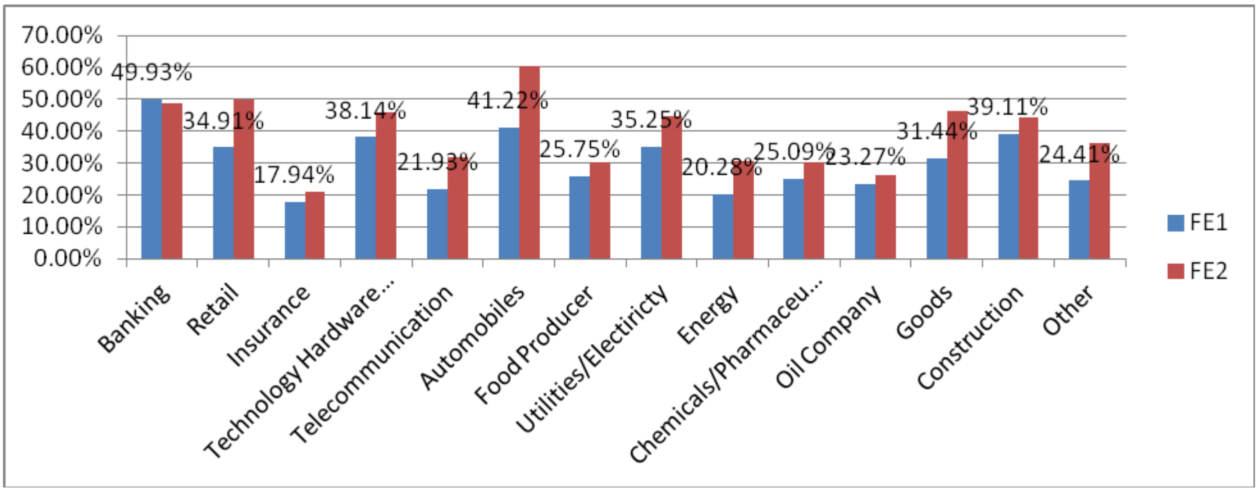
	(1)	(2)	(3)	(4)	(5)
VARIABLES	FE1	FE1	FE1	FE1	FE1
MM_FIN	-0.923**	0.0709		0.228	-0.104
	(0.0364)	(0.738)		(0.407)	(0.102)
MM_INC	-1.152**	-0.157	-0.228		-0.332
	(0.0249)	(0.639)	(0.407)		(0.220)
MM_MRATIO	-0.820*	0.175	0.104	0.332	
	(0.0601)	(0.407)	(0.102)	(0.220)	
MM_HYB	-0.994**		-0.0709	0.157	-0.175
	(0.0441)		(0.738)	(0.639)	(0.407)
MM_NAV		0.994**	0.923**	1.152**	0.820*
		(0.0441)	(0.0364)	(0.0249)	(0.0601)
BOLD	0.836***	0.836***	0.836***	0.836***	0.836***
	(0)	(0)	(0)	(0)	(0)
GROWTH	0.175***	0.175***	0.175***	0.175***	0.175***
	(2.99e-05)	(2.99e-05)	(2.99e-05)	(2.99e-05)	(2.99e-05)
SIZE	-0.658***	-0.658***	-0.658***	-0.658***	-0.658***
	(0)	(0)	(0)	(0)	(0)
Constant	7.380***	6.386***	6.457***	6.229***	6.560***
	(0)	(0)	(0)	(0)	(0)
Observations	232	232	232	232	232
R-squared	0.662	0.662	0.662	0.662	0.662
Number of sector	20	20	20	20	20

pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

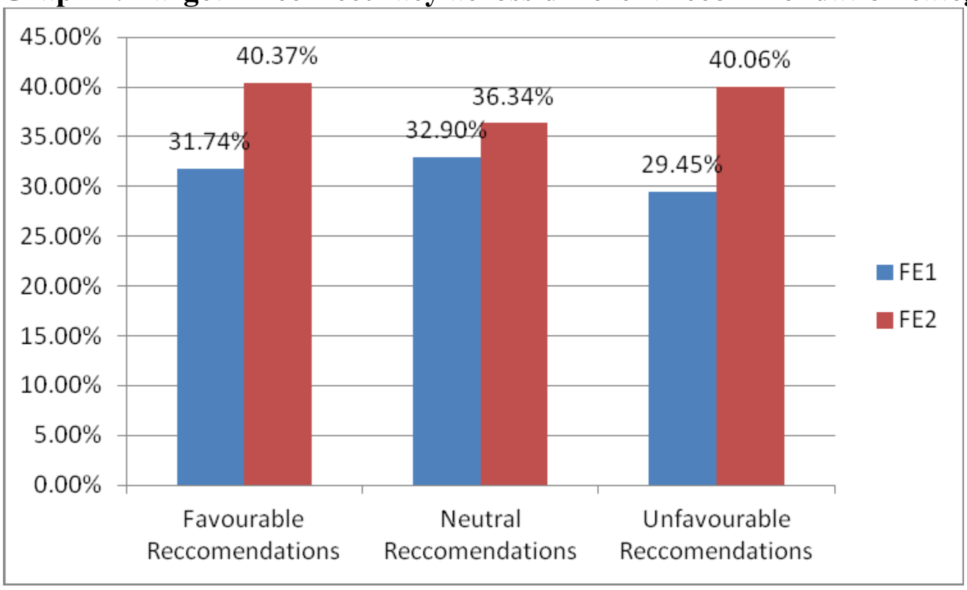
Notes. This table reports the main results of equation (10), testing the effect on the target price accuracy of different types of main valuation methods used. Table 2 defines all the variables used.

Graphs

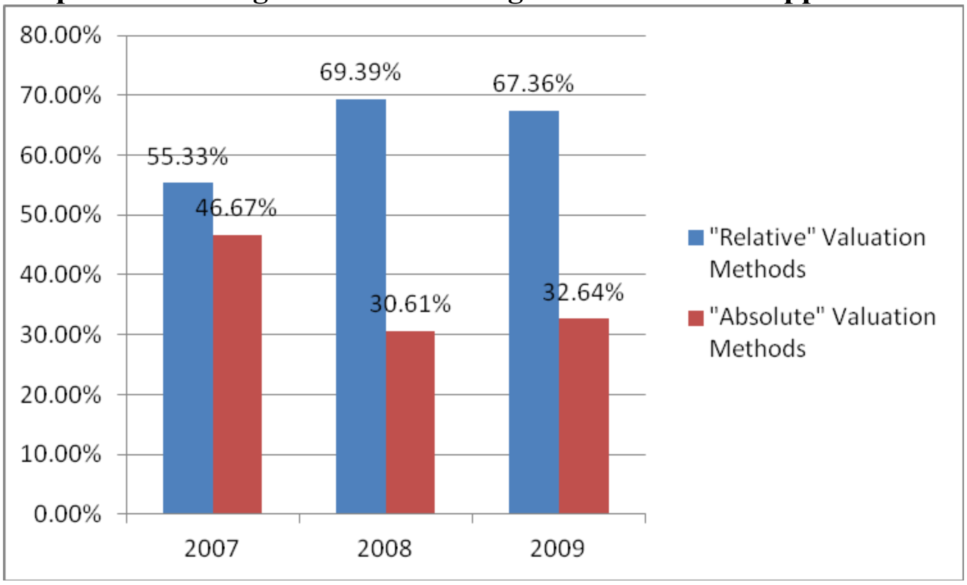
Graph 1. Target Price Accuracy across sectors



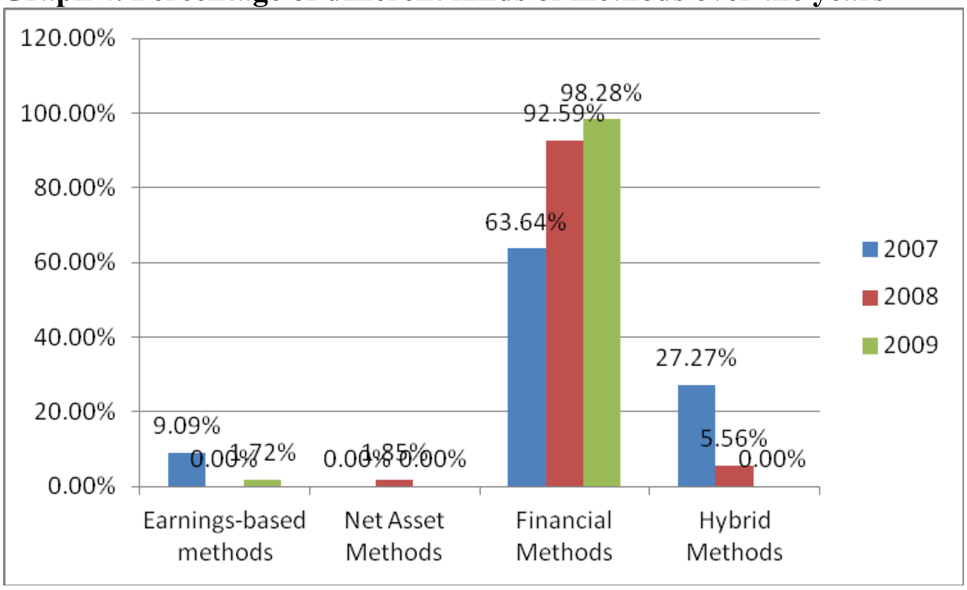
Graph 2. Target Price Accuracy across different recommendation categories



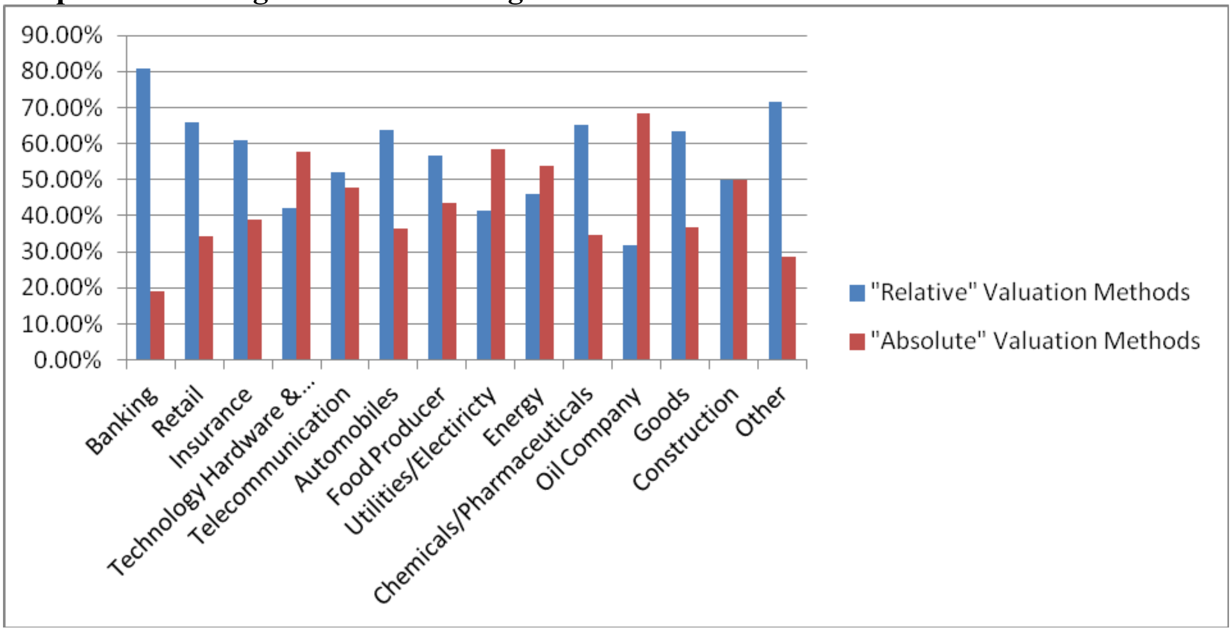
Graph 3. Percentage of different categories of valuation approaches over the years



Graph 4. Percentage of different kinds of methods over the years



Graph 5. Percentage of different categories of methods across sectors



CHAPTER 3

Paper II
Transparency and the Market Impact of Security Analyst Recommendations

1. Introduction

This paper investigates whether the level of transparency in the disclosures of financial analysts, conditional on the release of other information, is value-relevant for capital markets. According to the part of literature on company disclosure showing that the quality of the information disclosed is more value relevant than its quantity, our expectation is that analysts who disclose more relevant details about how they evaluate a company make the monitoring of companies by shareholders easier and generate greater market reaction.

An analyst report is the final product of the analyst's work which includes the collection and valuation of information related to the future performance of a specific company. The process starts with the company's disclosure of public information, such as their strategies, the competitive landscape, financial data and other non-financial factors, for example the quality of their management. With this information, analysts use their skills to process, through the use of one or more valuation methods, these heterogeneous data into a valuation of the firm. Then, by comparing their estimates to current trading prices, their forecasts result in a stock recommendation. This complex process of collecting and evaluating information results in a written report, which usually contains a minimum content, including at least three summary measures on its front page, that is, the actual recommendation level (i.e., buy, hold or sell), the earnings forecast and the target price forecast. In addition, sometimes the full text of the report can provide quantitative and qualitative analyses supporting the three summary measures. The further disclosed information of this additional part can be rich and extensive. In these cases, the analysts may show in a more or less transparent way the valuation method(s) which they have used to arrive at their final recommendation and, thus, provide the investors with the details of how the company valuation has been conducted. The degree of disclosure transparency in a report is not a straightforward measure. In general terms, disclosure is different from transparency. An analyst can disclose many company details, but investors are still left in the dark. Too much disclosed information has the potential to add noise to the observed equity returns, thereby making it difficult to assess company value. Therefore, the amount of information disclosed by an analyst should be irrelevant for the market.

On the other hand, how the analyst estimates company value should be relevant. In other words, we assume that the relevant information is that which is included in the report and thus translated into specific model assumptions by the analysts in their valuation procedures. From this perspective, the valuation method is important, as it is the synthesis of the information selected by the analyst. It is meta-information.

Under this assumption, the method of disclosure is a key indicator of the transparency of a report. This assumption is also supported by the European Commission in Directive 2003/125/EC, known as the Market Abuse Directive (MAD), the European counterpart of the US regulations on the fair disclosure and transparency of the financial markets, which requires investment banks to summarize adequately "…any basis of valuation or methodology used to evaluate a financial instrument or an issuer of a financial instrument, or to set a price target for a financial instrument" (article 4, Directive 2003/125/EC).

Therefore, we define a report as transparent when the valuation methods used to perform the analysis are clearly disclosed by the analyst. Conversely, in this framework, a report is opaque when the valuation methods are not disclosed. A set of criteria is developed to measure this level and reduce the subjectivity of assessment, and it has been cross-checked by different researchers.

Our results partially replicate the findings of prior literature, showing that changes of recommendation are significantly associated with market reaction to the release of analysts' reports. Results also show that the target prices may contain important information for the market, depending on how bold and unconventional the forecasts (target prices) are. However, these findings add new information about the nature and the source of the market reaction to the release of analysts' report. We show that market reaction is not symmetric and what causes this asymmetry is the level of disclosure transparency in the report. This means that, in general, markets react consistently to the signal provided by recommendations and target prices, but they also modify their reaction depending on the additional information provided. Interestingly, the positive reaction of investors to good news is unconditional with regard to the level of information disclosed by analysts. However, they only trust negative news when they are provided with the supporting elements which enable their understanding of the valuation procedures which underpin the estimates.

We then investigate whether the results are affected by other variables, such as the broker's reputation and/or the confounding effect derived from information releases which occur contemporaneously with the analyst's report. However, none of the variables used as a reputation measure or confounding effect proxy are statistically significant.

Although prior literature has documented that analyst reports usually trigger a significant market reaction around their release, it remains unclear which part of informational content of financial reports is relevant in terms of value for the capital market. Much of the previous analysis is only based on the minimum content of the reports (recommendations and target prices) or on the forecasts of earnings usually collected from commercial datasets (e.g. Womack (1996), Gleason and Lee (2000), Mikhail et al. (1997)). However, generally, these studies have not measured the value of analyst recommendations when these recommendations are released concurrently with other report information. Asquith et al. (2005) represent a noticeable exception in this context. They investigated the association between market returns and the content of analyst reports and their findings show that there is no correlation between the specific type of valuation methodology used by analysts and market reaction. However, examination of the justifications made to support investment recommendations, show that they provide significant information to the market. This result suggests that the investors are sensitive to the level of disclosure made by analysts, but the potential effect of this transparency on the stock market beyond quantity of disclosure is still an open empirical question. Although this paper is strongly related to Asquith et al. (2005), our study helps to fill a gap in the literature by providing a direct analysis of the relationship between the level of disclosure made by analysts and market reaction. Furthermore, it proposes a different definition of disclosure transparency, based on a new foundation and tests whether this notion may be relevant in determining how informative analyst research is. The dataset allows us to obtain more general results, dealing with the issue of selection bias, as characterised in Asquith et al. (2005)'s research. The authors, in fact, concentrated their analysis only on celebrity analysts, excluding others. Moreover, they collected reports from Investext, a commercial database which contains only those reports which investment banks are willing to make publicly available. Financial analyst reports are not usually freely available to the market. Therefore, the sample does not include the reports of famous investment banks which are relevant to the market, such as Goldman Sachs. From this perspective, Italy represents a uniquely advantageous research setting as the Italian market operates with a mandatory rule imposed on all investment banks, both domestic and international, which issue research reports on Italian-listed firms, to deposit them with the Italian Stock Exchange. Thus, these reports are available to all investors. We take advantage of this prescription and analyse 4,603 research reports issued by 50 different investment banks in relation to 28 Italian-listed firms over a four-year time range (2000-2003). We carefully read the full text of

the reports and catalogue by hand the information therein, both the summary measures and, whenever possible, additional information provided in the valuation methods used.
It is well documented that the disclosure of information is important in order to mitigate asymmetric information and agency problems. Financial analysts are important information providers in capital markets. Providing valuable research for investors, they facilitate optimal capital allocation and reduce information asymmetry. Therefore, analysis of the transparency of their disclosures is helpful for both investors and the regulators in the better control of the financial analyst profession. Furthermore, this study may also be important for the financial services industry in order to optimise the huge resources which it invests in security research and the issue of reports.

The remainder of the paper is organised as follows: Section 2 supplies a review of the issues addressed in the literature; Section 3 outlines the development of the research hypothesis; Section 4 describes the data used and the sample selection procedures; Section 5 provides an overview of the research methodology; Section 6 reports the empirical results; and Section 7 concludes the paper.

2. Literature review

Security analyst reports have already been the subject of extensive empirical and experimental research and there has also been considerable academic research on the value provided by financial analysts in reviewing company disclosures and in making their own disclosures on the firm. Research on the role of financial analysts in capital markets indicates that they play a valuable role in improving market efficiency. This paper is related to that field of research. Early investigations were primarily focused on the information provided to investors from two summary measures issued by analysts: earnings forecasts and investment recommendations. Most of these studies show that research reports are worthy and can improve market efficiency by conveying new information to the market. For example, Givoly and Lakonishok (1980) and Griffin (1976) documented significant abnormal returns at the same time as earning forecast revisions were released. Lys and Sohn (1990) found that each analyst forecast was informative on price, though preceded by other types of disclosure, including the forecast revisions of other analysts. Stickel (1992) highlighted that analyst members of the II-All American team issued more accurate forecasts which had a more significant impact on short-term pricing. Gleason and Lee (2000) analysed not only the immediate impact of the forecast changes on prices, but extended the time horizon of their monitoring up to two years after the time of the revision and detected a persistent price drift in each of these two years.

Research on revisions in analyst recommendations has also found a positive association between abnormal returns and the direction of a change of recommendation. For example, Womack (1996) analysed investment recommendations in the US market. In examining the time around the changes of recommendation, it was found that extra returns were registered after the issue of recommendations.

More recent research demonstrates that the documented market reaction also depends on some features either of the analysts or their forecasts, such as the expected accuracy and timing of forecasts, the analyst's experience, the broker's size and the frequency of forecasts (see Stickel (1992), Abarbanell et al. (1995), Mikhail et al. (1997), Clement (1999), Jacob et al. (1999), Park and Stice (2000) and Clement and Tse (2003)).

Particularly interesting for this research are the studies looking more in depth at report content and the properties which cannot be found in the commercial datasets, either through surveys or content analysis. Hill and Knowlton (1984), Previts et al. (1994) and Hirst et al. (1995) showed that analysts do not limit their studies to accounting information (so-called financial reports) but use much else. The application of a methodology based on questionnaires, interviews and, in particular, content analysis, allows a quick but inflexible and superficial filing of the reports' content. Given these and the other potential limitations of using such a methodology for the evaluation of the value of different valuation models to investors, a perspective focusing on the actual practices of equity analysts represents an alternative and better way to analyse the issue. Such a perspective is adopted in this paper, similarly to Asquith et al. (2005). They analysed the complete text of a sample of 1,126 actual analyst reports, summarising their content and then examining the reaction of the market to many of their features. In the first part of the work, their study replicated previous research analysing the market reaction to earnings forecasts, target prices, recommendations and revisions. The authors then demonstrated that other information, such as the arguments used by analysts to justify their reports, is also important and, if incorporated into the analysis, reduces and, in some models, eliminates the significance of the information available in earnings forecasts and revisions of recommendation. Their analysis also controlled for the simultaneous release of other information and showed that analyst reports do not merely repeat corporate information releases, but they convey independent news to the market. By examining whether the market's reaction differs by report type (i.e., upgrade, reiteration or downgrade), the results showed that the information provided in a report is more important for downgrades than for upgrades. Furthermore, the authors examined the accuracy of price targets and the importance of the valuation methodology used by the analysts. With regard to the latter, the authors failed to observe any systematic association between it and either the market's reaction or the probability of achieving a price target.

Though strongly related to Asquith et al. (2005)'s work, this paper differs from it in several ways. First, Asquith et al. adopted an analytical approach, though not exhaustive, to test how a list of quantitative and qualitative report information could affect market reaction. Specifically, their results show that the amount and consistency of the information supporting the investment recommendations are relevant to value. We, however, adopt a synthetic approach, defining the transparency of a report by looking at the disclosure of the method of valuation.

Furthermore, on a horizontal level, this work assumes a wider perspective since we analyse a significantly larger dataset. This structure of data allows us to cope with the problem of selection bias, which is characterised in Asquith et al.'s research. Since they employed only the top-ranked US analysts, they incurred a selection bias issue with respect to the valuation methods used by the analysts. The larger size of our dataset and the heterogeneity of this data allow us to obtain more generalised results.

3. Research hypothesis development

Investors require value-relevant information on the future profitability of a company in order to assess its equity value correctly. However, information asymmetries and agency problems prevent managers from providing investors with value-relevant information in an effective manner. One solution to this problem is represented by financial analysts, who can compensate for this inefficiency by disclosing and elaborating on their analysis. The effectiveness of their disclosure can be measured by the market reaction to the dissemination of the information therein.

As documented by prior literature on company disclosure, not only the quantity, but also the quality of disclosures is relevant for the capital markets.[12] Financial analysts are important intermediaries for company information. As discussed earlier, prior research has analysed how their investment recommendation, earnings forecast and target price releases affect the market. Similar to the importance of company disclosure, we investigate whether the level of disclosure of financial analyst reports, measured in terms of their transparency, influences the market reaction to their release.

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[12] See Verrecchia (2001) for a comprehensive review of the topic.

Our expectation is also supported by the laws regulating the financial analyst profession. With regard to the US, two major regulatory changes are worth mentioning: the Regulation Fair Disclosure (RegFD, October 2000) prohibits US firms from making selective disclosures and the Sarbanes-Oxley Act, Section 501 (SOX501, July 2002), reinforces investors' protection against analysts' conflicts of interest. In the same vein, in 2003, the European Parliament adopted Directive 2003/6/EC, known as the Market Abuse Directive (MAD), which is the European counterpart of the US regulations. The legislation makes it compulsory for analysts to disclose their interests, i.e. brokerage and investment banking ties, in the firms they recommend and to provide investors with a summary of "any basis of valuation or methodology used to evaluate a financial instrument or an issuer of a financial instrument, or to set a price target for a financial instrument" (MAD, Article 4, Point B). The regulator's aim is to confront analysts' conflicts of interest, thereby making their forecasts more reliable. This imposition suggests that in order to protect investors, there is a need to regulate financial analysts' disclosures to increase the amount of value-relevant information (recommendations, target prices and valuation methodologies) available to the public.

Therefore, our main research question is to investigate the relationship between the practice of analyst disclosure and market reaction, conditional on the presence of basic information, namely investment recommendations and target prices.

In general terms, an analyst can disclose many company details, but investors can still be left in the dark. If a disclosure provides low-quality incremental information, then it is likely to increase the level of noise, thereby making it difficult for investors to assess company value. Therefore the amount of information disclosed by an analyst should be irrelevant for the market (i.e. the quantity of disclosure). Conversely, how the analyst arrives at their estimate of the value of a company should be relevant. In other words, we assume that the relevant information is that which is contained in the reports and, thus, translated into specific model assumptions by the analysts during their valuation procedures. From this perspective, the method of valuation is important as it is the synthesis of the information selected by the analyst. It is meta-information. Working under this assumption, disclosure of the method is the key indicator of the report's transparency (i.e. the quality of disclosure).

Therefore, our expectation is to find a positive relationship between the level of transparency and market reaction. If an analyst discloses more relevant details about the information set used to evaluate a company, he or she facilitates the monitoring of companies by shareholders. Investor knowledge about the valuation method used should make the analyst forecasts appear more justified and reliable, which should be reflected in the market reaction.

4. Sample selection and description

Most of the earlier research on financial analysts was based on commercial financial databases (e.g. *I/B/E/S* or First Call), collecting only a small proportion of the overall information which could be included in a report. Usually, these datasets catalogue the basic elements of a report, such as earnings forecasts, target prices and analyst recommendations, but do not provide any other additional elements to support the evaluation procedure. On the contrary, the full body of the report, at least in some cases, could be more exhaustive and include the additional information used by analysts, such as accounting forecasts, valuation methods, qualitative analysis, discount rates, market risk premium or other justifications. The only way to find this information is to read the text of the reports and to code their content by hand.

As analyst reports are not usually available to the general investor public and because commercial datasets are not exhaustive, we need an alternative database to answer to our research questions. In this respect, Italy represents an advantageous and unique[13] research setting since a mandatory rule imposed on all of its investment banks which issue reports on firms listed on the Italian stock exchange makes it compulsory for them to submit the reports to the Security and Exchange Commission - the Consob - and to the managing company of the stock exchange - Borsa Italiana. Analysts have to send their reports on the day of issue to Consob, while they have to send it to Borsa Italiana within 60 days. Once the reports have been received, Borsa Italiana has to publish them on its website immediately. Thereafter, they become freely available to the general investor.

We collected and coded by hand 4,603 research reports issued by sell-side analysts working for 50 different intermediaries and covering 28 Italian blue chip companies belonging to four different industries over a four-year time period (2000-2003) to show the potential variation in analyst valuation practices.

With regard to the recommendations issued, since we refer to the original ones given by the analysts, caution is needed with regard to their classification. Most analysts use a three-level scale (i.e., ‘buy’, ‘hold’ and ‘sell’), while others use a larger scale, including ‘strong buy and ‘strong sell’. Furthermore, some analysts use different terminology such as ‘market perform’ and ‘market outperform’, ‘reduce’, ‘add’ and so on. We reduce all of the possible recommendations to three different categories: good, bad or neutral news. We also record all of the changes in recommendation. As shown in Table 1 and consistent with the previous literature on analyst

[13] As far as we know, the Italian regulatory system on financial analysts is unique.

optimistic bias (see, e.g., Dugar and Nathan (1995), Michaely and Womack (1999), Darrough and Russel (2002) and De Bondt and Thaler (1990)), more of the recommendations are positive (over 50%) than neutral (34.62%). There are negative recommendations in only a few cases (about 10% of the total).

Insert Table 1

In order to define the level of disclosure transparency, we focus on the analysts' disclosure of their method of valuation. Since valuation methods are the synthesis of all of the information used by analysts to evaluate a company, we assume that the level of transparency of valuation methods can act as a proxy for the level of transparency of report disclosure. Therefore, in this research, the identification and analysis of the valuation methods is essential. Using this assumption, we divide the report sample into two different categories: a low and a high level of disclosure of valuation methodology. Following this rule, reports providing investors with enough information to understand the valuation methodology used were classified as high disclosure reports and the others as low disclosure reports (for further details, see Section 5 below).

This classification is necessary since, different from Asquith et al. (2005),[14] our set of analysts seldom explains the specific valuation method employed. About the 35% of the reports are simply black boxes, stating just the final recommendations and target prices, not indicating how they have been assessed.

Finally, in order to identify the announcement date, we use the report date, on the assumption that it represents the actual date on which the report is made available for the market.

Table 2 presents a frequency summary for several of the data which we collected from each report. The frequencies reported are organised by industry, year and broker.

Insert Table 2

5. Research design

In order to test the informative value of the transparency of financial analyst reports, we perform an event study. This methodology allows for the verification of the market's efficiency in

[14] The authors found that approximately 99% of analysts mention the use of at least some sort of earnings multiple (e.g., a price-to-earnings ratio, EBITDA multiple or a relative price-to-earnings ratio). Only 12.8% of analysts report using any variation of discounted cash flow in computing their price targets.

incorporating new information by measuring the effects on stock returns on the event date, that is, the report issue date. In Italy, this corresponds, by definition, to the date on which the information is made available to brokerage firms' clients.

The market reaction to the level of disclosure in the reports depends on whether they convey new information. If this is the case and the market is efficient, abnormal stock returns should quickly disappear after the event. Around each event, we define a 21-day window in which the abnormal stock returns are calculated. The abnormal returns for stock *i* at time *t* (AR_{it}) are estimated using a market model using an estimation window of 121 days preceding the event window (Campbell et al. (1997)).

In order to assess the persistence of the impact around the event date and the overall effect of the issue of the report, we aggregate the abnormal returns, obtaining the *CAR* (Cumulative Abnormal Return) over three different windows: the pre-event window (-5 to -2 days), the around-the-event window (-1 to +1 days) and the post-event window (+2 to +5 days). All of the results have been tested by running the parametric tests proposed by Brown and Warner ((1980) and (1985)).

In the *OLS* regression models, we use as a dependent variable the around-the-event CAR_{it} (-1 to +1 days), where *i* represent the firm evaluated and *t* the report issue date.[15]

These empirical analyses require us to use both the variables provided in the examined analyst reports and several others not directly provided in these documents as independent variables. Some of them (model variables) summarise the report content and are used to define the analyst's disclosure transparency level, whilst others (control variables) control for other potential effects on market reaction. Therefore, we include firm-specific, analyst-specific and report-specific control variables.

Among the model variables, firstly, we replicate previous studies by including the final message of the report, such as target prices and recommendations (see Model (1)). Specifically, we add to the regression's recommendation dummies ($DGOOD_{it}$, $DBAD_{it}$ and $DNEU_{it}$), based on the three-class classification described above (see Section 3). Secondly, we compute the changes of recommendation (upgrades and downgrades) for firm *i* at time *t* and insert them in the models using dummy variables both for downgrades (DDW_{it}) and upgrades (DUP_{it}). Finally, we suppose that

[15] The more correct procedure should be to perform a panel data analysis instead of a simple linear regression. The panel data regression would allow us to consider the identity and the not observable features of the analyst (or of the group of analysts) writing the report. In my case it's not straightforward to figure out the panel as we have an unbalanced panel data, due to the nature of the data that are not regular over the time. The procedure of dummy variables (LSDV) is not practicable as well because we would have too many dummies.

another market-relevant attribute of the synthetic information of reports is the boldness of the analyst's target price. Our boldness measure ($BOLDNESS_{it}$) is calculated as the current target price divided by the average target price (the consensus) for the company *i* in year *t*, minus 1.

$$CAR_{it}(-1;+1) = \beta_1 DUP_{it} + \beta_2 DDW_{it} + \beta_3 DGOOD_{it} + \beta_4 DBAD_{it} + \beta_5 DNEU_{it} + \beta_6 BOLDNESS_{it} \quad (1)$$

Market reaction is measured by three-day market returns centred on the report's release date, *CAR(-1;+1)*. This allows for possible delays by brokerage firms in delivering their reports to Borsa Italiana SPA or for leaks of information prior to their public release.

Then, to test the specific hypothesis, we run a different model considering whether the report provides the investors with additional information or not. We expect to record different stock price reactions in correspondence to the different levels of disclosure of report information (see Model 2).

We divide the report sample into two categories: low and high levels of disclosure. The former are labelled opaque and the latter transparent. The first category includes those analyst reports which do not disclose any information other than summary measures, i.e. only investment recommendations and target prices, whereas the second refers to those reports which disclose the different evaluation methods used in the analysis and provide details to help understand the valuation procedure. Therefore, we define two dummy variables ($OPAQUE_{it}$ and $TRANSPARENT_{it}$), each representing one of the aforementioned two disclosure levels. However, we only include in the model these dummies[16] as interaction variables with other variables, i.e. the recommendation changes ($OPAQUE\_DW_{it}$, $OPAQUE\_UP_{it}$, $TRANSP\_DW_{it}$ and $TRANSP\_UP_{it}$), the recommendation levels ($OPAQUE\_GOOD_{it}$, $OPAQUE\_NEU_{it}$, $OPAQUE\_BAD_{it}$, $TRANSP\_GOOD_{it}$, $TRANSP\_NEU_{it}$, and $TRANSP\_BAD_{it}$) and the boldness measure (($OPAQUE\_BOLD_{it}$ and $TRANSP\_BOLD_{it}$). According to this point of view, the level of disclosure transparency has no value to the market by itself, but it may affect market reaction if considered together with recommendation upgrades or downgrades, good or bad news, and boldness levels. Therefore, this procedure allows us to detect potential asymmetric market reactions in correspondence to different combinations of transparency level and other information.

Tables 3 and 4 report the descriptives for the sets of independent and control variables.

Insert table 3

Insert Table 4

[16] In order to include all of the three variables of interest, we test the OLS model, omitting the constant α.

We find on average that approximately 30% of the reports which we analysed are transparent in terms of disclosure of their valuation methods. In the other 70%, the investors are also provided with specific information to enable them to understand the main method used for the analysis.[17] These percentages are similar regardless of the types of change in recommendation (downgrades, upgrades and reiterations).

Furthermore, with respect to boldness, the analysts show a greater 'boldness' in relation to the reiteration of recommendations, rather than in upgrade or downgrade cases.

We test the value relevance of the report disclosure transparency by running the following model:

$$\begin{aligned} CARit(-1;+1) &= \beta_1 OPAQUE\_DW_{it} + \beta_2 OPAQUE\_UP_{it} + \beta_3 TRANSP\_DW_{it} \\ &+ \beta_4 TRANSP\_UP_{it} + \beta_5 TRANSP\_GOOD_{it} + \beta_6 TRANSP\_NEU_{it} \\ &+ \beta_7 TRANSP\_BAD_{it} + \beta_8 OPAQUE\_GOOD_{it} + \beta_9 OPAQUE\_NEU_{it} \\ &+ \beta_{10} OPAQUE\_BAD_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

Finally, we also consider an extended version of Model 2, which includes some control variables (see Model 3).

At the analyst level, we control for the analyst's reputation (*REPUTATION*$_{it}$) but experienced some problems related to the specific nature of our analyst sample. Since the most famous financial analysts' rankings, i.e. those issued by *Institutional Investor* or *The Wall Street Journal*, are only focused on American investment banks and brokerage houses, many of the analysts in our dataset were not covered. To tackle this problem, we measured the analyst reputation variable using three different specifications. Firstly, we used the rankings from the leading Australian analyst survey, the East Coles Survey (*REP_ECS*$_{it}$). This is the Australian equivalent of the US *Institutional Investor* survey and is conducted on a large number of buy-side institutions annually. The data available from the East Coles Survey has a significant advantage over that from the *Institutional Investor* surveys as it provides significantly more detailed ranking information on analysts. For each industry and some stocks, we were able to observe the ranking for every analyst in that sector (e.g. down to the 56th-ranked small-cap analyst in 2000). This contrasts with the *Institutional Investor* survey where only the top three 'All-American' analysts (and up to four runners up) are shown for

[17] We controlled whether the different levels of transparency among transparent reports may affect market reaction to report release. However, none of the results is statistically significant. We interpret these results as the market only capturing the difference between opaque and transparent reports, regardless of the different levels of transparency and opacity. They do not capture the scale of these variables.

each sector. However, following this ranking, many of the analysts in our dataset were excluded again from the analysis as they were not covered (e.g. many of the Italian investment banks and brokerage houses). This could bias the results since, in our dataset, the Italian investment banks issue reports more frequently than the others. Thus, we used other reputation proxies, such as brokers' activity ($BROKERWEIGHT_{it}$) and their nationality ($NATIO_{it}$). We calculated the *BROKERWEIGHT* variable as the ratio of reports issued by each broker for a company divided by the total reports issued by that company. Our expectation is that more active brokers should be more trustworthy ones. With regard to the brokers' nationality, we inserted the dummy variable *NATIO* into the model, which distinguishes between European and US analysts, since the evidence shows that the biggest and most trusted (i.e. with a wider reputation) brokers are usually American.

We then investigate and control for the confounding effects of other information released simultaneously with the analyst report (*CEFFECT*). We focus on a type of information price indicator, that is, the earnings announcement, collect all of the quarterly earnings announcement dates from Factset and calculate three different measures for the confounding effect by declining *CEFFECT* into three alternative variables.

Specifically, the first ($CE\_DISTANCE_{it}$) is a dummy variable equal to 1 when the report publication date is within a specific time window, 0 otherwise. The time window is obtained by adding or subtracting a certain number of days (e.g. ten days) to the quarterly earnings announcement dates. This measure allows for the capture of the level of closeness of the analyst's report to the company earnings announcement, but suffers from a limitation in that it does not consider whether the report was issued before or after the event. To overcome this issue, we created a second measure (CE_TIMING_{it}). Given a specific time window, this variable takes a value equal to 1 if the report is issued after the quarterly earnings announcement, -1 if it was issued before and 0 if it was issued out of the time window considered. The third measure (CE_CONT_{it}) is more sophisticated than the previous two as it is based on the exponential function e^{-rt}, where r represents the information's decay rate and t the time between two consecutive quarterly earnings announcements. By definition, this measure does not make any assumptions about the length of the time window around the company event.

This variable is a continuous index between -1 and 1, so that values close to both 1 and -1 indicate reports which are very close to the announcement date but issued after and before the date respectively, while if the index is close to 0, this means that the analyst's report is contemporaneous with the announcement date.[18]

Finally, since the market reaction to analysts' forecasts change according to firms' information environment, we control for firm growth, measured as the price-to-book value, PBV_{it}. This variable allows us to determine whether the market's reaction to analyst reports differs between growth and value firms.

The final model we test is the following:

$$
\begin{aligned}
CARi(-1;+1) = {} & \beta_1 OPAQUE\_DW_{it} + \beta_2 OPAQUE\_UP_{it} + \beta_3 TRANSP\_DW_{it} + \\
& \beta_4 TRANSP\_UP_{it} + \beta_5 TRANSP\_GOOD_{it} + \beta_6 TRANSP\_NEU_{it} + \beta_7 TRANSP\_BAD_{it} \\
& + \beta_8 OPAQUE\_GOOD_{it} + \beta_9 OPAQUE\_NEU_{it} + \beta_{10} OPAQUE\_BAD_{it} \\
& + \beta_{11} OPAQUE\_BOLD_{it} + \beta_{12} TRANSP\_BOLD_{it} + \beta_{13} REPUTATION_{it} \\
& + \beta_{14} CEFFECT_{it} + \beta_{15} LNSIZE_{it} + \beta_{16} GROWTH_{it} + \varepsilon_{it}
\end{aligned} \tag{3}
$$

6. Empirical results

6.1. Market reaction to analysts' recommendations: a further investigation

We first analysed the market reaction to the issue of reports by looking at the daily $\overline{AR}$ trend over the event window (-10 to +10), distinguishing between bad, neutral and positive recommendations. The sample size is 2,415 for good recommendations, 441 for bad and 1,564 for neutral. The average abnormal returns and the market reaction plot are reported in Table 5 and Figure 1.

Insert Table 5

Insert Figure 1

The results are consistent with the previous literature, on the strength of the recommendations having informative content for the market. The empirical evidence shows that both the sign and the intensity of the reaction are consistent with expectations and statistically significant around the event day (*t=0*). The effect of financial analysts on the rise of under-valued stocks or, conversely, the fall of over-valued stocks is, therefore, documented.

Furthermore, negative recommendations have a bigger negative impact than other types of recommendation: the abnormal returns are slightly positive at the beginning of the event window,

[18] In the tables, we report the final results based on a model only including the variable *CE_TIMING*, calculated with a two-day time window. The other two measures (*CE_DISTANCE* and *CE_CONT*) were not significant.

but immediately before the day of the event and during the few days following, they fall significantly.[19] This is not really surprising as negative recommendations occur less frequently than others , so it is likely that investors give more weight to this type of recommendation rather others, therefore they have more informative value.

The neutral recommendation effect can be assimilated into that of the negative recommendation. This behaviour is consistent with the conflict of interest hypothesis (e.g. Michaely and Womack (1999), Lin and McNichols (1998), and Dugar and Nathan (1995)): analysts who have to issue a negative recommendation prefer to issue a neutral one in order that their relationship with the company's management is not compromised. Another behavioural explanation is related to the optimistic bias: analysts tend to have a too optimistic a view of the stocks which they evaluate.

Focusing on the pre-event period, and consistent with previous results (see Womack (1996) and Belcredi et al. (2003)), there is an anticipated effect on the market with respect to the event date. Negative recommendations cause negative abnormal returns since $t=-5$, even though they only become statistically significant at $t=-1$. For positive and neutral recommendations, the anticipated effect is more evident and significant from $t= -1$ onwards.

A possible explanation of this evidence (see also Belcredi et al. (2003), Michaely and Womack (1999), and Stickel (1995)) is that some private clients receive important news before the issue date printed on the report. This hypothesis, although widespread in the US, would violate the Italian regulation imposed on investment banks and brokerage houses to distribute their reports to all of clients on the date printed on the document; to select certain clients or transmit the documents in a selective way is prohibited.

Another possible hypothesis could instead be related to the fact that some important news may become public before the report date and so the effect on the market is caused by that, rather than dissemination of the report.

Looking at the post-event period, the abnormal returns disappear quite quickly in relation to positive and neutral recommendations, while the impact of negative recommendations does not have a clear trend after the event date, even though the abnormal returns are only statistically significant until $t=1$. This irregular variation in the market prices subsequent to the event could be related either to other news, independent of the report's disclosures, or simply some noise in the

[19] The *t-test* on the absolute value of the difference between the *ARs* is statistically significant at 1% level.

sample. This analysis needs further investigation taking into account, for instance, changes to the recommendations (upgrades vs downgrades).

The *CAR* analysis confirms the daily evidence shown above.

Insert Figure 1

Insert Table 6

Looking at the narrow pre-event window (-5 to -2), negative recommendations show a significant anticipatory effect on the market, but we do not find any significant abnormal returns for the other types of recommendation. On the contrary, and consistent with $\overline{AR}$ daily data, we document a significant market price reaction around the event window, regardless of the nature of the recommendation. The stronger effect, however, is still recorded for negative advice.

This asymmetry in market behaviour could simply be due to our recommendation classifications. We classified the recommendations in the three categories, neglecting to indicate whether they are a simple reiteration or a change from previous advice. It has been documented that there is a link between the size of reaction and the type of recommendation. As pointed out by Belcredi et al. (2003), for stocks added to a buy (sell) list, a stronger positive (negative) market impact may be expected than for those which are upgraded (downgraded) but still remain in the same category. In further investigations, we will control for this because if our results hold, they would confirm what has already been demonstrated by Womack (1996) and Stickel (1995) for the US market and by Belcredi et al. (2003) for Italy.

Finally, the post-event analysis for the window (+2 to +5) does not show evidence of significant abnormal returns for any of our recommendation categories.

Table 7 shows the correlation matrix among the variables. The tables do not suggest any multicollinearity issues.

Insert Table 7

6.2. Market reaction and the transparency of financial reports

In this section, we first replicate previous studies by testing Model 1. We then test the main crux of this work, i.e. whether the market reacts to the content of financial analyst reports and its level of transparency (Model 2). We also control for other variables both at firm- and analyst-level, included in the regression for firm size and growth, the confounding effect variable and a proxy for analysts' reputation (see Model 3).

Table 8 provides the results of Model 1.

Insert Table 8

Consistent with prior research, we find that the coefficients *DGOOD* and *DBAD* are in line with our expectations and statistically significant, suggesting that good (bad) news released by analysts has a positive (negative) impact on market returns. In addition, revisions of their investment recommendations have an informative value. As documented by existing research, changes to recommendations affect market reaction depending on their starting point. Specifically, the signs *DDW* and *DUP* suggest that an increase (decrease) in analyst recommendations positively (negatively) affect the market's abnormal returns.

Table 9 reports the results for Model 2.

Insert Table 9

The results show that the information transparency level of reports is important for the market, although in an asymmetric way. In particular, in relation to changes in recommendations, Column 4 shows that only the sign *TRANSP_DW* is significant, while *OPAQUE_DW* is not, suggesting that the market reacts to downgrades only when they are supported by additional information. *OPAQUE_UP* and *TRANSP_UP* are both not significant, meaning that the market is not interested in recommendation upgrades at all. However, looking at the recommendation levels, the signs *TRANSP_GOOD* and *OPAQUE_GOOD* are both significant, while in the case of bad and neutral recommendations, only the *TRANSP_BAD* and *TRANSP_NEU* variables are statistically significant, indicating that investors trust in the transparency of analysts' report disclosures when they issue negative opinions.

Overall, these findings confirm our hypothesis. They show that investors give different weights to analysts reporting good or bad news, depending on the level of information transparency. In particular, the market interprets as value-relevant positive recommendations, i.e. those which are good, regardless of the level of disclosure transparency. However, it needs more information in order to trust bad or neutral recommendations.[20] On the contrary, in terms of recommendation

[20] In line with the literature (e.g. Michaely and Womack (1999), Lin and McNichols (1998), and Dugar and Nathan (1995)), the neutral recommendation effect can be assimilated into the negative recommendation (see Column 4).

changes, the market reacts to downgrades which are well supported informationally, ignoring upgrades.

These asymmetric behaviours are complementary and not contradictory. They suggest that in order for it to be interpreted by the market as positive news, a good recommendation (i.e. a buy recommendation) is enough and does not need any additional specifications. The market does not consider it to be price informative to know whether the stock recommendation improves (i.e. from sell to buy) and its behaviour is not dependent on the transparency level of the reports released. The reaction to negative news is different. Investors respond to bad recommendations and downgrades only when there is a high level of disclosure. This evidence could suggest that investors react to good signals by using a different information set which is not captured in our models, but the result could also be driven by the market's habit of receiving positive recommendations. Investors often view analysts as experts on important sources of information about the securities they cover and, as demonstrated, they rely on their advice. For this reason, investors are used to positive recommendations and may be attracted more by unusual negative reports. Therefore, they would in these cases pay more attention to report details; in other cases, they ignore them.

In addition, the results in Columns 3 and 4 show that investors prefer transparent analysts with higher boldness in their target prices. They pay more attention to those analysts whose target prices are not too close to the consensus, provided that their extreme forecasts are justified in a comprehensible way and in great detail.

These results are interesting since they add an important piece of evidence to the findings of previous literature. The evidence shows that the market considers as value-relevant some of the synthetic information of the report, i.e. recommendations and target prices, but only conditional on other information.

Table 10 presents the results from estimating Model 3, including the control variables, such as the confounding effect, broker reputation and the firm-specific characteristics proxies.

Insert Table 10

The results do not change and, therefore, confirm the previous evidence.

7. Conclusions

This paper analyses the reaction of the market to the transparency of the information in financial analysts' reports. The work aims to examine the value-relevance of the report content, testing whether the level of disclosure transparency affects the market reaction to the news contained in the report.

This work is related to two main research fields which are well developed in the literature: the study of the properties of analysts' reports and their information value for the market. This research is also strongly related to Asquith et al. (2005)'s research, which assessed the market value of the information contained in security analysts' reports. They found that investors reacted to the content of a security analyst report conditionally with regard to whether the report was an upgrade, reiteration or downgrade. With regard to the evaluation methods used by the analysts, the authors failed to observe any systematic association between these and market reaction.

This work improves on the previous results and differs from Asquith et al. (2005) in many aspects. It analyses the valuation methods employed by analysts from a new point of view. First, we propose a new approach for collecting and cataloguing the most important information of financial analysts' reports. Specifically, we build a structured approach in order to catalogue their valuation methods. Furthermore, we elaborate on the disclosed information in order to identify the level of information disclosure transparency provided to the market. In this way, we revisit previous studies on the market impact of analyst recommendations and target prices, and provide new evidence on the value-relevance of other report components.

Finally, the structure of this research allows us to cope with the selection bias which characterizes Asquith et al.'s research. Since they only employed top-ranked US analysts, they incurred selection bias with respect to the analysts' evaluation methods. In order to differentiate ourselves from them, we extend the analysis to a new and more comprehensive sample of 4,603 reports issued by 50 different international investment banks and brokerage houses. This heterogeneity minimises any possibility of selection bias in relation to valuation methods.

The results partially replicate the findings of previous research, showing that changes in recommendation are significantly associated with market reaction to the release of analyst reports. The results also show that the target prices may contain important information for the market, depending on how bold and unconventional the forecasts (target prices) are. In particular, we find that market reaction to analyst changes of recommendation is stronger (greater R^2) when target prices move away from the consensus price rather than when they move toward the consensus target price for that stock. This result may indicate that the effect of changes in recommendation is partly driven by analysts' tendency to follow the herd. In fact, a convincing explanation for the relevance of the target price boldness proxy could lay in behavioural herding models. In these models, observable actions by agents act as signals of the quality of an agent's private information. Thus, everything else being equal, actions which differ markedly from what many other agents (analysts) do lead the market to assess that the agent with the unconventional action is more likely to be '*smarter*' than the others.

These findings also add new information about the nature and source of market reaction to the release of analyst reports. The results, in fact, indicate that market reaction is not symmetric and the cause of this asymmetry is the level of disclosure transparency in the report. This means that, in general, the market reacts consistently with the signal provided by recommendations and target prices, but it also modifies its reaction depending on the additional information provided. Interestingly, investors' positive reaction to good news is unconditional with regard to the level of information disclosed by analysts. On the other hand, they only trust negative news when they are provided with supporting elements which help them to understand the valuation procedure which underpins the estimates.

We then investigate whether the results are affected by other variables, such as the broker's reputation or the confounding effect derived from information releases which occur contemporaneously with the release of the analyst report. However, none of the variables used as a reputation measure or confounding effect proxy are statistically significant.

In summary, the results confirm prior evidence which demonstrated the market response to changes in financial analysts' recommendations. Furthermore, they show that the addition of boldness in analysts' forecasts is important in explaining the documented market reaction to financial analysts' reports. They also indicate that the report's transparency about the method used by the analyst to process information and thereby arrive at their final recommendation do affect market reaction. These results hold regardless of whether other information is announced contemporaneously by the company and also controlling for firm-specific variables.

Tables and Graphs

Table 1. Report frequency by recommendation

RECOMMENDATION CATEGORY	Freq.	%
Bad	441	9.73%
Good	2415	53.30%
Neutral	1564	34.52%
Not available	111	2.45%
Total	4531	100.00

Notes. This table reports descriptive on the recommendation categories composing the sample.

Table 2. Report frequency by industry, year and broker

Panel A: by industry and year

VARIABLES	REPORT TRANSPARENCY LEVEL		RECOMMENDATION LEVEL			RECOMMENDATION CHANGE	
INDUSTRY	**TRANSPARENT**	**OPAQUE**	**DGOOD**	**DBAD**	**DNEU**	**DDW**	**DUP**
Insurance	381	112	308	23	156	45	36
Banking	939	571	725	173	566	151	112
Utilities	1136	669	1090	138	534	109	104
Industrial	514	209	292	107	308	74	39
Total	**2970**	**1561**	**2415**	**441**	**1564**	**379**	**291**
	REPORT TRANSPARENCY LEVEL		**RECOMMENDATION LEVEL**			**RECOMMENDATION CHANGE**	
YEAR	**TRANSPARENT**	**OPAQUE**	**DGOOD**	**DBAD**	**DNEU**	**DDW**	**DUP**
2000	380	230	401	34	169	27	23
2001	788	371	612	108	417	107	74
2002	698	432	582	118	408	119	89
2003	1104	528	819	181	570	126	105
Total	**2970**	**1561**	**2415**	**441**	**1564**	**379**	**291**

Panel B: by broker

	REPORT TRANSPARENCY LEVEL		RECOMMENDATION LEVEL			RECOMMENDATION CHANGE	
BROKER	**TRANPARENT**	**OPAQUE**	**DGOOD**	**DBAD**	**DNEU**	**DDW**	**DUP**
ABN Amro	62	19	40	13	26	6	7
Actinvest Group	105	7	62	14	33	14	12
Albertini & C.	31	19	27	3	20	3	1
BNP Paribas	5	6	6	0	5	2	2
Banca Akros	64	46	61	6	39	12	8
Banca Aletti & C	1	0	1	0	0	0	0
Banca Commercial	9	3	10	1	1	0	0
Banca Finnat Eur	5	0	3	0	2	0	0
Banca Leonardo	28	24	37	3	12	3	6
Banca Popolare Di Verona e Novara	4	0	3	0	1	0	0
Banca Popolare d	3	0	1	0	1	0	0
Banca Sella	6	0	2	0	4	0	0
Banca d'Intermed	113	92	83	21	96	25	18
Bipielle Sim	1	2	3	0	0	0	0
Bnp Paribas	11	10	11	2	8	0	2
Borsaconsult Sim	0	1	1	0	0	0	0
Caboto Sim	137	65	112	7	73	23	14
Cazenove	8	2	4	0	6	0	0
Centrosim	30	109	68	9	59	6	6
Cheuvreux	112	12	83	36	0	11	4
Citigroup	21	1	13	1	6	1	1
Cofiri Sim	5	10	9	0	5	0	2
Consors	0	29	23	6	0	2	2
Credit Lyonnais	24	8	25	7	0	3	3
Credit Suisse	64	11	29	11	34	7	5
Deutsche Bank	213	253	261	27	178	28	22
Dresdner Kleinwo	92	28	71	3	41	6	7
Eptasim	60	16	40	5	28	7	6
Euromobiliare	319	86	264	32	107	34	29
Fortis Bank	12	18	18	11	0	2	1
Gestnord	3	0	2	0	0	0	0
Goldman Sachs	52	35	25	19	32	8	7
Idea Global	0	10	5	2	2	3	1
Ing Barings	20	11	7	1	23	2	2
Intermonte Secur	281	87	202	39	124	41	40
IntesaBCI	9	2	9	1	1	0	0
JP Morgan	8	0	6	0	2	0	1
Julius Baer	92	8	57	9	33	13	6
Lehman Brothers	88	9	54	20	21	6	5
Massimo Mortari	4	1	2	0	3	1	0
Mediobanca	93	73	97	2	61	11	11
Merrill Lynch	236	108	156	48	126	24	8
Metzler Italia	7	3	7	0	3	0	0
Rasbank	6	3	5	2	0	1	0
Rasfin	40	38	45	5	25	10	7
SG Securities Mi	11	13	21	1	2	1	0
Santander Centra	44	24	33	6	28	4	3
SocietÈ Generale	34	52	44	3	39	6	4
UBS Warburg	214	13	75	36	108	19	11
Unicredit Banca	168	188	182	25	139	33	27
Uniprof Sim	8	3	6	1	4	0	0
WebSim	7	3	4	3	3	1	0
Total	**2970**	**1561**	**2415**	**441**	**1564**	**379**	**291**

Notes. This table describes the dataset with respect to the report transparency, investment recommendation and recommendation changes by year, industry and broker.

$OPAQUE_{it}$ and $TRANSPARENT_{it}$ are two dummies, each one representing alternatively one of the two disclosure levels. $DGOOD_{it}$, $DBAD_{it}$, $DNEU_{it}$ are three dummy variables indicating whether the investment recommendation is good, bad or neutral. DDW_{it} is a dummy standing for downgrade in recommendations while DUP_{it} is for upgrades.

Table 3. Descriptive statistics of the main independent variables

STATISTICS	OPAQUE_UP	OPAQUE_DW	OPAQUE_GOOD	OPAQUE_BAD	OPAQUE_NEU	OPAQUE_BOLD
max	1	1	1	1	1	2.802
min	0	0	0	0	0	-.773
mean	.0194	.025	.181	.028	.132	-.021
sd	.138	.156	.385	.164	.338	.154
STATISTICS	**TRANSP_UP**	**TRANSP_DW**	**TRANSP_ GOOD**	**TRANSP_BAD**	**TRANSP_NEU**	**TRANSP_ BOLD**
max	1	1	1	1	1	.713
min	0	0	0	0	0	-.660
mean	.045	.059	.365	.072	.222	-.005
sd	.207	.235	.481	.259	.416	.0811

Notes. This table reports descriptives of the main independent variables of the models.
OPAQUE_DW$_{it}$, *OPAQUE_UP*$_{it}$, *TRANSP_DW*$_{it}$, *TRANSP_UP*$_{it}$) are interaction variables between the disclosure level and the recommendation changes; *OPAQUE_GOOD*$_{it}$, *OPAQUE_NEU*$_{it}$, *OPAQUE_BAD*$_{it}$, *TRANSP_GOOD*$_{it}$, *TRANSP_NEU*$_{it}$, *TRANSP_BAD*$_{it}$ are interaction variables between the disclosure and the recommendation levels; *OPAQUE_BOLD*$_{it}$ and *TRANSP_BOLD*$_{it}$ are interaction variables between the disclosure level and the analyst boldness.

Table 4. Descriptive statistics on the control variables

	BOLDNESS	BROKERWEIGHT	CE_TIMING	PBV
mean	-0.026	0.069	0.227	2.913
sd	0.173	0.054	0.768	2.731
median	-0.014	0.055	0.000	1.976
skewness	1.410	1.670	-0.410	2.698
kurtosis	26.266	7.019	1.799	12.676
p1	-0.473	0.005	-1.000	0.591
p5	-0.317	0.012	-1.000	0.737
p25	-0.105	0.031	0.000	1.204
p75	0.060	0.098	1.000	3.763
p95	0.218	0.165	1.000	7.913
p99	0.417	0.281	1.000	15.409

Notes. This table reports the descriptive statistics of the main control variables used in the different model specifications.
BOLDNESS$_{it}$ represents the analyst forecast boldness and it is calculated as current target price divided by the average target price (the consensus) for the company *i* in year *t*, minus 1. *BROKERWEIGHT*$_{it}$ indicates the broker activity and it is measured as the ratio of reports issued by each broker for a company over the total reports issued by for that company; *NATIO*, is a dummy variable distinguishing between European analysts and US ones. *CE_TIMING*$_{it}$ takes value equal to 1 if the report is issued after the quarterly earnings announcement, -1 if it was issued before, 0 if the analyst's report was issued out of the time window considered; *PBV*$_{it}$ is the company price-to-book value.

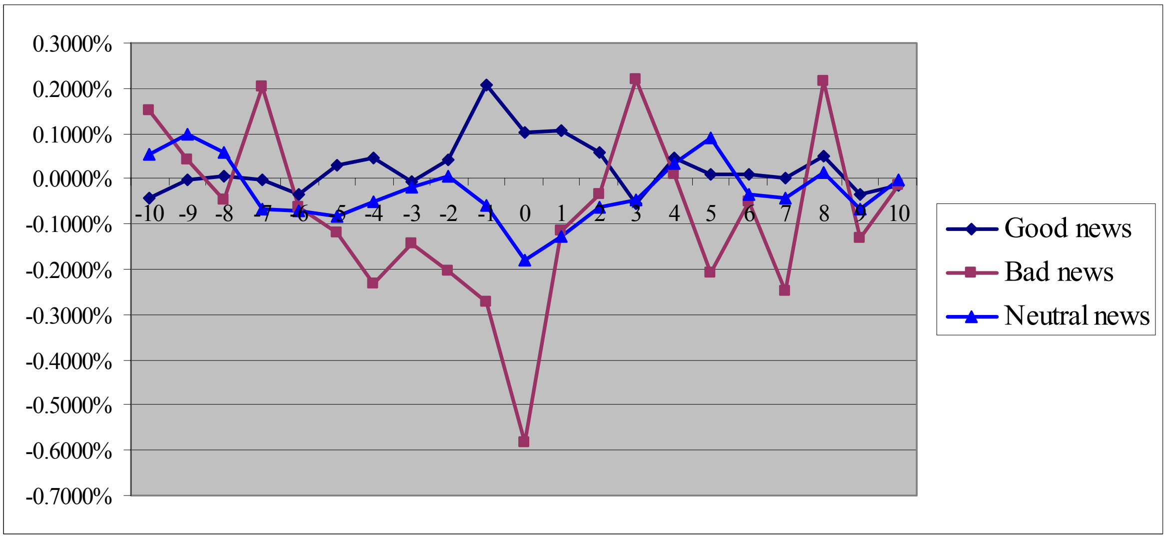
Table 5. Average Abnormal Return in correspondence to the report date

	Good news			Bad news			Neutral news		
T	**AR**	**T test**	**Sign.**	**AR**	**T test**	**Sign.**	**AR**	**T test**	**Sign.**
-10	-0.0417%	-1.1765		0.1500%	1.5798		0.0560%	1.2321	
-9	-0.0030%	-0.0829		0.0407%	0.4241		0.0995%	2.0249	**
-8	0.0073%	0.1982		-0.0480%	-0.5226		0.0589%	1.2180	
-7	-0.0018%	-0.0446		0.2025%	1.9420	*	-0.0679%	-1.5555	
-6	-0.0366%	-0.9499		-0.0612%	-0.6439		-0.0698%	-1.4340	
-5	0.0316%	0.8128		-0.1178%	-1.2333		-0.0832%	-1.6992	*
-4	0.0458%	1.2197		-0.2312%	-2.0574	**	-0.0494%	-0.8461	
-3	-0.0062%	-0.1530		-0.1450%	-1.3415		-0.0187%	-0.3840	
-2	0.0401%	0.9952		-0.2041%	-1.7407	*	0.0070%	0.1263	
-1	0.2067%	4.7467	***	-0.2741%	-2.0288	**	-0.0591%	-0.8935	
0	0.1017%	2.2003	**	-0.5835%	-3.4680	***	-0.1798%	-2.8844	***
1	0.1067%	2.5650	***	-0.1149%	-1.0623		-0.1267%	-2.3733	**
2	0.0595%	1.5914		-0.0364%	-0.3124		-0.0638%	-1.0178	
3	-0.0538%	-1.2544		0.2205%	1.8142	*	-0.0462%	-0.7242	
4	0.0446%	1.1684		0.0085%	0.0782		0.0356%	0.7151	
5	0.0106%	0.2883		-0.2074%	-2.2500	**	0.0887%	1.7927	*
6	0.0105%	0.2672		-0.0528%	-0.2899		-0.0355%	-0.7317	
7	0.0002%	0.0047		-0.2467%	-1.4330		-0.0432%	-0.9224	
8	0.0519%	1.3824		0.2158%	2.2198	**	0.0141%	0.3038	
9	-0.0367%	-0.8081		-0.1323%	-1.4020		-0.0685%	-1.4610	
10	-0.0131%	-0.3047		-0.0149%	-0.1510		-0.0024%	-0.0544	

Statistical significance: *** = at 1%, ** = at 5%, * = at 10%.

Notes. This table report the Abnormal Returns and their significance levels, calculated over a -10;+10 days window around the event date.

Figure 1. Average Abnormal Return in correspondence to the report date



Notes. This graphs indicates the Abnormal Return trends, depending on the investment recommendation type.

Table 6. Cumulative Abnormal Return in correspondence to the report date

Recomm.	**Good news**			**Bad news**			**Neutral news**		
N report	**N = 2415**			**N = 441**			**N = 1564**		
	CAR	**T test**	**Sign.**	**CAR**	**T test**	**Sign.**	**CAR**	**T test**	**Sign.**
(-5; -2)	0.1112%	1.3804		-0.6982%	-2.97673	***	-0.1442%	-1.3088	
(-1;+1)	0.4151%	5.7609	***	-0.9725%	-5.1923	***	-0.00365	-3.9530	***
(+2;+5)	0.0609%	0.8120		-0.0148%	-0.08025		0.0142%	0.1437	

Statistical significance: *** = at 1%, ** = at 5%, * = at 10%.

Notes. This table reports the Cumulative Abnormal Returns and theis significance levels, depending on the investment recommendation type.

Table 7. The correlation matrix among variables.

Panel A - The Pearson's correlation.

	CAR(-1;+1)	DUP	DDW	DGOOD	DBAD	DNEU	BOLDNESS
CAR(-1;+1)	1						
DUP	0.0366*	1					
DDW	-0.0629*	-0.0792*	1				
DGOOD	0.1049*	0.1097*	-0.2563*	1			
DBAD	-0.0747*	-0.0659*	0.1922*	-0.3654*	1		
DNEU	-0.0624*	-0.0729*	0.1464*	-0.8122*	-0.2464*	1	
BOLDNESS	0.0926*	0.0167	-0.1987*	0.3036*	-0.2777*	-0.1445	1
OPAQUE_UP	0.014	0.5372*	-0.0425*	0.0461*	-0.0414*	-0.0220	0.0063
OPAQUE_DW	-0.0281*	-0.0419*	0.5293*	-0.1326*	0.0817*	0.0869*	-0.0836*
TRANSP_UP	0.0341*	0.8267*	-0.0654*	0.0992*	-0.0504*	-0.0717*	0.0154
TRANSP_DW	-0.0555*	-0.0654*	0.8266*	-0.2139*	0.1722*	0.1148*	-0.1776*
OPAQUE_GOOD	0.0384*	0.0222	-0.1113*	0.4290*	-0.1567*	-0.3484*	0.1094*
TRANSP_GOOD	0.0778*	0.0957*	-0.1760*	0.6907*	-0.2524*	-0.5610*	0.2225*
TRANSP_BAD	-0.0753*	-0.0519*	0.1670*	-0.3061*	0.8378*	-0.2064*	-0.2521*
OPAQUE_BAD	-0.0177	-0.0386*	0.0880*	-0.1849*	0.5061*	-0.1247*	-0.1070*
TRANSP_NEU	-0.0454*	-0.0539*	0.1314*	-0.5865*	-0.1779*	0.7222*	-0.1406*
OPAQUE_NEU	-0.0324*	-0.0369*	0.0455*	-0.4274*	-0.1296*	0.5262*	-0.0308*
OPAQUE_BOLD	0.0106	0.0017	-0.1027*	0.1388*	-0.1111*	-0.0760*	0.4609*
TRANSP_BOLD	0.0988*	0.018	-0.1696*	0.2687*	-0.2541*	-0.1227*	0.8833*
CE_TIMING	-0.0189	0.0294*	-0.0061	-0.0236	0.0169	0.0139	0.0328*
PBV	-0.001	-0.0156	0.0081	-0.0509*	0.0646*	0.0124	-0.0044
BROKERWEIGHT	-0.0003	-0.0054	0.0061	-0.0019	-0.02	0.0146	0.0104

Panel B - The Pearson's correlation.

	OPAQUE_UP	OPAQUE_DW	TRANSP_UP	TRANSP_DW	OPAQUE_GOOD	TRANSP_GOOD	TRANSP_BAD	OPAQUE_BAD
OPAQUE_UP	1							
OPAQUE_DW	-0.0225	1						
TRANSP_UP	-0.0305*	-0.0346*	1					
TRANSP_DW	-0.0351*	-0.0399*	-0.0541*	1				
OPAQUE_GOOD	0.1929*	-0.0193	-0.1022*	-0.1182*	1			
TRANSP_GOOD	-0.1068*	-0.1217*	0.1844*	-0.1266*	-0.3569*	1		
TRANSP_BAD	-0.0393*	-0.0448*	-0.0353*	0.2262*	-0.1313*	-0.2114*	1	
OPAQUE_BAD	-0.0137	0.2201*	-0.0366*	-0.0423*	-0.0793*	-0.1277*	-0.0470*	1
TRANSP_NEU	-0.0753*	-0.0858*	-0.0137	0.2116*	-0.2516*	-0.4051*	-0.1491*	-0.0900*
OPAQUE_NEU	0.0614*	0.2283*	-0.0846*	-0.0978*	-0.1833*	-0.2952*	-0.1086*	-0.0656*
OPAQUE_BOLD	-0.0227	-0.2188*	0.0156	0.017	0.1133*	0.0526*	0.0187	-0.2683*
TRANSP_BOLD	0.0191	0.0214	0.0091	-0.2091*	0.0638*	0.2227*	-0.2933*	0.02
CE_TIMING	-0.0061	-0.0306*	0.0389*	0.0131	-0.0637*	0.0266*	0.0183	0.002
PBV	-0.011	0.0093	-0.0112	0.0034	-0.0392*	-0.0212	0.0659*	0.0141
BROKER WEIGHT	0.0102	0.0119	-0.0132	-0.0007	0.0313*	-0.0270*	-0.0163	-0.0109

Panel C - The Pearson's correlation.

	TRANSP_NEU	OPAQUE_NEU	OPAQUE_BOLD	TRANSP_BOLD	CE_TIMING	PBV	BROKERWEIGHT
TRANSP_NEU	1						
OPAQUE_NEU	-0.2081*	1					
OPAQUE_BOLD	0.0348*	-0.1599*	1				
TRANSP_BOLD	-0.1763*	0.0491*	-0.0088	1			
CE_TIMING	0.0260*	-0.0122	0.0300*	0.0211	1		
PBV	0.0358*	-0.0264*	0.0103	-0.0104	0.0168	1	
BROKERWEIGHT	-0.0138	0.0375*	-0.0043	0.014	0.0165	0.0773*	1

* denotes significance at the 10%

Notes. These tables report the correlation matrix of the different model specification variables. They are based on the Pearson's correlation definition. Some of the correlations are missing because of the variables definition.
$DGOOD_{it}$, $DBAD_{it}$, $DNEU_{it}$ are three dummy variables indicating whether the investment recommendation is good, bad or neutral. DDW_{it} is a dummy standing for downgrade in recommendations while DUP_{it} is for upgrades. $BOLDNESS_{it}$ represents the analyst forecast boldness and it is calculated as current target price divided by the average target price (the consensus) for the company *i* in year *t*, minus 1. $OPAQUE_{it}$ and $TRANSPARENT_{it}$ are two dummies, each one representing alternatively one of the two disclosure levels. $OPAQUE\_DW_{it}$, $OPAQUE\_UP_{it}$, $TRANSP\_DW_{it}$, $TRANSP\_UP_{it}$ are interaction variables between the disclosure level and the recommendation changes; $OPAQUE\_GOOD_{it}$, $OPAQUE\_NEU_{it}$, $OPAQUE\_BAD_{it}$, $TRANSP\_GOOD_{it}$, $TRANSP\_NEU_{it}$, $TRANSP\_BAD_{it}$ are interaction variables between the disclosure and the recommendation levels; $OPAQUE\_BOLD_{it}$ and $TRANSP\_BOLD_{it}$ are interaction variables between the disclosure level and the analyst boldness.
$BROKERWEIGHT_{it}$ indicates the broker activity and it is measured as the ratio of reports issued by each broker for a company over the total reports issued by for that company; *NATIO*, is a dummy variable distinguishing between European analysts and US ones. CE_TIMING_{it} takes value equal to 1 if the report is issued after the quarterly earnings announcement, -1 if it was issued before, 0 if the analyst's report was issued out of the time window considered; PBV_{it} is the company price-to-book value.

Table 7. The correlation matrix among variables.

Panel D - The Spearman's correlation.

	CAR(-1;+1)	DUP	DDW	DGOOD	DBAD	DNEU	BOLDNESS
CAR(-1;+1)	1						
DUP	0.0409*	1					
DDW	-0.0591*	-0.0792*	1				
DGOOD	0.0998*	0.1097*	-0.2563*	1			
DBAD	-0.0529*	-0.0659*	0.1922*	-0.3654*	1		
DNEU	-0.0707*	-0.0729*	0.1464*	-0.8122*	-0.2464*	1	
BOLDNESS	0.0594*	0.0123	-0.1976*	0.3393*	-0.2435*	-0.2036	
OPAQUE_UP	0.018	0.5372*	-0.0425*	0.0461*	-0.0414*	-0.0220	0.0048
OPAQUE_DW	-0.0310*	-0.0419*	0.5293*	-0.1326*	0.0817*	0.0869*	-0.0826*
TRANSP_UP	0.0364*	0.8267*	-0.0654*	0.0992*	-0.0504*	-0.0717*	0.0112
TRANSP_DW	-0.0491*	-0.0654*	0.8266*	-0.2139*	0.1722*	0.1148*	-0.1769*
OPAQUE_GOOD	0.0383*	0.0222	-0.1113*	0.4290*	-0.1567*	-0.3484*	0.1282*
TRANSP_GOOD	0.0725*	0.0957*	-0.1760*	0.6907*	-0.2524*	-0.5610*	0.2442*
TRANSP_BAD	-0.0501*	-0.0519*	0.1670*	-0.3061*	0.8378*	-0.2064*	-0.2212*
OPAQUE_BAD	-0.0176	-0.0386*	0.0880*	-0.1849*	0.5061*	-0.1247*	-0.0936*
TRANSP_NEU	-0.0474*	-0.0539*	0.1314*	-0.5865*	-0.1779*	0.7222*	-0.1945*
OPAQUE_NEU	-0.0418*	-0.0369*	0.0455*	-0.4274*	-0.1296*	0.5262*	-0.0481*
OPAQUE_BOLD	-0.0039	-0.0021	-0.0761*	0.1185*	-0.0608*	-0.0863*	0.4688*
TRANSP_BOLD	0.0728*	0.0168	-0.1584*	0.2950*	-0.2068*	-0.1801*	0.8310*
CE_TIMING	0.0053	0.0279*	-0.0085	-0.0260*	0.0179	0.0158	0.0370*
PBV	-0.0219	0.0011	-0.0042	-0.0004	0.0251*	-0.0153	0.0199
BROKERWEIGHT	-0.0069	0.0131	0.0256*	0.0058	-0.0092	-0.0003	0.0006

Panel E - The Spearman's correlation.

	OPAQUE_UP	OPAQUE_DW	TRANSP_UP	TRANSP_DW	OPAQUE_GOOD	TRANSP_GOOD	TRANSP_BAD	OPAQUE_BAD
OPAQUE_UP	1							
OPAQUE_DW	-0.0225	1						
TRANSP_UP	-0.0305*	-0.0346*	1					
TRANSP_DW	-0.0351*	-0.0399*	-0.0541*	1				
OPAQUE_GOOD	0.1929*	-0.0193	-0.1022*	-0.1182*	1			
TRANSP_GOOD	-0.1068*	-0.1217*	0.1844*	-0.1266*	-0.3569*	1		
TRANSP_BAD	-0.0393*	-0.0448*	-0.0353*	0.2262*	-0.1313*	-0.2114*	1	
OPAQUE_BAD	-0.0137	0.2201*	-0.0366*	-0.0423*	-0.0793*	-0.1277*	-0.0470*	1
TRANSP_NEU	-0.0753*	-0.0858*	-0.0137	0.2116*	-0.2516*	-0.4051*	-0.1491*	-0.0900*
OPAQUE_NEU	0.0614*	0.2283*	-0.0846*	-0.0978*	-0.1833*	-0.2952*	-0.1086*	-0.0656*
OPAQUE_BOLD	-0.0205	-0.1595*	0.01	0.0109	0.1111*	0.0337*	0.012	-0.1501*
TRANSP_BOLD	0.0218	0.0244	0.0062	-0.1979*	0.0724*	0.2426*	-0.2421*	0.0227
CE_TIMING	-0.0051	-0.0296*	0.0365*	0.0097	-0.0560*	0.018	0.0179	0.0045
PBV	-0.0136	0	0.0104	-0.005	-0.016	0.0124	0.0208	0.013
BROKER WEIGHT	0.0162	0.016	0.0048	0.0196	0.0227	-0.0121	-0.0001	-0.0166

Panel F - The Spearman's correlation.

	TRANSP_NEU	OPAQUE_NEU	OPAQUE_BOLD	TRANSP_BOLD	CE_TIMING	PBV	BROKERWEIGHT
TRANSP_NEU	1						
OPAQUE_NEU	-0.2081*	1					
OPAQUE_BOLD	0.0223	-0.1588*	1				
TRANSP_BOLD	-0.2464*	0.0558*	-0.0065	1			
CE_TIMING	0.0233	-0.0063	0.0204	0.0203	1		
PBV	0.0124	-0.0369*	0.0420*	0.0134	0.0051	1	
BROKERWEIGHT	-0.0219	0.0264*	-0.0001	0.009	0.0257*	0.0187	1

* denotes significance at the 10%

Notes. These tables report the correlation matrix of the different model specification variables. It is based on the Spearman's correlation definition. Some of the correlations are missing because of the variables definition. All the variables have been defined above.

$DGOOD_{it}$, $DBAD_{it}$, $DNEU_{it}$ are three dummy variables indicating whether the investment recommendation is good, bad or neutral. *DDW_{it}* is a dummy standing for downgrade in recommendations while *DUP_{it}* is for upgrades. *$BOLDNESS_{it}$* represents the analyst forecast boldness and it is calculated as current target price divided by the average target price (the consensus) for the company *i* in year *t*, minus 1. *$OPAQUE_{it}$* and *$TRANSPARENT_{it}$* are two dummies, each one representing alternatively one of the two disclosure levels. *$OPAQUE\_DW_{it}$, $OPAQUE\_UP_{it}$, $TRANSP\_DW_{it}$, $TRANSP\_UP_{it}$* are interaction variables between the disclosure level and the recommendation changes; *$OPAQUE\_GOOD_{it}$*, *$OPAQUE\_NEU_{it}$*, *$OPAQUE\_BAD_{it}$*, *$TRANSP\_GOOD_{it}$*, *$TRANSP\_NEU_{it}$*, *$TRANSP\_BAD_{it}$* are interaction variables between the disclosure and the recommendation levels; *$OPAQUE\_BOLD_{it}$* and *$TRANSP\_BOLD_{it}$* are interaction variables between the disclosure level and the analyst boldness.

$BROKERWEIGHT_{it}$ indicates the broker activity and it is measured as the ratio of reports issued by each broker for a company over the total reports issued by for that company; *NATIO*, is a dummy variable distinguishing between European analysts and US ones. *CE_TIMING_{it}* takes value equal to 1 if the report is issued after the quarterly earnings announcement, -1 if it was issued before, 0 if the analyst's report was issued out of the time window considered; *PBV_{it}* is the company price-to-book value.

Table 8. The market reaction to the report release: the effect of recommendations, their revisions and analyst boldness

VARIABLES	(1) CAR(-1;+1)	(2) CAR(-1;+1)	(3) CAR(-1;+1)	(4) CAR(-1;+1)
DGOOD		0.00415***		0.00410***
		(2.19e-07)		(6.58e-06)
DBAD		-0.00972***		-0.00702**
		(0.000480)		(0.0130)
DNEU		-0.00365***		-0.00215*
		(0.000941)		(0.0961)
DUP	0.00605**			0.00410
	(0.0166)			(0.150)
DDW	-0.0102***			-0.00737**
	(0.000174)			(0.0250)
BOLDNESS			0.0214***	0.0115**
			(0.000207)	(0.0365)
Observations	4,531	4,420	3,439	3,391
R-squared	0.005	0.013	0.008	0.022

pval in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes. This table reports the results of model (1) testing the market reaction to the report release: the effect of recommendations, their revisions and analyst boldness. $DGOOD_{it}$, $DBAD_{it}$, $DNEU_{it}$ are three dummy variables indicating whether the investment recommendation is good, bad or neutral. DDW_{it} is a dummy standing for downgrade in recommendations while DUP_{it} is for upgrades. $BOLDNESS_{it}$ represents the analyst forecast boldness and it is calculated as current target price divided by the average target price (the consensus) for the company *i* in year *t*, minus 1.

Table 9. The market reaction to the report release: the effect of the transparency disclosure

VARIABLES	(1) CAR(-1;+1)	(2) CAR(-1;+1)	(3) CAR(-1;+1)	(4) CAR(-1;+1)
OPAQUE_GOOD		0.00354***		0.00431***
		(0.00840)		(0.00459)
TRANSP_GOOD		0.00445***		0.00401***
		(7.67e-06)		(0.000379)
TRANSP_BAD		-0.0117***		-0.00742**
		(0.000850)		(0.0244)
OPAQUE_BAD		-0.00456		-0.00517
		(0.269)		(0.332)
TRANSP_NEU		-0.00368**		-0.00274*
		(0.0121)		(0.0961)
OPAQUE_NEU		-0.00361**		-0.00100
		(0.0279)		(0.631)
OPAQUE_UP	0.00417			0.00219
	(0.249)			(0.620)
OPAQUE_DW	-0.00865*			-0.00747
	(0.0726)			(0.236)
TRANSP_UP	0.00687**			0.00476
	(0.0352)			(0.177)
TRANSP_DW	-0.0108***			-0.00738*
	(0.000942)			(0.0562)
OPAQUE_BOLD			0.00512	-0.00616
			(0.621)	(0.542)
TRANSP_BOLD			0.0259***	0.0161**
			(0.000195)	(0.0144)
Observations	4,531	4,420	3,439	3,391
R-squared	0.005	0.013	0.009	0.024

pval in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes. This table reports the results of model (2) testing the market reaction to the report transparency. $OPAQUE_{it}$ and $TRANSPARENT_{it}$ are two dummies, each one representing alternatively one of the two disclosure levels. $OPAQUE\_DW_{it}$, $OPAQUE\_UP_{it}$, $TRANSP\_DW_{it}$, $TRANSP\_UP_{it}$ are interaction variables between the disclosure level and the recommendation changes; $OPAQUE\_GOOD_{it}$, $OPAQUE\_NEU_{it}$, $OPAQUE\_BAD_{it}$, $TRANSP\_GOOD_{it}$, $TRANSP\_NEU_{it}$, $TRANSP\_BAD_{it}$ are interaction variables between the disclosure and the recommendation levels; $OPAQUE\_BOLD_{it}$ and $TRANSP\_BOLD_{it}$ are interaction variables between the disclosure level and the analyst boldness.

Table 10. The market reaction to the report release: the effect of the transparency disclosure with other control variables

VARIABLES	(1) CAR(-1;+1)	(2) CAR(-1;+1)	(3) CAR(-1;+1)	(4) CAR(-1;+1)
OPAQUE_UP	0.00219	0.00221	0.00222	0.00223
	(0.620)	(0.617)	(0.616)	(0.614)
OPAQUE_DW	-0.00747	-0.00743	-0.00743	-0.00740
	(0.236)	(0.239)	(0.239)	(0.241)
TRANSP_UP	0.00477	0.00475	0.00476	0.00476
	(0.175)	(0.178)	(0.178)	(0.177)
TRANSP_DW	-0.00738*	-0.00742*	-0.00737*	-0.00740*
	(0.0562)	(0.0546)	(0.0564)	(0.0549)
OPAQUE_GOOD	0.00432***	0.00458***	0.00466***	0.00489***
	(0.00437)	(0.00669)	(0.00675)	(0.00899)
TRANSP_GOOD	0.00404***	0.00431***	0.00435***	0.00462***
	(0.000383)	(0.00151)	(0.00267)	(0.00483)
TRANSP_BAD	-0.00738**	-0.00700*	-0.00707**	-0.00670*
	(0.0244)	(0.0528)	(0.0342)	(0.0658)
OPAQUE_BAD	-0.00515	-0.00484	-0.00488	-0.00459
	(0.333)	(0.373)	(0.367)	(0.403)
TRANSP_NEU	-0.00271	-0.00242	-0.00240	-0.00211
	(0.103)	(0.199)	(0.212)	(0.321)
OPAQUE_NEU	-0.000977	-0.000709	-0.000620	-0.000369
	(0.641)	(0.755)	(0.795)	(0.885)
OPAQUE_BOLD	-0.00612	-0.00607	-0.00617	-0.00606
	(0.546)	(0.548)	(0.541)	(0.549)
TRANSP_BOLD	0.0161**	0.0161**	0.0161**	0.0162**
	(0.0146)	(0.0139)	(0.0144)	(0.0140)
CE_TIMING	-0.000118			-9.84e-05
	(0.897)			(0.913)
PBV		-0.000105		-9.61e-05
		(0.742)		(0.763)
BROKERWEIGHT			-0.00504	-0.00454
			(0.734)	(0.758)
Observations	3,391	3,391	3,391	3,391
R-squared	0.024	0.024	0.024	0.024

pval in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes. This table reports the results of model (3) testing the market reaction to the report transparency, conditionally to some control variables. $OPAQUE\_DW_{it}$, $OPAQUE\_UP_{it}$, $TRANSP\_DW_{it}$, $TRANSP\_UP_{it}$ are interaction variables between the disclosure level and the recommendation changes; $OPAQUE\_GOOD_{it}$, $OPAQUE\_NEU_{it}$, $OPAQUE\_BAD_{it}$, $TRANSP\_GOOD_{it}$, $TRANSP\_NEU_{it}$, $TRANSP\_BAD_{it}$ are interaction variables between the disclosure and the recommendation levels; $OPAQUE\_BOLD_{it}$ and $TRANSP\_BOLD_{it}$ are interaction variables between the disclosure level and the analyst boldness.

$BROKERWEIGHT_{it}$ indicates the broker activity and it is measured as the ratio of reports issued by each broker for a company over the total reports issued by for that company; *NATIO*, is a dummy variable distinguishing between European analysts and US ones. CE_TIMING_{it} takes value equal to 1 if the report is issued after the quarterly earnings announcement, -1 if it was issued before, 0 if the analyst's report was issued out of the time window considered; PBV_{it} is the company price-to-book value.

CHAPTER 4

Paper III

Proximity to Hubs of Expertise in Financial Analyst Forecast Accuracy

1. Introduction

Does geographical proximity enhance financial analysts' accuracy? Results from recent literature about the financial analyst forecasting process show a systematic difference in earnings forecast accuracy dependent on the geographical distance of analysts from the companies which they follow (see, e.g. Malloy (2005) and Bae et al. (2008)).

This paper investigates whether the geographical proximity of financial analysts to hubs of information and expertise can influence their forecasting accuracy.

The literature argues that local analysts issue more accurate forecasts because they have an informational advantage over analysts who are further away.[21]

In general, financial analysts are 'intermediaries' between the managers of the firms which they follow and financial markets. They use a heterogeneous set of information (hard and soft, explicit and tacit) about the company which they follow, the industry and the economic system in order to arrive at earnings forecasts, company value and an investment recommendation. Thus, the evaluation process performed by financial analysts has a sequential structure '*input-processing-output*'.

In this framework, local informational advantage could be related either to different information sets available to local and remote analysts or to the superior skills of local analysts in processing the same information set. Specifically, a different set of information could be derived from an analyst's direct contact with company management and premises or from lower information gathering costs. In an international setting, the superior skills could be related to better knowledge of the local language, culture or customs.

The purpose of this study is related to this latter idea, introducing a new concept of proximity. Drawing on both international- and industrial economics-based research and on network analysis

[21] Alternative explanations are related to incentive arguments, including compensation and career incentives, and not to information asymmetries.

and cluster theories, this work aims to explore the role of proximity of analysts to centres of production of soft and not structured knowledge in order to explain the performance of financial analysts.
Industrial centres can constitute important knowledge spillovers by creating formal and informal networks amongst firms and higher education and research institutions. In such a hub, information can easily flow and propagate. Our hypothesis is that physical proximity to these hubs is an advantage for financial analysts, leading to the issue of more accurate forecasts.

Prior literature provides mixed results with respect to geographical advantage. We hypothesise that unstudied aspects of analysts' locations may add important evidence to prior literature.

We test our hypothesis by the collection of both macroeconomic data - to identify the hubs of expertise - and financial analyst data, specifically earnings forecasts, dates of research reports and details about the financial analysts' location. The final filtered sample of 205 matched-observations related to 33 firms, across seven countries and ten sectors over four years (from 2004 to 2008).

Specifically, we first establish the location of the hubs of expertise of the country and industry of our sample, drawing on concepts from industrial and international economics.

Secondly, we test whether the accuracy of financial analyst forecasts depends on the location of financial analysts in regard to the hubs of expertise identified.

Our results are consistent with the hypothesis. In order to establish the robustness of this approach, we employed different measures of both earnings forecast accuracy and proximity.

Even though preliminary, and probably in part biased by sample selection issues, overall, the empirical evidence confirms the benefit of being part of a network, formal or informal, in which information, knowledge and expertise sharing can flow easily. We try to give some new evidence on what can cause variations in financial analyst accuracy by exploring these concepts, well known and analysed in other fields, but new in the context of financial analysts.

We believe that the identification of the drivers which affect forecast accuracy is important for at least three reasons. First, investors should benefit from being able to identify more accurate forecasts (and forecasters) as a good knowledge of these drivers can help them to spot more reliable information sources. Second, as earnings forecast are part of the input to analysts' valuation methods and their stock recommendations, more accurate forecasters could issue more profitable recommendations. Third, forecast accuracy is also important to brokerage houses and investment banks as it enhances the quality of their output. Trading commissions and portfolio performance, which are strongly based on analyst ability, in fact generate part of their revenues. Thus, forecast accuracy should be important in turn to analysts, who can be rewarded by their brokerage houses according to their accuracy. Finally, the results of this study could also contribute to the organisation of the research operations and financial research departments of investment banks and brokerage houses. The identification of a link between hubs of expertise and financial analyst performance could induce a change in the structure of financial research, from being country- or industry-based to expertise hub-based.

The paper is organised as follows: Section 2 explains the literature on financial analyst accuracy; Section 3 reports the methodology adopted to measure proximity to hubs of expertise; Section 4 describes the data and research design; Section 5 reports the main results; Section 6 illustrates the conclusions of this research, suggesting new patterns of analysis; and the Appendix reports the technical details of the procedure used to identify the hubs of expertise.

2. Literature Review

Many papers have investigated the link between geography and information asymmetries in a number of financial and economic contexts.

Focusing on investors, for example, it is well known that they are biased towards their home country. The literature explaining this home bias is extensive, but still far from having obtained conclusive results. An important stream has underlined the differences in information available to domestic and foreign investors. Early papers focused on this area, for example Gehrig (1993) and Kang and Stulz (1997). A number of papers attempted to identify more directly whether foreign investors have an informational disadvantage. Hau (2001) investigated trading data for professional traders and showed that local investors perform better than foreign traders. Choe et al. (2005) and Dvorak (2005) found that foreigners trade at worse prices in Korea and Indonesia, respectively.

On the institutional investors' side, Grinblatt and Keloharju (2000) and Seasholes (2000) argued that better resources and access to expertise allows foreign institutions to perform better than domestic institutions. Grinblatt and Keloharju (2000) found that in the Finnish market over a two-year period, foreign and domestic financial corporations bought more stocks which performed well over the next 120 trading days than domestic individual investors. Seasholes (2000) found that foreign investors buy (sell) ahead of good (bad) earnings announcements in Taiwan, while domestic investors do the opposite. Froot, O'Connell and Seasholes (2001) and Froot and Ramadorai (2001) used flow data to show that foreign investors have some ability to predict returns. These papers are consistent with the better information and greater sophistication on the part of foreign investors.

However, evidence on the performance of foreign investors is mixed. For instance, Shukla and van Inwegen (1995) showed that UK money managers underperform in comparison with their American counterparts when picking US stocks. Using 18 years of annual data, Kang and Stulz (1997) found no evidence that foreign investors outperformed domestic investors in Japan.

A new strand of literature looked at the impact of distance on portfolio choice within countries. Coval and Moskowitz (1999), using only U.S. stock returns, provided evidence that investor location matters, in that mutual fund managers overweight the stocks of firms located closer to them. In another paper, the same authors (2001) found that mutual fund managers are better at picking stocks of firms which are closer to where they are located than those from a more distant location. Huberman (2001) found local concentration in the ownership of the Baby Bells in the US. Ivković and Weisbrenner (2005) used data from a large discount brokerage house and found the striking result that one out of six US individuals in their sample only invested in companies headquartered within 250 miles of their household. Recent papers show that social networks are also important for stock holdings. Hong, Kubik and Stein (2005) showed that mutual fund managers were more likely to hold a particular stock when other managers in the same city held the same stock.

With specific regard to financial analysts, a number of papers have investigated how the geography of security analysts can affect their forecast performance. Some have analysed whether the country-related features have an impact on financial analyst accuracy. Chang, Khanna and Palepu (2000) and others documented considerable variation across countries in the accuracy of analyst forecasts, depending on specific country characteristics. However, the international evidence seems mixed and inconclusive. For instance, while Chang, Khanna and Palepu (2000) found evidence that a country's legal system helps us to understand the accuracy of analysts, Ang and Ciccone (2001) reached the opposite conclusion. Hope (2003) found that the enforcement of accounting standards and firm-level disclosure were important determinants of forecast accuracy.

Only a handful of papers investigate, directly or indirectly, how analysts' physical distance to evaluated companies affects the accuracy of their forecasts. Malloy (2005), for instance, found evidence that, US analysts located close to the evaluated firm are more accurate than those who are further away. He argued that the ability of local analysts to make house calls rather than conference calls and the opportunity to meet CEOs and survey company operations directly provide them with an opportunity to obtain valuable private information. Following this logic, geographic proximity is a proxy for the quality of analyst information.

In an international setting, analysts cover those countries which are open to foreign investors. Bae et al. (2008) showed that the financial opening of a country[22] is followed by the increasing interest of foreign analysts. Bacmann and Bolliger (2001) directly examined the relative performance of analysts from local and foreign brokerage houses in seven Latin American stock markets. They concluded that foreign analysts outperformed local analysts in their study which focused on seven Latin American countries. When they compared the mean difference in forecast error between local and foreign analysts, it was not significantly positive for all of the countries in their sample, with the exceptions of Mexico and Colombia. In contrast, Orpurt (2004) found evidence of a significant local advantage in a sample of seven European countries. In his study, local analysts were defined as resident in that country. He found that his evidence was driven by Germany. However, while Bolliger (2004) focused on local versus foreign brokerage houses (not analysts) and found an advantage for local brokerage houses in Europe, Orpurt (2004) did not find this type of local advantage. Conroy, Fukuda, and Harris (1997) also found a local brokerage house advantage in Japan. Finally, Chang (2003) compared specifically the stock recommendations of foreign and expatriate analysts covering Taiwanese firms. He found that there was a local advantage, as expatriate analysts outperformed foreign analysts. He also found that expatriate analysts outperformed local analysts working for domestic firms. This result is consistent with the hypothesis that local analysts working for foreign institutions have the advantage of belonging to more sophisticated and resourceful organisations. Bae et al. (2008) showed that there is a significant local advantage for analysts in a sample of 32 countries. This local analyst advantage holds after having controlled for analyst characteristics as well as firm characteristics. However, it varies substantially between countries. The local analyst advantage is stronger in countries where disclosure is weaker, institutional investors are less important and corporate ownership is more concentrated.

These results are very interesting, consistent with and complement another part of the literature, which analyses the information needs of financial analysts. Previts et al. (1994), for instance, performing a content analysis of 479 sell-side analyst reports, showed that analyst information needs to extend beyond that contained in financial reports and include softer, more subjective information. Breton and Tafler (2001) presented a content analysis of 105 analyst reports in order to assess the information used by analysts. Non-financial information seemed to be equally

[22] By financial opening the authors mean the opening of the country to foreign investors.

important as financial information. The financial analysts were particularly interested in non-financial information about management and strategy, as well as the trading environment of the firm. According to the distance-related literature, this information is probably easily gathered if the analysts are closer to the firm being evaluated. This is also supported by Barker's results (1998). Performing a survey, he found that analysts considered personal contact to be more important than earnings announcements and financial statements. Since proximity can help analysts to keep frequent personal contact, according to the local information advantage hypothesis, the accuracy of analysts who are close to the evaluated company should improve. The author provided four possible reasons underlying this evidence. First, personal contact can improve the timeliness of the disclosure of information. Second, analysts can question company managers directly. Third, it helps analysts to have comparative advantage over their peers, and, fourth, they can focus on strategic and forward-looking issues.

In summary, prior research has documented significant variation in the quality of analysts' forecasts, with some being more accurate others. According to previous results, Brown et al. (1985) and Brown (1993), it is possible to conclude that the accuracy of earnings forecasts depends on the difficulty or complexity of the task. Proximity to a source of informational advantage can help and simplify the complexity of the valuation task, thus improving the forecasting accuracy. Empirical evidence is inconclusive on this issue, but there is some evidence that geographical distance between the analyst and the followed company is an important factor in forecast accuracy. Other authors argue that local analysts may gather better quality and more timely information about the company, thereby gaining an informational advantage over their peers, the so-called local information advantage.

We do not fully agree with this theory. In fact, in such a globalised context, where physical presence can be easily substituted by virtual contact and distances are shortened by technology which facilitates communication, we argue that the physical proximity of analysts to firms is not associated with an informational advantage. Therefore, in our hypothesis, the information advantage derives from another form of geographical proximity which is more industry knowledge-related.

We therefore provide a new concept of proximity related to distance from centres of knowledge, which we define as hubs of expertise. While Malloy (2005) measured proximity as the number of kilometres between analysts and firms and Bae et al. (2008) defined an analyst as local if he or she was located in the same country of the followed firm, in our study, the distinction between local and foreign analysts is based on the analyst's location with respect to the hubs, which are identified by looking at the industrial specialisation of countries.[23]

According to the comparative advantage theory (Ricardo (1963)), each nation tends to shift its resources to its more productive industries, while increasing trade for goods in their less productive industries. So, each nation tends to have a specialisation in a specific industry. This is often associated with the development of industrial clusters. In the sphere of financial services, for instance, previous research has shown that large, medium and small financial service companies have a tendency to cluster in metropolitan areas because of the need to access a large pool of specialist and support services (e.g. accounting, actuarial, legal etc.), be in close proximity to the markets, benefit from agglomeration economies, reduce transactions costs, develop and innovate intrinsic skills through the sharing of knowledge and practice (e.g. Davies, 1990).

Since clusters provide knowledge-rich environments which are associated with innovation, knowledge spillover, the building of relationships and synergies, proximity to these centres of specialisation may allow financial analysts to improve their knowledge of value-relevant factors and use them to their advantage in the evaluation of companies in that industry. Therefore, in our opinion, the geographical proximity of financial analysts to hubs of expertise improves the quality of industry knowledge and allows analysts to develop unique expertise and skills, resulting in an informational advantage and greater forecast accuracy.

3. Hypothesis development and research design

3.1. Modelling the analyst accuracy

The set of information that analysts use to evaluate a company can be divided in two groups. A first group composed by commercial and structured information, easily collected by all analysts and a second group of soft (tacit) information that can be privileged and produced by the environment in which analysts work. Therefore, an analyst has an information advantage if it has access to the soft information, derived by his context.

Our basic hypothesis is that analysts located close to sources of soft knowledge have an information advantage. Therefore, the primary aim of this research is to test whether the accuracy of financial analysts depends of their proximity to hubs of expertise, generating soft knowledge.

The conceptual model used is therefore:

[23] See also Section 3 and the Appendix to the paper.

Analyst Forecast Accuracy = f (analyst stock of knowledge deriving from the proximity to the hubs, other control variables)

We adopt two estimation techniques in order to investigate the accuracy of financial analysts and in both cases we employ the Newey-West procedure[24] in order to provide consistent inferences on the estimated coefficients.

The former is a classic OLS regression, assuming a linear relationship between the analyst's accuracy, which is our dependent variable, and all of the independent variables.
The latter is a fixed effects model based on the within transformation. This model allows us to take into account the differences between the firms covered which are not controlled by our independent variables, thereby allowing us to manage time-series observations and cross-sectional units at the same time. We stress that the assumption underlying the fixed effect model is that the relationship between the explained and the explanatory variables is assumed to be constant both cross-sectionally and over time.

As a measure of relative forecast accuracy, we initially made two different definitions of accuracy: a simple and a more sophisticated one. The simplest one (*AFE*) is the Absolute Forecast Error calculated as:

$$AFE_{ijt} = \frac{ACTUAL_{jt} - FORECAST_{ijt}}{ACTUAL_{jt}} \qquad (1)$$

where *ACTUAL* indicates the actual earnings per share for the company *j* in the fiscal year *t* and *FORECAST* is the forecast of earnings per share, issued by the analysts *i* for the company *j* in fiscal year *t*, no more than 100 days before the announcement date. As previous research has proved, this measure is too naïve and can be biased.[25] We also defined another measure, the Proportional Mean Absolute Forecast Error (*PMAFE*), calculated as:

$$PMAFE_{ijt} = \frac{AFE_{ijt} - AAFE_{jt}}{AAFE_{jt}} \text{ (-1)} \qquad (2)$$

This measures the difference between the absolute forecast error (*AFE*) of analyst *i* forecasting earnings for firm *j* in the fiscal year *t* and the average absolute forecast error across all analyst forecasts of firm *j*'s fiscal year *t* earnings, expressed as a fraction of the average absolute forecast

[24]Brooks (2008) explains that the Newey-West procedure implies 'HAC' (Heteroscedasticity and Autocorrelation Consistent) standard errors. This adjustment allows us to deal with the coefficients' standard errors since it produces a variance-covariance estimator which is consistent in the presence of both heteroscedasticity and autocorrelation.
[25] Clement (1998) documented that *PMAFE* improves the chances of identifying the differences in individual analyst forecast accuracy. Jacob et al. (1999) discussed these benefits in more detail.

error across all analyst forecasts of firm *j*'s fiscal year *t* earnings. *PMAFE* controls for firm-year effects by subtracting the mean absolute forecast error, *AAFE*, from the analyst's absolute forecast error. Deflating by *AAFE* reduces heteroskedasticity in forecast error distributions across firms (Clement (1999)) and multiplying by -1 ensures that higher values for *PMAFE* correspond to higher levels of accuracy.[26]

Jacob et al. (1999) explain that the *PMAFE* variable is a relative measure of forecasting accuracy which is not affected by inter-temporal changes and cross-sectional differences in the price-to-earnings ratios. We rely on this variable in order to compare data from different firms and different years which could therefore allow us to provide more interesting figures on the relationship between knowledge and analyst accuracy.

3.2. Modelling analysts' stock of knowledge and other control variables

In order to assess whether the analyst's location with respect to hubs of expertise influences the quality of their knowledge and enhances the accuracy of their forecasts, we first identify the hubs, where the spill-overs of knowledge originate. Secondly, we test whether the accuracy of financial analysts' forecasts depends on their proximity to the source of spill-overs (the hubs) identified.

Since empirical measurement of knowledge spill-overs would be impossible because "knowledge flows are invisible, they leave no paper trail by which they may be measured and track[ed]" (Krugman, 1991, 125), we draw on concepts from industrial and international economics to find a proxy.

Specifically, we assume that there are three alternative methods for the study of knowledge generation: cluster-, sector- and network-based approaches. All of these three approaches are based on the basic assumption that the intensity of knowledge generated by a sector is related to its level of production, but they offer different ways to measure it.

The first approach is based on the idea that the knowledge derives from intensive and privileged exchanges amongst industries which are strongly related in agglomerates of sectors (clusters). In this approach, the structural relationships among sectors which characterise a cluster produce privileged knowledge. Therefore, even though a sector may be small, it is part of a cluster, and therefore generates an amount of knowledge dependent on the cluster of which it is part. Cluster

[26] As in all the regressions these latter accuracy measures were the best, and consistently with previous literature (see Clement (1999 and 1998) and Jacob et al. (1999)), we report only the results obtained using this accuracy measure.

literature explains how clusters retain privileged knowledge which can be spread amongst their members.

Since Marshall's (1920) seminal discussion about highly localised districts in the UK, a new perspective has been developed about the geographical clustering of firms from similar industries.[27] More recently, some pieces of research have conceptualised clusters as sources of enhanced knowledge creation (e.g. Lawson & Lorenz, 1999; Lorenzen & Maskell, 2004; and Malmberg & Maskell, 2002). In this regard, participating in a cluster would increase the spill-over effects of new technologies, knowledge and innovations. For instance, Forni and Paba (2001) show how strong linkages induce a relatively fast diffusion of knowledge and new technologies. Cluster analysis provides a possible solution to the identification of strongly interrelated sectors. By dividing the economic system into clusters of interrelated sectors, the clusters show exactly which sectors are closely related to each other.

Therefore, we associate this kind of 'clustered' knowledge with our concept of hubs of expertise, the source of shared knowledge.

The very basic definition of an industrial cluster is "geographical concentrations of industries that gain performance advantages through co-location" (Doeringer and Terkla (1995), page 225). This definition of clusters is similar to that of agglomeration economies, but in fact it is within industrial clusters that agglomeration economies are likely to be observed. Beyond the basic definition, however, there is little consensus on how to define an industrial cluster. Michael Porter extended the concept of industrial clusters in his book, *The Competitive Advantage of Nations* (1990) and developed the 'Diamond of Advantage', four factors which create a competitive advantage for firms. The four corners of the diamond include factor conditions, demand conditions, industrial strategy, and related and supporting industries. He used this diamond to determine which firms and industries had competitive advantage. A more in-depth discussion of the different definitions of industry clusters was presented by Jacobs and DeMan (1996) and Rosenfeld (1996, 1997).[28] They expanded on the definitions of vertical and horizontal industry clusters in order to identify the key dimensions which can be used to define clusters. These include the geographic or spatial clusters of economic activity, the horizontal and vertical relationships between industry sectors, the use of common technologies, the presence of a central actor (e.g., a large firm, research centre, etc.), the quality of the firm's network and its level of co-operation (Jacobs and DeMan (1996)). In addition to vertical and horizontal relationships, Rosenfeld (1997) included criteria for defining a cluster, including its size, economic or strategic importance, the range of products produced or services

[27] See Storper (1997) for a review.

[28] Jacobs and DeMan (1996, p. 425) argue that "there is not one correct definition of the cluster concept…different dimensions are of interest."

used and the use of common inputs. He did not define clusters exclusively by the size of the industries or the scale of employment.

We assume that analysts have access to enhanced and privileged knowledge on the basis of their geographical proximity to clusters and also benefit from a cultural information advantage that improves forecasts issued for companies (local or not) which belong to the same sectors of the proximate cluster. To be close to a cluster is in fact a source of informative advantage.

The second perspective that we use is a sector-based approach. The theory behind this approach is that if a sector is very productive in terms of output, it also has a strong competitive position with respect to other sectors. This advantaged position within the national economy generates specialisation and greater knowledge generation than other sectors less relevant for the economy. To be close to relevant sectors in terms of output can be a source of informational advantage.

Finally, the third approach is based on network logic. The basic assumption is that knowledge is generated by sharing and is the effect of cross-fertilisation between sectors, composing a network., The intensity of the knowledge therefore depends on the exchanges between the sectors of the network. In this case, proximity to the most relevant nodes of a network could be a source of informational advantage.

Our operational framework is therefore based on three steps in order to assess three proxies of knowledge intensity.

The first step is to define the hubs as industrial clusters. The empirical identification of clusters is not a straightforward procedure and the related literature shows how tricky it can be. There are no conclusive solutions for this.

Economic theory suggests several methods for identifying clusters. However, Hoen (2002), after describing how cluster analysis contributes to the study of linkages among sectors, shows that the cluster identification method based on a block diagonal matrix,[29] called the *diagonalisation method*, gives the best results. For this reason, we use this latter method in our analysis. According to this approach, we start from the input-output (I-O) matrix of each country. First, we calculate an I-O matrix of only the intermediate consumption[30] of different industries of a country. Therefore, the main diagonal elements, which represent the intermediate consumption of the same industry, are zeros. The off-diagonal elements are expressed as a percentage of the largest intermediate consumption between two industries, the benchmark for which has been set as equal to 100%. As per the literature, we also set a minimum threshold for input and output entries for being part of the

[29] A block diagonal matrix can be split up in parts that have no connection with each other. By rearranging sectors appropriately (details of this method are reported in Appendix A), the matrix would look like blocks of matrices along the main diagonal.

[30] The intermediate consumption is an economic concept that represents the monetary value of goods and services consumed or used as inputs in production by firms of a sector in a country.

matrix at 2%. After setting all of the elements that do not satisfy these restrictions to zero, putting the matrix in the block diagonal form shows which sectors belong to which clusters.[31] Each off-diagonal value (S_{ij}) in the same block (cluster) indicates the intermediate consumption between two sectors that is greater than the selected threshold. According to Hoen (2002), S_{ij} represents the strength of the link between two industries, *i* and *j,* belonging to the same cluster.

Once the different clusters (hubs) have been identified, we need to attribute a value for the knowledge spill-overs coming from each one. Assuming that the level of knowledge spill-over depends on the level of total production achieved by related sectors belonging to the same cluster, as defined by Hoen's procedure, we define a first proxy (*CLUSTER*). It is measured as the log transformation of the sum of S_{ij} of each cluster. In more formal terms, *CLUSTER* is:

$$CLUSTER_{zx} = Ln \sum_{ij} S_{ij} \tag{3}$$

where *z* indicates the country, and *i* and *j* two of the sectors composing the cluster *x*.

In other words, *CLUSTER* is a proxy of the level of information spill-over of which local analysts can take advantage of and it is based on the relevance of a sector depending on the cluster (approximated by the total production) of which it is part. Therefore, focusing on analysts' geographical location, we associate with each of them the value of the *CLUSTER* variable, depending on their location.

Let us assume, therefore, that a UK-based analyst evaluates (UK or foreign) companies in the oil industry. According to our framework, we will attribute to this analyst the stock of knowledge measured by the *CLUSTER* variable assigned to the UK of the cluster containing the oil sector. Should a specific sector not be contained in any of the identified UK clusters, the value of the variable will be forced to zero. Therefore, analysts located in different countries will benefit from different stocks of knowledge assigned to the clusters identified in their own country.

Analysts close to the most important clusters will show higher *CLUSTER* values, indicating higher spill-overs and informational advantages, which help them to issue more accurate forecasts in relation to national or international companies in industries belonging to that cluster. Thus, we expect this variable to have a positive impact on the accuracy of earnings forecasts.

The second approach when dealing with the hub identification issue is sector-based. Input-output tables are a useful tool used in the literature for studying the linkages between industries as they

[31] There are several possible algorithms for making the block diagonal matrix by rearranging sectors. Appendix A describes an algorithm which does not involve complex computations and is easy to program. An algorithm based on eigenvalues, which has the advantage of ordering clusters according to the strength of their linkages, can be found in Dietzenbacher (1996).

allow the measurement of the effect of a specific sector on the other sectors or the effect of each sector on the economic system as a whole. Therefore, by using the input-output tables, we can measure the importance of a sector in a country in terms of its production and level of specialisation. We can then assume that the value of production of a sector is a proxy for the knowledge produced. According to this framework, each sector represents a hub, but hubs with higher values of production contain more important sectors for the overall economy of a country.

We start with a Use table[32] and calculate the variable *OUTPUT* by industry, which is defined as the sector output at basic prices (without considering relationships with other sectors). The reason for doing this is to measure the total output value produced by each sector. This variable is measured as the log transformation of the sum of the intermediate consumption and the value added of each sector, scaled for the country's power purchase parity (*PPP*), in order to compare the same variables across different countries. In more formal terms:

$$OUTPUT_{zi} = Ln\left[\frac{(intermediate\ consumption_{zi} + value\ added_{zi})}{PPP_z}\right] \qquad (4)$$

where z indicates the country, while i the industry. The informative value of *OUTPUT* is that it shows how much a sector is relevant in terms of production for the economy.

Therefore, since our framework production is associated with knowledge, a higher value of the variable with respect to a certain sector i are in general related to higher levels of knowledge spill-over spreading to that sector. Hence, similarly to the *CLUSTER* variable, we predict this variable to have a positive impact on the accuracy of local analysts' forecasts as a higher level indicates a greater informative advantage for them. For example, let us assume that a UK-based analyst evaluates a (UK or foreign) bank. According to our framework, we attribute to this analyst the stock of knowledge, measured by the *OUTPUT* variable, assigned to the financial sector in UK. Therefore, analysts located in different countries benefit from different stocks of knowledge depending on the sector's relevance, in terms of output, for the country.

Finally, we also apply a third approach in order to identify hubs, based on methods from social network analysis. We assume that the economy of a country can be represented as a network of sectors (nodes) which are more or less interrelated. The ties among the nodes measure the strength of their relationships.

[32] Please see Appendix A for a detailed general definition of this table.

Similarly to clusters, networks can also produce spill-overs of knowledge. The extensive literature on this field has generated a wide set of techniques and related measurements for capturing the many facets of information embedded in the network structure.

One of the primary aims of social network analysis is to identify the 'important' actors in the network. The concepts of centrality and prestige have been introduced in the network field in order to quantify an individual actor's prominence within a network by summarising structural relationships among the *g* nodes. We draw from this literature to assess the prominence of economic centres (hubs) across countries, using the tools which it suggests.

In order to do this, we replicate the procedure proposed by Cetorelli and Peristiani (2009). The authors, using methodologies developed in social network analysis, elaborate measures to rank the relative degree of dominance of financial centres around the world. With such measures, they were able to assess more effectively whether US financial markets have lost their position of global leadership and the extent to which competition from other centres may have strengthened over time. The most complete measure which they implemented was the 'prestige index'. In network analysis, indices of prestige allow for the measurement of the dispersion or inequality of the prominence of all of the actors. Formally, the prestige index (*Pr*) for a node (in our case, a sector) *i* (*ni*) is calculated as:

$$Pr\ (n_i) = x_{1i}\, P(n_1) + x_{2i}\, P(n_2) + \ldots + x_{Ni}\, P(n_N) \qquad (5)$$

where the weights are represented by the flows from each of the nodes of the network onto n_i.

Therefore, by adapting and applying Cetorelli and Prestiani (2009)'s procedure for financial centres, we assess a prestige index for each sector (node) of all the countries (networks) of the dataset.

In order to represent the network, its nodes and the ties between nodes, we assume that the production value between sectors and within the same sector can be a proxy of the links of the network and indicate its knowledge intensity. Therefore, we measure flows between nodes through tables of intermediate consumption and the values added of each country. Specifically, the production of each country is represented by a matrix which exhibits the flow of intermediate consumption between each pair of sectors on the off-diagonal entries, while the main diagonal shows the sum of the intermediate consumption flow within each sector and the sector value added.

We apply the algorithm (5) proposed in the literature by Cetorelli and Peristiani (2009) to the whole network. Therefore, we have *N* equations in *N* unknowns for each network.

As shown by Katz (1953), this system has a finite solution if one first standardises the original network matrix. For this reason, firstly, we divide each column of the matrix by the column's sum.

After this standardisation, the system of equations becomes a more common matrix-characteristic equation, where the solution (that is, the vector of prestige indicators) is the eigenvector associated with the largest eigenvalue of the standardized matrix (SM). Since we do not use any specific mathematical software to calculate the eigenvalue of the matrix, we apply the 'power method'.[33] This is an iterative method and thus does not require any specific software to solve the problem.

In order to apply this method, we raise each cell value to the *n*th power until the matrix converges into a table of equal vectors (by column) so that we can find out the eigenvector associated with the largest Eigen value of the matrix.[34] This eigenvector contains the index of prestige associated with each sector. We call this eigenvector a *NET* variable and it is dependent on the flows exchanged (approximated to the intermediate consumption) between sectors in the same country. In more formal terms, for a country/network *z*, the variable *NET* can be calculated as:

$$NETz = eigenvector\ of\ SMz \qquad (6)$$

A node (sector) will thus have high prestige if it is chosen, in terms of flows, by a low number of highly prestigious other nodes or by a high number of other nodes with lower index value.

NET is therefore also our proxy for the extent of knowledge spill-overs of different sectors in a specific country. Its informative value is that it allows the knowledge of how much a sector is relevant in terms of exchanged flows of knowledge (approximated by the intermediate consumption) between the different sectors of the network. A greater value of this variable is associated with higher levels of knowledge spill-overs spreading from the specific sector *i*. Each analyst will be associated with a *NET* value, depending on their location and the sector which they are evaluating. For instance, a UK-based analyst evaluating a (UK or foreign) bank has a stock of knowledge measured by the *NET* variable, which is assigned to the financial sector in UK in relation to the 'prestige' of this sector with respect to others in the same country. Therefore,

[33] In mathematics, the power iteration is an algorithm: given a matrix *A*, the algorithm will produce a number λ (the eigenvalue) and a non-zero vector *v* (the eigenvector), such that $Av = \lambda v$. The algorithm is also known as the Von Mises iteration.

[34] Appendix B reports further technical details.

analysts located in different countries will benefit from different stocks of knowledge depending on the sector's relevance to the country.

Hence, similarly to the aforementioned proxies, we predict that this variable has a positive impact on the accuracy of local analysts' forecasts as a higher level indicates a greater informative advantage for them.

Therefore, in more formal terms, the model that we test is:

$$ACCURACY_i = \alpha + \beta_1\, STOCK\ OF\ KNOWLEDGE_i + \beta_2\, CONTROL\ VARIABLES_i + \varepsilon_i \qquad (7)$$

where the *ACCURACY* variable is defined in Section 3.1 and the *STOCK OF KNOWLEDGE* is alternatively measured by the *CLUSTER*, *OUTPUT* and *NET* variables.

With regard to the *CONTROL VARIABLES*, we include in the model a limited number of control variables because of the small size of the sample. Specifically, we insert the variable *AGE*, measuring the number of days from the date of the release of the report to the end of the fiscal year and *VOL*, which is a control variable measuring the coefficient of the variation in the firm's quarterly EPS over the past three years. We hypothesise that the greater the variability of the actual EPS over time, the greater the complexity of the analysts' forecasts. Finally, we employ dummy variables in order to control for the inter-temporal changes in analyst accuracy.[35] We do not expect to find any significant results as the *PMAFE* variable provides an adjustment for the inter-temporal variability of the analysed topic itself (see Section 3.1.).

4. Data

The sample construction started with a rich dataset of observations on analyst forecasts collected from Factsect over four fiscal years, from 2005 to 2008.

For each earnings forecast, we have the research date, the recommendation issued, the previous research date and forecast by the same analyst, and the type of report issued. We also collected information about analyst characteristics, such as their full name, brokerage house and office telephone number. The latter allowed me to infer their geographical location. As we had some missing data with regard to the last piece of information, we collected some of them by hand from *Nelson's Directory of Investment Research*, which provides extensive information about analysts, which companies they follow and brokerage houses. Each volume of *Nelson's Directory* in year *t* is

[35] We include *D05*, which is a dummy variable equal to 1 if the observation obtained was in 2005, 0 otherwise; *D06* is a dummy variable equal to 1 if the observation obtained was in 2006, 0 otherwise; and *D07*, which is equal to 1 if the observation obtained was in 2007, 0 otherwise.

based on the analysts' information from year *t-1*. As the 2008 volume is not available, we used the 2007 volume as a proxy for the 2007 analysts' missing data. As we did not find any clear information on some analysts, we excluded these missing observations.

These raw data needed to be filtered in order to match the restrictions based on the aim of our research.

Firstly, since the computation of the knowledge variable based either on the cluster or the sector concept is only available for specific countries, i.e. Italy, Germany, the United Kingdom and France, we eliminate all of the observations associated with analysts who are not located in these countries. Moreover, we cancel out all of the observations produced by teams of analysts placed in different countries. Following these adjustments, we can manage a dataset which satisfies our assumptions about the relevance of the proximity between the location of analysts and the hubs of expertise.

Secondly, we identify the end date of the fiscal year and eliminate all of the analyst reports released more than one hundred days before this reference point. We adjust the data in this way in order to have homogenous annual EPS forecasts.

Furthermore, Jacob et al. (1999) point out that each analyst benefits from both public information released by firms and previous information released by other analysts. In order to control for these sources of information, we compute a control variable which represents the age of the forecast, assuming that more recent reports benefit from the information released in earlier firm reports and from new public information.
The *CLUSTER* variable is adjusted to the data from the 2002 input-output tables because of a lack of data availability. Moreover, the *OUTPUT* variable is also based on these 2002 input-output tables. The *NET* variable is entirely based on data from 2000 and 1995 for the UK. We expect that this is not a big issue as our variables capture the structural relationships amongst the sectors which should not constantly change over time.

The final dataset is composed of 205 observations related to 33 firms, from 2005 to 2008.

The stated variables can be summarised by their descriptive statistics in Table 1.

Insert Table 1.

On the basis of these statistics, we could assert that, on average, analysts provide accurate forecasts but with relevant outliers and high variability amongst them. Moreover, in looking at the coefficients of variation, we can appreciate how the analyst accuracy variable exhibits a coefficient which should require more explanatory variables in order to be almost completely explained. However, since this research aims to focus on the role of knowledge in analyst accuracy and the sample size is not large, we only focus on the aforementioned explanatory variables. Table 2 reports the correlation matrix among variables.

Insert Table 2.

Furthermore, we notice that the literature on the argument provides regressions in which the adjusted R-squared hits a value of approximately 0.15, which is an argument for this type of research in order to shed more light on the topic.

The firms which comprise the final sample belong to ten different sectors and seven countries, as summarised in Table 3.

Insert Table 3.

The dataset does not have many control variables but we assert that this provision could be sufficient since this attempt only represents the preliminary stage of the research on the relationship between knowledge and analyst accuracy.

5. Results

We start the empirical analysis by applying the OLS technique, running different models in order to examine the impact of each knowledge variable on *PMAFE*, which represents analyst accuracy.

Insert Table 4.

All of the models are somewhat poor in explaining analyst accuracy. Firstly, all of the values of the F-statistic only allow us to argue that all of the coefficients are not significantly different from zero. Similarly, all of the t-statistics of the knowledge variables only allow us to argue that each knowledge variable is not significantly different from zero. Finally, the adjuster R-squared is negligible for all of the models; therefore the dependent variable could be better explained by looking at its mean.

From this discussion we could appreciate the apparent relevance of the *AGE* coefficient, which confirms our expectation that more recent reports would benefit from past analyst reports and incremental public information.

We explain these preliminary results by recognising that the OLS estimate does not account for the differences between firms. In order to control for these unexplained dynamics, we should analyse the analysts' accuracy conditionally on the firm's identity. Indeed, by using this perspective, we can appreciate the impact of the independent variables in explaining the variability of the analysts' accuracy without the requirement of control variables at the firm level. Moreover, these firm level control variables could be regarded as omitted variables, and thus their absence could debase the OLS results.

Since we only have the *VOL* variable as a control variable at the firm level, we employ a within transformation at firm-level in order to tackle this issue. We label the new variables with the suffix '*D*' and eliminate the constant term on the basis of the within transformation.

Insert Table 5.

After controlling for company identity, we notice that *AGE* is still significant, which is consistent with our expectation. Indeed, we can confirm that an analyst gains in accuracy when he or she provides his or her report close to the actual EPS issue. This figure could be motivated by our assumption of the benefits of incremental public information and the information contained in reports previously released by other analysts.

The control variable *VOL* is not significant. On the basis of this result, we cannot confirm our expectation of a negative relationship between the coefficient of variation of the historical actual EPS and analyst accuracy. A plausible reason for this result is that the literature refers to the variability of the actual EPS only in order to explain the distribution of the analyst forecasts, not the topic of analyst accuracy.

We also note that the dummy variables do not provide any contribution to the explanation of the dependent variable. This is probably due to the formulation of the *PMAFE* variable, since it accounts for inter-temporal changes in analyst accuracy.

This introduction allows us to focus on the explanatory power of our knowledge variables. First of all, we notice that *CLUSTER_D* is not significantly different from zero (Model 2). This result could derive from the aforementioned difficulties in measuring cluster boundaries and the knowledge contained therein. Therefore, this inconsistency could be caused by the drawbacks in the procedure of identification of clusters and in the representation of cluster knowledge.

Following this argument, we use the *NET_D* variable, which recognises hubs of expertise at a sector level rather than at a cluster level (Model 3). From this setting, we report a coefficient that is significantly different from zero. Focusing on knowledge at a sector level allows us to confirm our expectations on the role of proximity in increasing analysts' stock of knowledge. The positive sign of the coefficient means that the proximity between the analyst and the hub of expertise represents a source of analyst accuracy. Moreover, the adjusted R-squared of Model 3 increases significantly after the inclusion of the *NET_D* variable. Above all, if we multiply the coefficient of *NET_D* by this standard deviation, we can evaluate the variable impact on analyst accuracy between -8% and 8%.

This result is a preliminary confirmation of the relevance of analyst proximity to hubs of expertise. It is obtained by elaborating on the input-output tables on the basis of network analysis. As explained above, we measure sector knowledge on the basis of an index which represents the sector prestige recognised by all of the other sectors of the national economy. In order to check the usefulness of the network analysis, we define a third variable which considers sector output as a proxy of the stock of knowledge within the sector. In reality, this choice of proxy is not arbitrary since it represents the variable which we have split in the network information matrix and then elaborated in order to obtain the *NET_D* variable. If we obtained the same results, we could assert that all of the information on sector knowledge is contained in the sector attributes. Therefore, the analysis of sector ties should not provide incremental information.

We notice that the coefficient of the *OUTPUT* variable (Model 4) is not significantly different from zero. On the basis of this result, we confirm the benefits of exploiting network analysis in order to trace the availability of knowledge amongst units of analysis.

To sum up, network analysis synthesises network interactions, thereby providing a holistic analysis of knowledge amongst sectors within a national economy. Moreover, thanks to this approach, we demonstrate the relevance of knowledge about production to explain analyst accuracy on the basis of proximity to centres of knowledge.

6. Conclusions

This research aims to provide new insights on the issue of analyst accuracy, by developing a set of variables which should represent part of the stock of knowledge owned by analysts and help them in their task.

First of all, we point out that the analysis of analyst accuracy is essential in order to increase employers' reputations. Investment banks and brokerage houses would offer the services of analysts for free in order to benefit from analysts' reputations, a fact which is recognised by the financial markets.

Secondly, we argue that prior research on analyst accuracy has been more about analysts' characteristics rather than on the knowledge which is available to them. We recognise the utility of the first approach but try to develop the knowledge framework in order to provide a new stream of research.

We point out that each analyst has a certain stock of knowledge available: the firm's public information and the information contained in previous reports. The definition of our knowledge variables refers to the analyst's personal knowledge. We assume that the concept of proximity is essential for the detection of this source of personal expertise.

The results of this research confirm our main expectation since we find some evidence of greater accuracy associated with forecasts issued by analysts who are close to so-called hubs of expertise. This result is not based on the concept of cluster since the empirical identification of clusters is not straightforward. We ground our results by considering that hubs of expertise represent knowledge associated with single sectors of a national economy. Using this perspective, we report on the relevant role of sector knowledge on production for local analysts, even if they cover firms which are established abroad.

We conclude this research by suggesting plausible steps in order to improve the analysis. Firstly, further improvements are needed in terms of cluster identification and the knowledge available to the analyst. We have suggested network analysis as a reliable algorithm which could be used to detect concentrations of sectors within the input-output framework, thus providing a new approach to the evaluation of the stock of knowledge within the clusters. We suggest the development of this network analysis in order to measure the stock of knowledge within each unit of analysis. In the next steps of this work, each analyst will represent a unit of analysis.

Secondly, we suggest increasing the number of observations since the size of this sample is only reliable for preliminary results and insights. The plausible direction is to expand the group of countries analysed, thereby providing a more comprehensive picture of the European continent. Furthermore, it would be useful to collect firms' quarterly EPS's in order to increase the number of observations over time.

Finally, we propose the merger of these knowledge variables with the explanatory variables based on analyst characteristics. Using this, we could verify the relationships between these two classes of explanatory variables in order to improve our understanding of analyst accuracy.

Tables

Table 1: Summary statistics of the main variables of the dataset.

Statistics	*PMAFE*	*AGE*	*VOL*	*CLUSTER*	*NET*	*OUTPUT*
Mean	0.0204	50.85	0.2462	6.75	0.0379	11.31
Median	0.0277	49.00	0.2102	7.90	0.0276	11.36
Max.	0.9947	100.00	0.9141	10.41	0.2108	12.65
Min.	-2.0789	2.00	00.0267	0.00	0.0023	9.94
Std. Dev.	0.4667	24.27	0.1928	3.17	0.0433	0.5932
Coeff. of variation	22.87	0.47	0.78	0.46	1.14	0.05

Notes: This table reports the main descriptives of the model variables. The *PMAFE*, representing the analyst accuracy, while *CLUSTER*, *NET* and *OUTPUT* are defined above and represent alternatively measures of different analysts knowledge. *VOL* and *AGE* are 2 control variables indicating, respectively, the company earnings volatility and the age of the analysts forecast.

Table 2. The correlation matrix among variables

Panel A. The Pearson's correlation.

	pmafe	age	lncluster	net	lnoutput	vol
pmafe	1					
age	-0.1489*	1				
lncluster	-0.0623	-0.1864*	1			
net	0.0451	0.0458	0.2062*	1		
lnoutput	-0.0482	0.0334	0.5081*	0.5157*	1	
vol	-0.0025	0.0315	-0.0601	-0.1307*	0.044	1

This table reports the correlation matrix of the different model specification variables. It is based on the Spearman's correlation definition.

* denotes significance at the 10%.

Table 2. The correlation matrix among variables

Panel B. The Spearman's correlation.

	pmafe	age	lncluster	net	lnoutput	vol
pmafe	1					
age	-0.1980*	1				
lncluster	-0.1288*	-0.0872	1			
net	0.0923	-0.0793	0.0218	1		
lnoutput	-0.1431*	0.0071	0.6989*	0.2171*	1	
vol	-0.1187*	0.0693	-0.0766	-0.076	0.0222	1

Notes. This table reports the correlation matrix of the different model specification variables. It is based on the Spearman's correlation definition.

* denotes significance at the 10%

Table 3: Sector and country weights in the dataset.

Sector weight	%	Country weight	%
Banks	24.24%	**Finland**	0.00%
Insurance	12.12%	**France**	18.18%
Telecommunications Services	15.15%	**Germany**	18.18%
Technology	9.09%	**Italy**	9.09%
Non-Cyclical Consumer Goods & Services	9.09%	**Netherlands**	18.18%
Energy	6.03%	**Spain**	6.06%
Pharmaceuticals	12.12%	**Sweden**	0.00%
Utilities	3.03%	**Switzerland**	9.09%
Healthcare	6.06%	**United Kingdom**	21.21%
Basic Materials	0.00%		
Cyclical Consumer Goods & Services	3.03%		

Notes. This table reports the weights of each industry and country in the whole dataset.

Table 4: The effect of different knowledge variables on the analysts' accuracy – OLS estimation

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.247***	0.267***	0.225**	0.527	0.986
AGE	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**
VOL	-0.023	-0.023	-0.007	-0.019	0.015
CLUSTER		-0.003			-0.0001
NET			0.697		12.013
OUTPUT				-0.025	-0.069
D05	-0.094	-0.088	-0.087	-0.093	-0.081
D06	-0.104	-0.098	-0.106	-0.099	-0.093
D07	-0.108	-0.100	-0.124	-0.103	-0.121
R-squared	0.031	0.032	0.035	0.032	0.041
Adj. R-squared	0.007	0.002	0.006	0.003	0.002
Durbin Watson	2.055	2.052	2.056	2.05	2.061
Prob (F-stat)	0.266	0.366	0.299	0.357	0.397

OLS Estimates; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Notes: This table describes the main results obtain by OLS estimations of different model specifications. The independent variable is always *PMAFE*, representing the analyst's accuracy, while *CLUSTER*, *NET* and *OUTPUT* are defined above and represent alternatively measures of different analysts knowledge. *VOL* and *AGE* are 2 control variables indicating, respectively, the company earnings volatility and the age of the analysts forecast. Finally, *D05*, *D06* and *D07* are dummy variables controlling for a time effect.

Table 5: The effect of different knowledge variables on the analysts' accuracy – Fixed effect estimation

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5
AGE_D	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
VOL_D	0.060	0.068	0.166	-0.005	0.16
CLUSTER_D		-0.026			-0.023
NET_D			9.59*		9.40*
OUTPUT_D				-0.164	-0.009
D05	0.0008	0.001	0.007	-0.0005	0.007
D06	0.0013	0.002	0.016	0.006	0.017
D07	0.0002	-0.0008	-0.016	-0.003	-0.017
R-squared	0.041	0.047	0.069	0.045	0.075
Adjusted R-squared	0.021	0.024	0.045	0.022	0.042
Durbin-Watson stat	2.084	2.072	2.10	2.08	2.09

Fixed-effect Estimates; *, ** and *** denote significance at the 10%, 5% and 1% levels respectively.

Notes: This table describes the main results obtain by Fixed effect estimations of different model specifications. The independent variable is always *PMAFE*, representing the analyst's accuracy, while *CLUSTER*, *NET* and *OUTPUT* are defined above and represent alternatively measures of different analysts knowledge. *VOL* and *AGE* are 2 control variables indicating, respectively, the company earnings volatility and the age of the analysts forecast. Finally, *D05*, *D06* and *D07* are dummy variables controlling for a time effect.

APPENDIX A

This appendix illustrates how we identify and define the hubs of expertise following a cluster-based approach.

The key point is the definition of an index allowing us to rank the European sectors by knowledge intensity. The methodology, based on the literature about cluster theory, is for the identification of two different proxies of hub of expertise.

Firstly, in order to identify the boundaries and size of hubs of expertise, we apply the Hoen algorithm (Hoen, 2002), based on symmetric input-output tables.[36] Hoen asserts that any sector needs linkages with other sectors in order to develop its own business. The symmetric input-output tables of different countries should represent these relations. Therefore, by analysing the input-output tables, we identify the strongest linkages between sectors and thus the clusters, i.e. aggregations of sectors within a national economy.

Input-output analysis can be used to evaluate the impact of different policies on macroeconomic variables, such as gross domestic product, employment, consumption, productivity, competitiveness, etc, as well as the environment. In the 1930s, the economist Wassily Leontief described the inter-industry relations in the economy from which it had developed. The structure of each sector's production activity was represented by appropriate structural coefficients, which described in quantitative terms the relationships between the inputs that it absorbs and the output that it produces. The input-output framework was based on three types of table: supply tables, use tables and symmetric input-output tables. A synthetic description of each table is given below.
Eurostat defines the supply table as a product-by-industry-based table, in which products are placed in the rows and industries and imports in the columns. A simplified illustration can be represented in the following way:

[36] The OECD defines an input-output table as a tool for the presentation of a detailed analysis of the process of production and the use of goods and services (products), and the income generated in that production for any European country.

Industries Product	Industries			Import	Total
	Agriculture	Industry	Services Activities		
Agricultural products	Output by product and by industry			Import by product	Total supply by product
Industrial products					
Services					
Total	Total output by industry			Total imports	Total supply

Table A.1. A simplified supply table. Source: Eurostat (Eurostat, 18)

The supply table's rows exhibit the supply of goods and services to sectors by the type of product, differentiating between domestic supply and imports. The columns indicate the domestic output of industries by product.

The use table is a product-by-industry-based table with products and components of value added in the rows and industries, categories of final use and imports in the columns. A use table shows the use of goods and services by product and by type of use, i.e. as intermediate consumption by industry, final consumption, gross capital formation or export. A simplified illustration is the following:

Industries Product	**Industries**			**Final uses**			Total
	Agriculture	Industry	Services Activities	Final consumption	Gross capital formation	Exports	
Agricultural products Industrial products Services	Intermediate consumption by product and by industry			Final uses by product and by category			Total use by product
Value added	Value added by component and by industry						Value added
Total	Total output by industry			Total final uses by category			

Table A.2. A simplified use table. Source: Eurostat (Eurostat, 20)

The symmetric input-output tables are analytical tables derived from the supply and use system. An input-output table is a quantitative economic tool which represents the interdependencies between different branches of the national economy or different, even competing, economies. The transformation procedure converts the product-by-industry system of the supply and use tables into a product-by-product system or industry-by-industry system. Input-output tables are used to identify economically-related industry clusters and also so-called ‘key’ or ‘target’ industries of a specified economy.

<table>
<tr><td rowspan="2">Products

Products</td><td colspan="3">Homogeneous units of production</td><td colspan="3">Final uses</td><td rowspan="2">Total use</td></tr>
<tr><td>Agricultural products</td><td>Industrial products</td><td>Services</td><td>Final consumption</td><td>Gross capital formation</td><td>Exports</td></tr>
<tr><td>Agricultural products</td><td colspan="3" rowspan="3">Intermediate consumption by product and by
homogeneous units of production</td><td colspan="3">Final uses by product and by category</td><td rowspan="3">Total use by product</td></tr>
<tr><td>Industrial products</td><td colspan="3"></td></tr>
<tr><td>Services</td><td colspan="3">Final uses by product and by category</td></tr>
<tr><td>Value added</td><td colspan="3">Value added by component and by homogeneous units of production</td><td colspan="3"></td><td></td></tr>
<tr><td>Imports for similar products</td><td colspan="3">Total imports by product</td><td colspan="3"></td><td></td></tr>
<tr><td>Supply</td><td colspan="3">Total supply by homogeneous units
of production</td><td colspan="3">Total final uses by category</td><td></td></tr>
</table>

Figure A.3. A simplified input-output table. Source: Eurostat (Eurostat, 25)

Input-output tables often contain an enormous amount of detailed data. In order to deal with these data, it is necessary to aggregate the data. One possibility is to search for clusters of sectors with strong linkages. The clusters then denote how the sectors may be aggregated (Aroche-Reyes, 2001).

Hoen (2002) developed an algorithm based on these symmetric input-output tables. His algorithm aggregates sectors into clusters after the following rule: two sectors compose a cluster if their relations, the so-called linkages, to economic growth, are large, compared to the whole economic system.

This algorithm is based on the matrices of intermediate consumption across industries. Then, to identify a cluster empirically, the author uses the block diagonal matrix method[37].

As suggested by Hoen, to apply his procedure we first have to set a threshold of significance level for the elements of the input-otput matrix that we use. We use a cut-off point of 2%. Then, we have to select all elements that belong to the 2% of largest elements. Elements that do not satisfy this restriction are put to zero.

Then we have to select, check if the intermediate consumption matrix is decomposable and rearrange the sectors so that the elements are given in blocks.

A block diagonal matrix can be split up into parts with no connections to each other. The algorithm reported below rearranges the sectors appropriately. All of the elements between sectors which are not in the same block are zero. Hence, all off-diagonal blocks would consist entirely of zeros. The zeros denote the boundaries of the clusters, while each block of matrix represents a cluster.

According to Hoen, (Hoen, 2002, 25), the algorithm to use for rearranging sectors and dividing them into clusters is the following one:

Step 1. Start at the upper-left part of the input-output table, with the element in the first column and the first row. The sector belonging to this element is the first temporary cluster.

Step 2. Move to the sector in the next row. Compute the sum of the deliveries from this sector to all sectors of the temporary cluster and the deliveries from all sectors of the temporary cluster to this sector. If this number is zero, go to step 3. Otherwise, add this sector to the temporary cluster and repeat step 2.

Step 3. Move to the next sector and compute the sum of the deliveries from this sector to all sectors of the temporary cluster and the deliveries from all sectors of the temporary cluster to this sector. If this number is zero, go to step 4. Otherwise, repeat step 3. If the last sector is reached, go to step 5.

Step 4. Swap the sector just found with the first sector right below the last sector of the temporary cluster. (For example, if the temporary cluster consists of the sectors 1, 2, and 3, and sectors 4 and 5 have no linkages with the first three sectors whereas sector 6 does, swap sectors 4 and 6). Swap the rows and the columns. Next, add the sector just found and swapped to the temporary cluster (in the example, add sector 6 to the temporary cluster). Continue with the last sector of the temporary cluster (in the example, let's say, sector 6, which is now the fourth row (and column) of the new matrix) and move to step 2.

[37] Hoen (2002) shows that this method brings to same results also selecting other input-output tables.

Step 5. The temporary cluster is now a definitive cluster. Go to the first sector directly beneath the last sector of this cluster. This sector is the starting sector of the new temporary cluster. Move to step 2.

Hoen's algorithm allows us to identify hubs by the intermediate consumption flow in a national perspective.

APPENDIX B

This appendix illustrates how we identify and define the hubs of expertise following a network-based approach.

We base our methodology on Cetorelli and Presotiani (2009)'s approach, which adopted network analysis to deal with a comparison of stock exchanges in a global perspective. Following their procedure, we determine the so-called prestige index which allows us to compare hubs of expertise from different countries. We regard each country as a network and the sectors of tha country as nodes of the network. The production patterns are indicates ties between nodes.

As in the approaches used previously, we start from an input-output matrix and we build a network matrix. Each element of the matrix is considered as a bidirectional flow.

Figure B.1 describes a typical network matrix, used in our framework. The row entries represent the origin of the flow, while the column entries present the destination of it. In this way, the main diagonal accounts for flows due to the sector activity (measured by the sum of intermediate consumption and value added of each sector) and off-diagonal entries represent interactions between different nodes. For instance, $I.C._{11}+V.A._{11}$ indicates the flow produced and accumulated by industry 1 itself, $I.C._{12}$ indicates the flow of intermediate consumption from industry 1 (origin) to industry 2 (destination), while $I.C._{21}$ is the flow of intermediate consumption from industry 2 to industry 1.

	Industry 1	**Industry 2**	**Industry 3**	**Industry 4**	**Industry 5**
Industry 1	$I.C._{11}+V.A._{11}$	$I.C._{12}$	$I.C._{13}$	$I.C._{14}$	$I.C._{15}$
Industry 2	$I.C._{21}$	I.C.+V.A.	0	0	0
Industry 3	$I.C._{31}$	$I.C._{32}$	I.C.+V.A.	$I.C._{34}$	0
Industry 4	$I.C._{41}$	0	0	I.C.+V.A.	0
Industry 5	$I.C._{51}$	0	0	0	I.C.+V.A.

Figure B.1. A network matrix example

By analysing the matrix by row, we can identify the intensity of the interaction of each unit towards other destination nodes. This indicator is called the out-degree index and is calculated as the row sum, excluding the main diagonal entry. In examining the matrix by column, it is possible to compute the so-called in-degree index, which represents the ability to influence the origin of flows. Neither index offers details about where flows are coming from.

In order to consider the out-degree and in-degree indices simultaneously, Cetorelli and Peristiani (2009) suggested using the betweenness index, which exploits network ties and captures the uniqueness of a given node in a network. Let $m_{jk}(n_i)$ be the maximum flow between nodes (*nj ,nk*) which goes through node n_i. Aggregate across all possible pairs of nodes in the network, other than n_i, and obtain the overall betweenness of node n_i as $\sum_j \sum_k m_{jk}(n_i)$. In order to allow for comparison over time, normalisation is recommended, so that the betweenness index of node n_i is:

$$P(ni) = \sum_j \sum_k \frac{m_{jk}(n_i)}{m_{jk}} \qquad \text{(eq. B1)}$$

Therefore, the prestige index of node n_i is:

$$Pr\ (n_i) = x_{1i}\ P(n_1) + x_{2i}\ P(n_2) + \ldots + x_{Ni}\ P(n_N) \qquad \text{(eq.B2)}$$

where the weights are represented by the flows from each of the nodes onto n_i . We have N equations in N unknowns for each network.

This sophisticated and standardised index allows for the judgement of the importance of each node in a network, fully exploiting the information contained in the entire network structure.

This metric allows us to normalise the data from symmetric input-output tables and identify an international ranking for hubs of expertise. This index is a proxy for the knowledge level of every industry in each country. The greater values in this index are associated with the greater influence of the sector in the production of goods and services for the whole economy.

In basic terms, we dispose the flows of intermediate consumption between every pair of sectors on the off-diagonal entries, while the main diagonal includes the sum of the intermediate consumption flows within every sector with the sector value added. This matrix represents all of the data on a country's production. We divide every column of the matrix by the column sum and apply the power method in order to calculate the eigenvector associated with the largest eigen value of the matrix. This eigenvector contains the index of prestige of any sector. Lastly, we identify the main sector of each firm and assign to each analyst covering that firm the index of prestige associated with that analyst's country location.

APPENDIX C

This appendix illustrates and summarises the application of the theoretical framework through an illustrative example: calculate the variables *CLUSTER*, *OUTPUT* and *NET* for the UK, assuming that this economy has just six sectors.

The cluster-based approach:

We start from the following input-output table[38] where the off-diagonal elements are the intermediate consumption between two industries. The main diagonal elements are the sum of the intermediate consumption and the value added of a sector:

Sectors	1	2	3	4	5	6
1	33000	200	57	4500	7000	5000
2	200	500	3000	20000	30000	100
3	57	3000	10000	300	1000	1500
4	4500	20000	300	2000	2500	3000
5	7000	30000	1000	2500	20000	6000
6	5000	100	1500	3000	6000	45000

Table C.1. Input-output tables among UK industries.

We calculate an I-O matrix of only the intermediate consumption between a country's different industries. The off-diagonal elements are expressed as a percentage of the largest intermediate consumption between two industries, the benchmark for which has been set as equal to 100% (in this case, 45,000 is set as 100%). The main diagonal elements, which represent the intermediate consumption of the same industry, are zeros. We also set a minimum threshold for input and output entries to be part of the matrix at 2%. Therefore we should delete the elements highlighted in yellow.

Sectors	1	2	3	4	5	6
1	0,00	0,44	0,13	10,00	15,56	11,11
2	0,44	0,00	6,67	44,44	66,67	0,22
3	0,13	6,67	0,00	0,67	2,22	3,33
4	10,00	44,44	0,67	0,00	5,56	6,67
5	15,56	66,67	2,22	5,56	0,00	13,33
6	11,11	0,22	3,33	6,67	13,33	0,00

Table C.2. Input-output tables of intermediate consumption among industries express as percentages.

[38] These numbers are hypothetical. This is just an exemplification.

Hence, the matrix becomes:

Sectors	1	2	3	4	5	6
1	0,00	0,00	0,00	10,00	15,56	11,11
2	0,00	0,00	6,67	44,44	66,67	0,22
3	0,00	6,67	0,00	0,00	2,22	3,33
4	10,00	44,44	0,00	0,00	5,56	6,67
5	15,56	66,67	2,22	5,56	0,00	13,33
6	11,11	0,22	3,33	6,67	13,33	0,00

Table C.3. Input-output tables of intermediate consumption among industries express as percentages and values greater than the threshold.

That can be expressed in absolute values as:

Sectors	1	2	3	4	5	6
1	0	0	0	4500	7000	5000
2	0	0	3000	20000	30000	100
3	0	3000	0	0	1000	1500
4	4500	20000	0	0	2500	3000
5	7000	30000	1000	2500	0	6000
6	5000	100	1500	3000	6000	0

Table C.4. Input-output tables of intermediate consumption among industries express in absolute values and values greater than the threshold.

Putting the matrix in the block diagonal form by rearranging sectors according to Hoen (2002)'s algorithm, the matrix shows which sectors belong to which clusters.

Let us assume that the *diagonalisation* technique applied to this example,[39] result in the identification of the two clusters coloured in the diagonal blocks below. The elements of the matrix are the intermediate consumptions.

Sectors	1	6	4	3	2	5
1	0	5000	4500	0	0	0
6	0	0	3000	0	0	0
4	0	0	0	0	0	0
3	0	0	0	0	3000	
2	0	0	0	0	0	30000
5	0	0	0	0	0	0

Table C.5. Input-output tables of intermediate consumption among industries rearranged by clusters.

[39] The diagonalisation procedure implemented by Hoen is reported step by step in the Appendix A. In this example, we are not following the indicated steps, because it is difficult to make it effective in this simplified example. Therefore, we are assuming its implementation and the results indicated in Table 5.

We can now calculate the *CLUSTER* value for each sector composing the cluster.

Clusters	Sector	Sum of Sij	CLUSTER=LN(Sum of Sij)
Cluster 1	1	12500	9.434
	6	12500	9.434
	4	12500	9.434
Cluster 2	3	33000	10.404
	2	33000	10.404
	5	33000	10.404

Table C.6. Input-output tables of intermediate consumption among industries rearranged by clusters in UK.

Cluster 1 is composed of sectors 1, 4 and 6, while cluster 2 contains sectors 2, 3 and 5. We associate the sum of the intermediate consumption of the corresponding cluster to each sector and by applying the natural log transformation, we obtain the variable *CLUSTER*.

The second step is to attribute the *CLUSTER* values to analysts. Following our hypothesis, analysts located in the UK who evaluate companies based either in the UK or in another country, and belonging to one of the sectors 1, 4 or 6, will have a stock of knowledge of about 9.43. The same analysts who evaluate companies belonging to sectors of cluster 2 (sectors 2, 3 or 5) will have a higher stock of knowledge of about 10.40.

Let us assume that another country, for example Italy, could have the same sectors agglomerated in a different way. The stock of knowledge (*CLUSTER*) values would be different. Let us suppose, for instance, that Italy has a cluster value for sector 1, 2 and 3 equal to 5 and for sectors 4, 5 and 6 equal to 12, as summarized in the following table:

Clusters	Sector	CLUSTER=LN(Sum of Sij)
Cluster 1	1	5
	2	5
	3	5
Cluster 2	4	12
	5	12
	6	12

Table C.7. Input-output tables of intermediate consumption among industries rearranged by clusters in Italy.

According to our framework, an Italian analyst evaluating a company belonging to sector 4, 5 or 6 would perform better than the UK analyst because he or she has a bigger stock of knowledge produced by the agglomeration of these sectors (12 vs 10.404), while the UK analyst will issue better forecasts for companies in sectors 1, 2 or 3 (9.434 vs 5).

The sector- based approach:

In order to apply the sector-based approach and calculate the variable *OUTPUT*, we start with a Use table (see Appendix A for a detailed definition)[40] using the same numbers used in the previous approach:

Sectors	1	2	3	4	5	6
1	33000	200	57	4500	7000	5000
2	200	500	3000	20000	30000	100
3	57	3000	10000	300	1000	1500
4	4500	20000	300	2000	2500	3000
5	7000	30000	1000	2500	20000	6000
6	5000	100	1500	3000	6000	45000
Intermediate consumption	33000	500	10000	2000	20000	45000
V.A.	100	150	300	50	20	500
Total output at basic price	**33100**	**650**	**10300**	**2050**	**20020**	**45500**

Table C.8. Use table of UK industries.

We then scale the total output values for the country power purchase parity (PPP) in order to compare the same variables across different countries.

If UK PPP is equal to 0.98, applying the formula of *OUTPUT*, our variable assumes the following values for each of the six sectors.

Sectors	1	2	3	4	5	6
OUTPUT	10,42749127	6,49717507	9,260101882	7,645797779	9,92468976	10,74567031

Table C.9. Output values for UK industries.

Therefore, we have to associate the *OUTPUT* variable for each analyst in the dataset.

According to our framework and to these numbers, an analyst located in UK evaluating a firm from sector 1 will have a bigger stock of knowledge (10.42) than a colleague evaluating firms belonging to sector 2 (a stock of knowledge equal to 6.49), regardless to the company's location.

At the same time, if France, for instance, has different *OUTPUT* values, all else being equal, analysts located in that country will have a different informational advantage in evaluating the same companies. It depends on the stock of knowledge produced by France in relation to the six sectors.

[40] A Use table is a product-by-industry-based table with products and components of value added in the rows and industries, categories of final use and imports in the columns

The network-based approach:

Finally, in order to implement this procedure, we assume that the production value between sectors and within the same sector can be a proxy of the links of the network. Specifically, the production of each country is represented by a matrix which exhibits the flow of intermediate consumption between each pair of sectors on the off-diagonal entries, while the main diagonal shows the sum of the intermediate consumption flow within each sector and the sector value added.

Therefore, if the matrix we are looking for is the following one:

Sectors	1	2	3	4	5	6
1	33100	200	57	4500	7000	5000
2	200	650	3000	20000	30000	100
3	57	3000	10300	300	1000	1500
4	4500	20000	300	2050	2500	3000
5	7000	30000	1000	2500	20020	6000
6	5000	100	1500	3000	6000	45500

Table C.10. Table of the UK production.

We apply the algorithm (5) proposed in the literature by Cetorelli and Peristiani (2009) to the whole network.

As indicated above, we divide each column of the matrix by the column's sum.

Sectors	1	2	3	4	5	6
Sum per column	49857	53950	16157	32350	66520	61100

Table C.11. Sum of the UK production values by column (sector).

And we obtain the standardised matrix (SM):

Sectors	1	2	3	4	5	6
1	0,66	0,00	0,00	0,14	0,11	0,08
2	0,00	0,01	0,19	0,62	0,45	0,00
3	0,00	0,06	0,64	0,01	0,02	0,02
4	0,09	0,37	0,02	0,06	0,04	0,05
5	0,14	0,56	0,06	0,08	0,30	0,10
6	0,10	0,00	0,09	0,09	0,09	0,74

Table 12. The standardized matrix (SM) of UK production values.

After this standardisation, the system of equations becomes a more common matrix-characteristic equation, where the solution (that is, the vector of prestige indicators) is the eigenvector associated with the largest eigenvalue of the standardised matrix.

Since we do not use any specific mathematical software to calculate the eigenvalue of the matrix, we apply the 'power method'.

Sectors	1	2	3	4	5	6
1	0,48	0,11	0,02	0,12	0,12	0,13
2	0,12	0,49	0,16	0,08	0,17	0,08
3	0,01	0,05	0,42	0,04	0,04	0,04
4	0,08	0,05	0,09	0,25	0,20	0,05
5	0,15	0,21	0,17	0,40	0,37	0,12
6	0,16	0,09	0,14	0,10	0,11	0,58
Sectors	1	2	3	4	5	6
1	0,29	0,15	0,09	0,16	0,16	0,17
2	0,16	0,31	0,20	0,16	0,19	0,13
3	0,03	0,06	0,20	0,06	0,05	0,05
4	0,10	0,10	0,11	0,16	0,15	0,08
5	0,21	0,23	0,22	0,30	0,29	0,18
6	0,21	0,15	0,18	0,16	0,16	0,39

Table 13. First two iterations to calculate the eigenvalue of the SM.

And after a number of iterations, the matrix converges to the following:

Sectors	1	2	3	4	5	6
1	0,011	0,011	0,011	0,011	0,011	0,011
2	0,004	0,004	0,004	0,004	0,004	0,004
3	0,001	0,001	0,001	0,001	0,001	0,001
4	0,001	0,001	0,001	0,001	0,001	0,001
5	0,020	0,020	0,020	0,020	0,020	0,020
6	0,000	0,000	0,000	0,000	0,000	0,000

Table 14. The eigenvectors of the SM.

Where all the equal columns are the eigenvectors of the SM.
NET for the UK is therefore equal to the following vector of values which represents the prestige index of each sector in that country:

Sector	**NET**
1	0,011
2	0,004
3	0,001
4	0,001
5	0,020
6	0,000

Table 15. NET values for UK sectors.

According to this approach, a UK analyst evaluating companies belonging to sector 1 has a stock of knowledge equal to 0.011, whereas whilst evaluating companies in sector 6 he or she has an informational advantage equal to zero. Each country (network) has a proper *NET* vector and, therefore, analysts located in different countries have different informational advantages deriving from the network to which they are closest.

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