Université de Neuchâtel

Faculté de droit et des sciences économiques

On The Properties of Financial Analyst Earnings Forecasts: Some New Evidence

Thèse

Présentée à la Faculté de droit et des sciences économiques pour obtenir le grade de docteur ès sciences économiques

par

Guido Bolliger

Sous la direction du

Professor Michel Dubois

Membres du jury de these:

Professeur Yadolah Dodge
Professeur Bertrand Jacquillat
Professeur Henri Loubergé
Professeur Michael Rockinger
Professeur René Stulz

Neuchâtel 2003

Monsieur Guido Bolliger est autorisé à imprimer sa thèse de doctorat ès sciences économiques intitulée:

“On The Properties of Financial Analyst Earnings Forecasts: Some New Evidence”.

Il assume seul la responsabilité des opinions énoncées.

Neuchâtel, le 13 octobre 2003

Ernest Weibel

Doyen de la faculté de droit
et des sciences économiques

Acknowledgements

I gratefully acknowledge the advice and support of my dissertation committee, Michel Dubois, Yadolah Dodge, Bertrand Jacquillat, Henri Loubergé, Michael Rockinger, and René Stulz. I owe a special debt to Michel Dubois, whose guidance, encouragements, ideas, and trust have stimulated my research in countless ways and whose friendship is yet more valuable. I have also learned much from my teachers and colleagues during the FAME Ph.D. program and during my time at the University of Neuchâtel. I am particularly grateful to Jean-François Bacmann, Dusan Isakov, Manuel Kast, Pierre Jeanneret, and Roger Walder. This thesis has benefited from the comments of Pascal Dumontier, Christophe Pérignon, William Rees, Olivier Scaillet, and Ernst-Ludgwig von Thadden. I thank the International Center for Financial Asset Management and Engineering (FAME), the University of Neuchâtel, and the Swiss National Science Foundation for financial support. I also acknowledge the support of Thomson Financial for providing earnings per share forecast data, available through the Institutional Brokers Estimate System.

Table of contents

List of Tables

Chatper 5

List of Figures

Introduction

The importance of information in the formation process of security prices has a long history. The dissemination of information can take on different forms depending on the legal constraints. However, in all developed financial markets, financial analysts play a prominent role in collecting, analysing and diffusing information. Financial analysts typically supply future earnings estimates and stock picking advices in the form of recommendations. Earnings estimates are the essential part of security valuation by analysts and investors. They have even become an integral part of financial reporting in the financial press. Early research has accumulated evidence that these estimates are optimistically biased. More recently, empirical studies have found that analysts' optimistic bias is lessening, that its extent differs across analysts, firm characteristics and countries.

Broadly speaking, this dissertation investigates the determinants of financial analyst forecasts bias. In the first essay, I examine the relative accuracy of European financial analysts' earnings forecasts and its determinants. I show that the results obtained for US analysts can not be generalised to European analysts who face a seemingly different job market as well as several different institutional and economic environments.

In the second essay, I investigate the influence of financial analysts' location on their performance. More precisely, I examine the relative performance of local versus foreign analysts on Latin American stock markets. I find foreign analysts to be more timely and more accurate than their local counterparts. In addition, I document stronger price reactions after foreign analysts' forecast revisions than after those of local analysts.

The third essay is related to the declining pattern of financial analyst forecast bias. In particular, I investigate whether US CEOs compensation arrangements give CEOs incentives to manipulate analysts' expectations downward in order to release earnings that meet or beat market estimates. The results confirm this hypothesis. I document a strong link between expectations management and the relevant option component of CEO compensation, bonus plans, and the percentage of the company's shares owned by the CEO who manages it.

The remainder of this document is structured as follows. In Chapter 1, I describe the activity of financial analysts and I review the general properties of analyst forecasts highlighted by past empirical studies. In Chapter 2, I review the literature that investigates the determinants of financial analysts' forecast accuracy. Chapters 3, 4, and 5 present the three essays of my dissertation. A final conclusion is provided at the end of this document.

Chapter 1: What do financial analysts do?

In this chapter, I first provide a description of financial analysts' main activity: fundamental or security analysis. A precise description of the security valuation process sheds light on the potential factors that may explain the properties of financial analyst forecasts and can help the reader to understand the underlying process behind analyst forecasts. Furthermore, it underlines the key role played by analysts' earnings forecasts in the valuation process. Second, I describe the general properties of financial analyst earnings forecasts. More precisely, I review the literature devoted to financial analysts' accuracy, with respect to time-series models, and rationality.

1.1 Fundamental analysis

Analysts produce information that is important for the market. As of today, a large fraction of the money invested by institutional and individual investors is still actively managed with fundamental analysis acting as the guiding principle of most of the investors. The importance of financial analysts' activity for financial markets has also been acknowledged by the Securities Exchange Commission (SEC) in a November 1998 statement[1]: "Analysts fulfill an important function by keeping investors informed. They digest information from Exchange Act reports and other sources, actively pursuing new company information, put it all in the context, and act as a conduits in the flow of information." In this section, I first provide a detailed description of fundamental analysis as well as its uses and proceeds. Second, I explain the reasons that motivate research on earnings forecasts and describe the two principal bodies of research that investigate their properties.

---

[1] The report of the SEC "Analyzing Analyst Recommendations" is downloadable from: http://www.sec.gov/investor/pubs/analysts.htm

Figure 1.1: Fundamental analysis

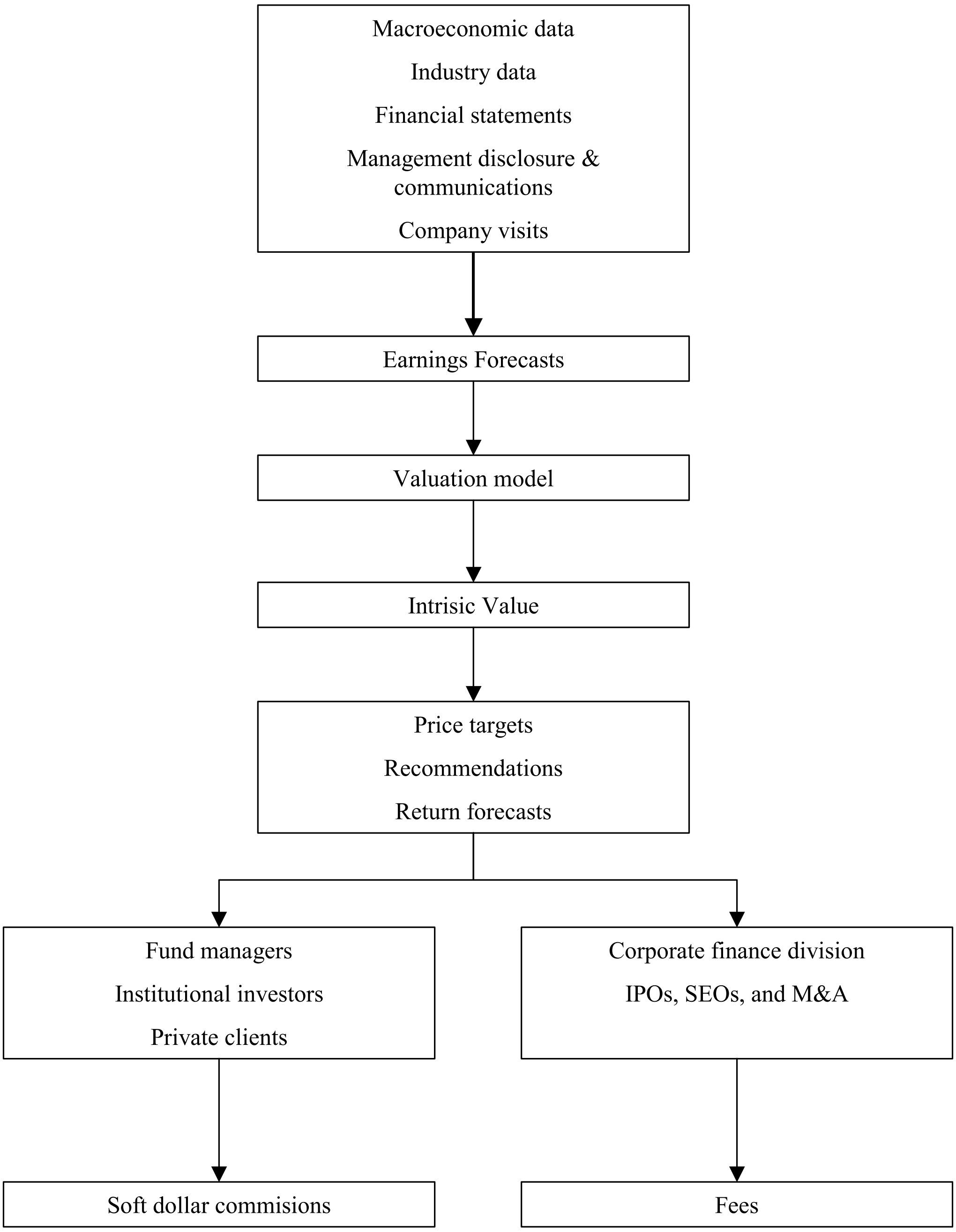


Figure 1.1 depicts the various steps of fundamental analysis as well as its uses and proceeds.

1.1.1 Description

Fundamental analysis is the principal activity of financial analysts. Figure 1.1 depicts the various steps of fundamental analysis as well as its uses and proceeds. Analysts evaluate a company's operations. They use publicly available information, such as past and current financial statements, regulatory fillings, information gathered from their own research, their own knowledge and expertise as well as from company management, in order to obtain earnings and growth prospects at different horizons. A valuation model is used in conjunction with these estimates, or numbers directly derived from them, in order to convert the set of forecasts into a firm's intrinsic value. Using the difference between its market and intrinsic value, analysts typically assign recommendations (e.g. "buy", "hold", "sell"), price targets or return forecasts to the firm[2].

The information produced by sell-side analysts, who are employed by broker-dealers, can be addressed to internal (e.g. in-house fund managers) or external investors, both institutional and individual; and, in some cases, to the bank's corporate finance department[3]. Buy-side analysts, who typically work for institutional investors, principally produce information for internal use. For investor customers, financial analysts' information serves as a basis for investment decisions. Typically, banks do not directly charge external investors for research. However, external customers are supposed to direct part of their trades to the bank that provides them with investment research. The practice of exchanging research services for commissions is referred to as "soft dollar payments". Analysts' most important contribution for the corporate finance department comes in assisting, in carrying out due diligence responsibilities with regard to initial public offerings, private placements, mergers and acquisitions, and secondary offerings; see Securities Industry Association (2001). Corporate finance clients pay direct fees to the bank for its services. A proportion of these fees is

---

[2] Some empirical evidence are inconsistent with this practice. In particular Cornell (2001) investigates analysts' reactions following the publication of a press release by Intel that leads to a 30% price drop in September 2000. He shows that none of the 28 recommendations changes issued by financial analysts was consistent with a discounted cash flow valuation.

[3] As underlined in the Securities Industry Association research report published in August 2001: "Analysts' role with regard to corporate financing departments varies widely across firms. Many securities analysts do not due diligence in order to further corporate financing objectives. Sometimes those departments have their own analysts."

attributed to analysts as compensation for the specific services provided to the corporate finance department[4].

1.1.2 Research on fundamental analysis

There is a huge amount of empirical and theoretical literature on fundamental analysis. Almost each stage of the process depicted in Figure 1.1 has given rise to academic research. However, a large body of literature focuses on the properties of financial analysts' earnings forecasts. Three reasons can explain the emphasis put on earnings forecasts. First, every valuation model[5] either directly or indirectly uses earnings forecasts. Second, asset pricing and cost-of-capital models generally involve earnings expectation variables for which proxies must be provided if these models are to be tested empirically or implemented in practice; see Hamon and Jacquillat (1999) and Brav and Lehavy (2003) among others. Third, if analyst forecasts measure market expectations, then evidence of excess volatility or irrationality in analysts' expectations may help to explain the excessively volatile asset returns (see Shiller, 1981) and anomalous market behaviour (see De Bondt et Thaler, 1985, 1990) documented by past research.

As underlined by Kothari (2001), analyst forecast research can be broadly divided in two categories. The first examines the properties of analysts' consensus earnings forecasts. Consensus forecast can be defined as the mean or median of all outstanding analyst forecasts for a particular horizon (quarterly, annual or long term). More precisely, this literature focuses on the accuracy and the rationality of financial analyst forecasts. In the following section, I review the literature classified in this category.

The second category focuses on the properties of individual analyst forecasts either cross-sectionally or temporally. More precisely, this body of literature puts emphasis on the determinants of financial forecasts bias as well as on the differences in forecast accuracy across analysts, firms, and countries. It will be reviewed in Chapter 2 of this document. As noted by Kothari (2001), there is an overlap between these two areas of research. Therefore, the conclusions drawn in one area can sometimes by applicable to both.

---

[4] In the U.S., the Securities Exchange Commission (SEC) prohibits firms from basing research analysts' compensation upon specific investment banking services transaction since May 2002; see Hensley and Strouse (2002).

[5] See Fama and Miller (1972) and Ohlson (1995) among others.

This thesis focuses on the factors that influence the properties of financial analyst forecasts. Therefore, I restrict my literature review to the two areas of research mentioned above. Doing this, I leave aside two important bodies of research related to financial analyst forecasts. First, I do not review the literature that examines the investment value of financial analyst forecasts (see Womack, 1996; Barber et al., 2001; Chan et al., 1996 among others) and the investment performance of various valuation models that use financial analyst forecasts; see Frankel and Lee (1998), Lee et al. (1999), and Liu and Thomas (2000) among others.

Second, I do not consider the body of research that examines the relationship between some properties of analyst forecasts (e.g. dispersion, number of analysts following the firm) and a firm's cost of capital (see Ghyssel and Juergens, 2001; Diether et al., 2002), stock return variability (see Ajinkya and Gift, 1985) trading volume (see Ajinkya et al., 1991; Bildersse et al., 1996), or stock price informativeness; see Brennan and Subrahmanyam (1995) and Hong et al. (2000).

1.2 The properties of financial analyst forecasts

The first objective pursued by early research on financial analyst forecasts is to compare the accuracy of the earnings forecasted by analysts with those drawn from various econometric models. In other words, these investigations seek to answer the following question: "Are financial analysts' earnings forecasts useful?". The second objective is to examine whether financial analysts are rational. More precisely, these studies examine the cross-sectional forecast errors and how available information is integrated in their earnings forecasts. Typically, these studies were performed with consensus data on the US market. In this section, I first give a brief overview of the main analysts' data sources available to academic researchers. Actually, the characteristics of the data and the evolution of their availability through time help to understand how research has developed. Then I review the literature devoted to analysts' accuracy and rationality. Finally, I address the potential research design and statistical problems which may question some of the results obtained by past research.

1.2.1 Data sources

There are three major providers of financial analyst forecasts. Their main activity is to provide investors and academics with earnings per share forecasts (annual and quarterly), long term growth forecasts, and recommendations generally collected from brokerage institutions that employ sell-side analysts. They typically provide individual as well as consensus data. Some years ago, they also began to provide portfolio management tools, market or industry-aggregated forecasts, and some other facilities[6]. The main differences between these providers lies in their international coverage, the date of data initiation, and the characteristics of the analysts reporting to the institution.

For the US market, Thomson Financial Corporation's International Brokerage Estimate System (I/B/E/S) has been providing monthly consensus data since 1976 and daily individual data since 1983. These data initially included earnings per share and long-term growth forecasts. Since the takeover of First Call by Thomson Financial, recommendations are also available. I/B/E/S initiated international coverage in 1987 for both consensus and individual data. As of January 2002, I/B/E/S was providing estimates for more than 13'000 companies in 59 different countries.

Zacks Investment Research collects earnings per share forecasts, long-term growth forecasts, and recommendations from approximately 250 brokers. The database covers more than 6'000 US stocks (including ADR's) for which consensus and individual data are available. Zacks does not provide international data.

Since the early 1970's, Value Line provides earnings per share forecasts in the Value Line Investment Survey published every Friday. There are more than 2'900 different US firms covered by Value Line that accounts for approximately 91 percent of the total market value of all securities on CRSP (see Brav and Lehavy, 2003). Stocks are analysed once every 13 weeks, and their earnings predictions are updated four times a year. Contrary to other providers, the analysts that issue the Value Line forecasts are independent analysts. Typically, one or two professional analysts follow a given firm. Consequently, Value Line does not issue individual analyst data. Besides earnings forecasts, Value Line provides various other

[6] For instance, Zacks provides its clients with lists of earnings and sales surprises as well as trading facilities for its clients.

measures such as price targets and earnings predictability ratings. International companies are not covered by Value Line.

Associés en Finance is the only European company that provides analysts' data. Associés en Finance has provided consensus and individual earnings per share forecasts for the French market since 1977. During the 1990s, coverage was extended to include the 1'200 largest European quoted companies in terms of market capitalization. Forecasts are collected from more than 160 different research departments. Besides earnings per share forecasts, Associés en Finance provides an estimate of the Security Market Line for each covered company.

With the availability of individual data, a large body of research devoted to the properties of individual analyst forecasts has emerged. Access to larger international data sets has enabled comparisons of analysts' forecast properties and their determinants across countries.

1.2.2 Financial analyst forecasts compared to time-series forecasts

Early research examines whether financial analyst forecasts are a better surrogate for market expectations than time-series forecasts. Brown and Rozeff (1978) are the first to document superior accuracy on the part of financial analyst forecasts over time-series forecasts for quarterly earnings. Fried and Givoly (1982) find that analyst forecasts are more accurate than time-series model forecasts and that analyst forecast errors are relatively more associated with abnormal stock price movements. The authors attribute the superiority of financial analyst forecasts to the broader information set available to analysts and to a timing advantage because they issue their forecasts after time-series model forecasts are generated. Brown et al. (1987) show that analyst forecasts' superiority is robust to many factors such as forecast horizon and forecast error definition. O'Brien (1988), however, favours the time-series model in the prediction of quarterly earnings for a 60 days' trading horizon. Overall, despite some conflicting evidence, past studies indicate that analysts outperform econometric models in forecasting earnings.

1.2.3 The rationality of financial analyst forecasts

A forecast is rational in Muth's (1961) sense if it contains no systematic errors (unbiasedness) and can not be improved by using information available when the forecast was made (efficiency). Numerous past academic studies have concluded that analyst forecasts contain an optimistic bias. Optimism is inferred form a systematic positive difference between the forecast and actual earnings per share. An optimistic bias is documented for US firms by Crichfield et al. (1979), Abarbanell (1991), and Lim (2001) among others. The same evidence is reported for French companies (see Jacquillat and Grandin, 1994), European companies (see Capstaff et al., 2001), as well as emerging market firms; see Chang et al. (2000). Some recent research on financial analysts' forecast bias documents a decrease in analysts' optimism in recent years for US companies; see Brown (1997, 2001a) and Richardson et al. (1999). Brown (2001a) attributes the recent decrease in financial analyst forecast error to management behaviour. He shows that profit-reporting firms generally meet or slightly beat analysts' estimates, so the forecast error is rarely negative and extreme. Managers of these firms succeed in doing so either by issuing pessimistic earnings pre-announcements or by managing earnings; see Degeorge et al. (1999). In contrast, when a firm reports a loss, managers generally do not attempt to meet or beat analysts' consensus estimates. They often do not tell analysts that they are about to report a loss, sometimes accompanied by a big bath. As a result, the expected earnings tend to be greater and extremely high. Richardson et al. (1999) find evidence of a switch from upward biased to downward biased annual forecasts as the earnings announcement date approaches. They also show that pessimistic analyst forecasts are more prevalent for firms with the highest incentives to avoid earnings disappointments. Their finding also suggests that the reduction in analyst forecast bias can be partly attributed to managerial behaviour. Kothari (2001) argues that the improvement in the quality of the data can also give rise to a decrease in financial analyst forecast bias.

In addition to the clear evidence favouring a systematic bias in analyst forecasts, past research results suggest that financial analyst forecasts fail to accurately incorporate new information on a timely basis. Several studies document analysts' tendency to misinterpret new information for US firms. These studies typically model the information set available to analysts with past earnings and past forecast errors. Lys and Sohn (1990), Ali et al. (1992), and Teoh and Wong (1997), suggest that analysts underreact to new information. De Bondt and Thaler (1990) find that analysts systematically overreact to new information, whilst Easterwood and Nutt (1999) find that analysts underreact to negative information and overreact to positive information. Capstaff et al. (2001) report results that are consistent with an overreaction by financial analysts in European countries. Note that the efficiency of financial analyst forecasts has been investigated in order to test the rational expectation hypothesis but also to examine whether the post-earnings announcement drift is attributable to financial analysts' underreaction to past information; see Abarbanell and Bernard (1992).

Overall, results from past research show that financial analysts are irrational. This irrationality suggests that analysts fail to appropriately integrate available information (e.g. macro-economic prospects) in their forecasts. An other explanation is that their forecasts are influenced by non informational factors, such as incentives arising from the market on which financial analysts evolve.

1.2.4 Research design and statistical problems

Kothari (2001) identifies five potential research design problems that may influence the results obtained so far on analyst forecast rationality. First, financial analyst forecast errors are highly skewed. Gu and Wu (2003) and Abarbanell and Lehavy (2003) find that a small number of forecast-error observations disproportionately contributes to the observed bias. This high skewness also increases the sensitivity of the results to the treatment of outliers; see Kothari et al. (2001). Second, there are differences in the actual earnings that are used to compute financial analyst forecast errors; see Phillbrik and Riks (1991). Analysts generally provide earnings forecasts that are free of special items and other one-time gains and losses. Therefore, earnings forecasts and actual earnings can be different, especially when Compustat actual earnings are used. Data providers adjust the actual reported earnings for special items and write-offs. However, Kothari (2001) argues that these adjustments are somehow subjective and may contribute to the observed bias and noise in financial analyst forecasts. Third, the decline observed in the size of the bias during recent years may not be due to managerial behaviour but to the improvement of the coverage of firms in the databases. Fourth, Kothari (2001) suspects the existence of survival biases in the data. He argues that this bias may arise because some firms go bankrupt but mostly because of mergers and acquisitions. Finally, the practice of mixing stale and recent forecasts in order to compute consensus estimates may contribute to the optimistic bias documented in past research. If analysts' proclivity to revise forecasts decreases for firms that perform poorly (e.g. firms that report poor quarterly earnings), using stale forecasts may generate an optimistic bias.

Keane and Runkle (1998) demonstrate the importance of statistical inference and data selection in testing the rationality of financial analyst forecasts. They use a Generalized Method of Moments regression methodology where they model the correlation of analyst forecast errors across firms and industries in a given period. In addition, they eliminate observations with important asset write-downs. Their results fail to reject the hypothesis of analysts' rationality.

Chapter 2: The determinants of financial analysts' forecast bias

In addition to the forecast bias documented in the literature reviewed in the previous chapter, there are two additional findings that are important to mention in order to understand the development of research conducted on financial analysts. First, some analysts present superior forecasting ability than others; see Stickel (1992) and Sinha et al. (1997) among others. This finding has important practical implications for investors who generally receive information from multiple different investment research providers. Second, the characteristics of financial analyst forecasts differ across countries; see Chang et al. (2000) and Capstaff et al. (2001). Starting from there, subsequent literature puts emphasis on three different issues:

1. What are the determinants of financial analysts' cross-sectional forecast accuracy?
2. What are the explanatory factors of financial analysts' relative forecasting performance?
3. What are the country-variables that contribute to explain international differences in analyst forecasts properties?

The objective of this chapter is to review the literature that seeks to answer these questions. The literature reviewed in Section 1 investigates the relationship between analyst forecasts and the macroeconomic situation. Section 2 is devoted to the research that examines the impact of institutional factors on financial analysts' activity. Differences in these factors at the firm-level contribute to explain differences in analyst forecast accuracy across firms (see Brown, 1997) whereas differences at the country-level provide a potential explanation for the international differences in financial analyst forecast properties. In Section 3, I review the literature relating the conflicts of interests arising from the multiple use of research and from the reliance of analysts on corporate management information. These agency problems entail optimism in analyst forecasts as well as differences in the relative performance of financial analysts. Finally, in Section 4, I review the recent body that examines the relationship between analysts' activity and their career concerns. Results drawn from this literature are important in order to understand the incentives faced by analysts and their tendency to herd. I do not review empirical studies that investigate the impact of analyst portfolio complexity and available resources on forecast-error properties. These investigations will be reviewed in details in Chapter 3 of this document.

2.1 Macroeconomic situation

As depicted in Figure 1.1, a firm's prospects are closely tied to those of the broader economy. Therefore, a "top-down" analysis of a firm's prospects must start with the global economy. Typically, brokers employ macroeconomists, sometimes called "strategists", to perform this task for a particular country or money zone. Once the prospects of the broad economy have been defined, financial analysts consider the implication of the outside environment on the industry in which the firm operates. Finally, the analyst has to consider the firm's position within the industry.

Despite the crucial importance of macroeconomic prospective for industries and firms, very little research have attempted either to examine the impact of macroeconomic fluctuations on financial analysts' activity, or to understand how financial analysts are able to incorporate macroeconomic fluctuations in their forecasts. Using I/B/E/S aggregated one-year earnings per share forecasts for the S&P 500 index, Chopra (1998) shows that analyst forecast errors are the most important when the business cycle is reversing. The same is true for financial analyst forecast dispersion. He concludes that the worst economic environment for analyst forecasts is that of an accelerating or decelerating economy. Richardson et al. (1999) investigate the behaviour of US individual analyst one-year earnings forecasts during booms and recession periods. They show that analysts are more pessimistic during boom years and overestimate earnings during recession years. Analysts have a tendency to underestimate earnings in boom years and to overestimate earnings in recession years. Consistent with the view that some industries are more sensitive to the business cycle than others, Brown (1997) shows that financial analyst forecast error differs by industry. He reports a very low forecast error for firms operating in the food and kindred products industry, which is a defensive industry. On the other hand, he reports a very high forecast error for firms operating in the oil and gas industry.

Guay et al. (2003) investigate how financial analysts incorporate macroeconomic shocks affecting individual companies into their earnings forecasts. They use three different macroeconomic risk variables: the absolute change in the level of interest rate, the absolute change in the level of foreign exchange rate, and the absolute level of the change in commodity prices. They show that analysts encounter difficulties incorporating macroeconomic shocks into their expectations. However, analysts are able to resolve part of the uncertainty created by the shocks. They attribute their finding either to analysts having incomplete information about corporate macroeconomic exposure or to analysts' failure to utilize available information about corporate risk exposure. A third reason could be that analysts face incentives that prevent them from incorporating appropriate economic information into their forecasts. Krische and Lee (2000) investigate the relation between analyst stock recommendations and several variables that have predictive power for stock returns. They find that analysts generally pay little attention to the predictive attributes of these variables.

2.2 Institutional factors

Institutional factors characterize the informational environment in which the firm evolves. Broadly speaking, these factors will influence the quality and quantity of information available to the analysts (supply side of information) as well as the demand of information on the part of investors. There are two reasons why institutional factors play an important role in the investigation of financial analyst forecast properties. First, as the major determinant of a firm's information environment, they will influence financial analyst forecast accuracy. Their influence will be either direct, through the quality and quantity of information available to the analysts, or indirect through their impact on the properties of reported earnings. Second, differences in institutional factors across countries may explain part of the documented differences in financial analyst forecasts' properties reported by international studies; see Higgins (1998), Chang et al. (2000), and Capstaff et al. (2001).

In this section, I give a description of the main institutional factors that affect a firm's informational environment and I describe their impact on this environment. Then, I review the literature that investigates the impact of these factors on earnings' properties. Finally, I review the studies that examine the direct influence of institutional factors on financial analyst accuracy. I do not review the body of research that investigates the influence of institutional factors on the market demand for information (see Lang et Lundholm, 1993; Lang et al., 2002 among others) nor do I review the branch of research that studies their impact on firms' cost of capital and value; see Miller (1999) and Foerster and Karolyi (1999) among others.

2.2.1 Institutional factors and the corporate informational environment

Three categories of institutional factors can be distinguished. First the factors related to the firm's reporting requirements. In particular, the characteristics and the flexibility of the accounting standards adopted by the company. The flexibility of the accounting standards determines the extent of reporting choices available to managers. According to Nobes and Parker (1998), management's degree of discretion entails differences in the format of financial statements, accounting principles, and disclosure level.

Second, the investor protection rules and the extent of their enforcement affect corporate policy choices; see La Porta et al. (2000). In our framework, they influence managers' reporting decisions. The threat of shareholder litigation affects the adequacy and timeliness of management's disclosures (see Skinner, 1994; Miller and Piotroski, 2000 among others). The strength of enforcement of the investor protection rules particularly influences the extent to which firms conform to the accounting regulations; see O'Brien (1998).

Third, the type of ownership structure influences the firm's informational environment. Perotti and Von Thadden (2003) develop a theoretical model that highlights the impact of the ownership structure on the information diffusion. They show that lender-dominated firms discourage informative prices. In contrast, firms dominated by shareholders encourage greater price informativeness. In other words, firms with concentrated ownership have a poorer information environment: They disclose less to the market in order to protect their vested interests and they attract less private information acquisition.

2.2.2 Institutional factors and the properties of accounting earnings

Institutional factors alter corporate reported economic performance as well as the relationship between economic income (stock price changes) and accounting earnings. Research investigating the link between institutional factors and accounting choices has either followed a firm-level approach or a country-level approach.

Abarbanell and Lehavy (2003) argue that a firm's accounting environment influences the extent to which companies engage in systematic forms of earnings management. Earnings management activities contribute to systematic errors in analyst forecasts. They show that the cross-sectional optimistic bias documented by past research is attributable to a relatively small number of observations. These observations result from extreme decreasing income strategies (big baths) on the part of firms that are not able to meet some specified earnings targets. The accounting reserves created by these decreasing income strategies will enable firms to reach relevant earnings targets in subsequent periods. Abarbanell and Lehavy's (2003) results are consistent with Burgstahler and Dichev (1997) and Degeorge et al. (1999) who show that firms pursue specific earnings threshold strategies. Leuz et al. (2003) provide comparative evidence on corporate earnings management across thirty one countries. They report systematic differences on the level of earnings management across countries. Their analysis suggests that insider economies, with concentrated ownership, weak investor-protection countries and small stock markets exhibit higher levels of earnings management than outsider countries with relatively dispersed ownership, strong investor protection and large stock markets. They conclude that there is an important link between investor protection and the quality of accounting earnings reported to market participants. Zimmermann and Gontcharov (2003) investigate the influence of accounting standards on earnings management for German firms. More precisely, they examine whether the level of earnings management differs between German firms presenting consolidated accounts under German-GAAP, IAS or US-GAAP. They find significant lower level of earnings management for firms reporting under US-GAAP. The manipulations under German-GAAP and IAS are shown to be the same.

Capstaff et al. (2001) argue that the level of association between stock returns and accounting earnings may influence the incentives that financial analysts have in order to produce accurate earnings forecasts. Indeed, the potential usefulness of accurate earnings forecasts as inputs for valuation models depends heavily on the return-earnings relation or the earnings response coefficients. Alford et al. (1993) compare the informational content and timeliness of accounting earnings in several countries using the U.S. as a benchmark. Their results reveal significant differences in the timeliness and informational content of accounting earnings across countries. Accounting earnings from Australia, France, Netherlands and U.K. are more timely than US accounting earnings. On the other hand, annual accounting earnings from Denmark, Germany, Singapore, and Sweden reflect less timely or less value-relevant information than US accounting earnings. Similarly, Ball et al. (2000) show that accounting incomes in common-law countries are significantly more timely than in code-law countries.

2.2.3 Institutional factors and financial analyst accuracy

Several research investigate the (direct) impact of institutional factors on the properties of financial analyst forecasts. A few of them are conducted on a country-level. For instance, Lang and Lundholm (1996) find a positive (negative) relationship between the quality of US firms' disclosure and analyst forecast accuracy (dispersion). Most of the research in this area tries to relate the differences in analyst forecast accuracy across countries with international differences in institutional factors. Examples of such investigations are Chang et al. (2000), and Hope (2003). Chang et al. (2000) report strong positive (negative) correlations between financial analysts' accuracy (dispersion) and the quality of accounting disclosures as well. In addition, they find that forecast error is much lower in the countries with English legal code. Hope (2003) focuses on the influence of accounting-related institutional factors on financial analyst forecasts. Investigating the properties of analyst accuracy in nineteen different countries, he finds the annual report disclosure and the extent of accounting standards enforcement to be positively (negatively) correlated with forecast accuracy (dispersion). On the other hand, the degree of flexibility of accounting standards is found to be negatively (positively) associated with forecast accuracy (dispersion). Lang et al. (2003) investigate the impact of increased disclosure requirements on analysts' accuracy for non-US firms that are listed on US exchanges as American Depositary Receipts (ADRs). They report that non-US firms that are listed as ADRs display increased forecast accuracy than other non-US firms.

Overall, past research reports a positive (negative) relationship between the richness of a firm's informational environment and analyst accuracy (dispersion). This body of research also suggests that international differences in analyst forecast accuracy can be partly attributed to differences in institutional factors across countries.

2.3 Conflicts of interest faced by financial analysts

In their 2001 Investor Alert "Analyst Recommendations", the SEC's office of Investor Education and Assistance warns investors about the potential conflicts of interest faced by financial analysts: "While analysts provide an important source of information in today's market, investors should understand the potential conflicts of interest analysts may face. For example, some analysts work for firms that underwrite or own stocks in the companies they cover – either directly or indirectly, such as through employee stock-purchase pools in which they and their colleagues participate". The same report identifies six factors that may influence analysts' independence and objectivity. These factors can be broadly categorized in four different issues: (1) corporate financing business conflicts, (2) pressure from the management of the companies the analyst covers, (3) internal pressure to increase brokerage commissions, and (4) conflicts created by analyst's ownership interest in the companies.

In this section, I give a brief explanation of each of these issues and review the relevant existing academic literature associated with them. The academic literature related to conflict of interests focuses on the US market. As of today, there is no existing research that formally documents the existence of conflict of interests on other stock markets[7]. I do not review the regulatory measures that have been taken by the legislator to address these problems, nor their impact on financial analysts' activity. I let the reader refer either to Hensley and Strouse (2002) for a summary of the proposed rules aimed at solving conflicts of interest in the investment research business, or to Boni and Womack (2002) for a discussion on their implications and appropriateness.

2.3.1 Corporate financing business conflicts

As depicted in Figure 1.1, analysts may take part in investment banking deals such as IPOs and SEOs. As the SEC notes in its report on analysts: "They generally assist the investment banking team with *due diligence* research into the company, participating in investor road shows, and helping to shape the deal". For analysts participating in investment banking deals, brokerage houses' compensation arrangements link (either directly or indirectly) analysts' compensation and bonus to the number of investment banking deals in which they take part or to the profitability of the firm's corporate finance division. This gives analysts strong incentives to issue optimistic forecasts since these forecasts help the corporate finance division generate business. In particular, optimistic recommendations, before and after IPOs, increase the likelihood that the analyst's bank will be selected as underwriter for the IPO or the next security offering. Furthermore, as underlined by Michaely and Womack (1999), the underwriter generally initiates coverage for the newly issued securities in the aftermarket. It is therefore hardly believable that the underwriter's analyst will initiate coverage with a negative opinion on the newly listed firm's prospects.

Empirical evidence is consistent with the hypothesis that analysts working for companies whose employer is affiliated with a company through an underwriting relationship issue more

[7] This is merely due to the fact that, in other countries, detailed information on IPOs and SEOs has not been collected in a public database such as the SDC New Issues Database so far.

optimistic forecasts than unaffiliated analysts. Lin and McNichols (1998) show that, around SEOs, lead and co-underwriter analyst growth forecasts and recommendations are significantly more favourable than those made by unaffiliated analysts. However, they do not document a significant difference in earnings forecast accuracy between both groups of analysts. In addition, they confirm that analysts, both affiliated and unaffiliated, issue optimistic forecasts in the period preceding the equity offering in order to maintain or attract investment-banking business. Michaely and Womack (1999) examine recommendations disseminated by brokerage houses in the period following IPOs. They report that analysts employed by lead underwriter companies issue 50% more "buy" recommendations than do analysts from other brokerage firms. Dugar and Nathan (1999) and Dechow et al. (2000) also offer empirical evidence consistent with the conflicts of interest hypothesis.

2.3.2 Pressure from companies' management

The success of fundamental analysis highly depends on the accuracy and the timeliness of the information available to the analysts. In this environment, corporate management is a key source of information for the analysts. As a result, analysts cooperate with firms to gain and maintain access to the management. Analysts who do not cooperate, by issuing unfavourable forecasts, bear the risk of losing one of their most important information sources. Furthermore, investment professionals value the ability of brokerage analysts to arrange meetings for them with companies; see Boni and Womack (2001) and Dini (1999).

Lim (2001) shows that financial analysts rationally issue optimistic forecasts in order to improve management access. The extent of the bias is larger for companies presenting greater potential information asymmetries (small-size companies and companies with low analyst coverage) and for analysts who are more reliant on management access as source of company information (e.g. junior analysts). This finding appears inconsistent with recent evidence of increasingly pessimistic cross-sectional forecast errors attributed to managerial behaviour; see Richardson et al. (1999) among others. However, if managers are able to influence analysts so that they issue optimistic forecasts, there are strong reasons to believe that they may also be able to put pressure on analysts so that they reduce their earnings forecast estimates as the end of fiscal year approaches.

2.3.3 Internal pressure to increase brokerage commissions

Analysts derive part of their compensation from the brokerage business they help to generate with their research reports. The willingness to generate trading commissions provides analysts with incentives to issue optimistic forecasts as “buy” recommendations will generate more trading commissions than “sell” recommendations. Indeed, unless the client already owns the stock, he will not trade following a “sell” recommendation and only few investors are ready or able to sell short. Michaely and Womack (1999) argue that it is difficult to define analysts’ precise contribution to trading volume. However, Irvine (2001) provides empirical evidence on the relationship between trading volume and analyst coverage on the Canadian stock exchange.

2.3.4 Analysts’ ownership in the companies

Regarding this issue, the SEC notes “An analyst, other employees, and the firm itself may own significant positions in the companies analyst covers. Analysts may also participate in employee stock-purchase pools that invest in companies they cover. And in a growing trend called *venture investing*, an analyst’s firm or colleagues may acquire a stake in a start-up by obtaining discounted, pre-IPO shares. These practices allow an analyst, the firm he or she works for, or both to profit, directly or indirectly, from owning securities in companies the analyst covers”. These types of conflicts of interest is probably the one that is the easiest to understand. However, this issue remains anecdotal since no formal empirical test has, as yet, investigated the consequences of stock ownership on financial analyst forecasts.

In summary, we see that the multiple uses of research and the importance of information obtained from corporate management creates agency problems on the part of financial analysts. Crockett et al. (2003) argue that the only solution to these problems is to align analysts’ incentives with their compensation. A solution would consist in indexing analysts’ compensation arrangements on their forecast accuracy. However, as noted by Crockett et al. (2003) this issue is not obvious: “There are divergences between their [analysts’] success at picking stocks and correctly forecasting earnings and other fundamentals. During the recent boom, some stock prices appeared to move away from fundamentals, burnishing the reputation of those who were good stock pickers at the expense of who were more focused on fundamentals”. Furthermore, investment banking deals are an important source of financing for the research departments whose direct profits are less important and more difficult to measure. In this context, the issue is whether investors would be willing to pay more brokerage fees in order to receive independent research.

2.4 Analysts' career concerns

There are two major reasons why analysts' career concerns have a determinant impact on analyst accuracy. First, financial analysts' accuracy will be influenced by their incentives to forecast accurately. These incentives are highly dependent on the relation between analysts' forecasting performance and career concerns such as reputation, compensation, and career termination. Different incentives to produce accurate forecasts across international labor markets for financial analysts may also cause differences in financial analyst forecast accuracy across countries. Second, career concerns such as reputation, have been shown by academic theory (see Scharfstein and Stein, 1990; Trueman, 1994) to influence imitation or herding among financial agents. This means, herding among analysts may contribute to the optimistic bias documented by past research and to some differences in forecast accuracy among analysts. In this section, I review the literature that examines the relationship between accuracy and career concerns as well as the literature that investigates the link between analysts' career concerns (reputation) and herd behavior.

2.4.1 Analysts' career concerns and forecast accuracy

An important number of past research investigates whether relative analysts' accuracy improves as analysts age. Examples of such research include Mikhail et al. (1997), Jacob et al. (1999), and Clement (1999) for the US market as well as Clement et al. (2000) for a few non-US markets. The evidence appears mixed and sensitive to the variable used to measure financial analyst experience. However, a majority of the investigations conducted on the US market show that relative analysts' accuracy improves with age; that is, analysts have incentives to improve their accuracy during their careers. For non-US markets, a weak or insignificant relationship between analysts' experience and accuracy has been documented. Unfortunately, these studies do not consider the nature of the implicit incentives (career concerns) faced by security analysts. In other words, they do not investigate why analysts may (or may not) have interests to improve their forecast accuracy during their careers.

Stickel (1992) is the first to document a positive relationship between analysts' performance and career concerns. He finds that Institutional Investor All-American analysts, who are typically better compensated than other analysts (see Michaely and Womack, 1999 among others), provide more accurate earnings forecasts and tend to revise their recommendations more frequently than other analysts. Mikhail et al. (1999) document that poor relative performance among analysts leads to job turnover. Both studies suggest a positive relationship between forecast accuracy and positive career concerns. More recently, Hong and Kubik (2003) find that relatively accurate analysts have a greater probability of being hired by a prestigious brokerage house (i.e. to get higher compensation) than other analysts. Conversely, relatively inaccurate analysts are more likely to move down the brokerage house hierarchy. Furthermore, controlling for forecast accuracy, they find that analysts who issue relatively optimistic forecasts (forecasts greater than the consensus) are more likely to move up the brokerage house hierarchy. They conclude that brokerage houses do not only reward accurate forecasts but also relatively optimistic forecasts. This suggests that accurate analysts experience favourable job separations outcomes and that, among the group of accurate analysts, the more optimistic analysts experience even more favourable career-development outcomes.

2.4.2 Analysts' career concerns and herding

Analysts may be influenced by the recommendations of other analysts. The degree to which they are influenced may be related to their career concerns. Scharfstein and Stein (1990) suggest that analysts herd to protect their reputation. Specifically, analysts may herd because, at some stages of their careers, it is less costly for their reputation to be wrong when other analysts make the same mistake than to be wrong alone. Welch (2000) tests for herding in analysts' recommendations. He detects behaviour consistent with mutual imitation among analysts. More precisely, he reports a significant influence of the prevailing consensus on subsequent analyst forecasts. This influence is not significantly stronger when the consensus turns out to be correct in its prediction of future stock price movements suggesting that analysts herd based on little or no information. Even if he does not identify the reasons why analysts herd, his results are consistent with reputation-based theories. Hong et al. (2001) are the first to investigate whether analysts herd in order to manage their reputation. They find younger analysts to herd more (they forecast closer to the consensus) than their older counterparts. Older analysts issue more timely forecasts and revise less than younger analysts.

They conclude that the young analysts' need for preserving their reputation leads them to herd more than older analysts whose reputation is generally established. Phillips and Zuckermann (2001) also provide evidence consistent with theories relating herd behaviour and reputation. They find that Institutional Investor All-American analysts issue significantly more "sell" recommendations than other analysts. Cooper et al. (2001) report significant differences in the accuracy of lead analysts (timely analysts) and follower analysts (who are suspected to herd). They find that lead analysts provide less accurate forecasts than follower analysts. They conclude that lead analysts trade timeliness against accuracy. However, the stock price reaction following analyst forecast revisions is significantly higher for lead analysts than for followers ones. Their results suggest that herding influences the relative accuracy of financial analysts as well as the relative informativeness of their revisions.

Chapter 3: The characteristics of individual analyst forecasts in Europe

3.1 Introduction

Financial analysts, the bull market heroes, are now the principal targets for criticism. The implosion of the "technological bubble" and scandals such as Enron have led to increased attention on analysts practices by the press, regulators and even analysts' employers. Analysts' tendency to issue over-optimistic forecasts in order to attract investment banking business (see Michaely and Womack, 1999) or to maintain good relationship with firms' management (see Lim, 2001) are two stylised facts that have already been documented by academic research. Beside this, the closer examination of analysts' practices raised even more crucial questions for investors and banks: Are financial analysts really competent?[8] And, if they are, what factors drive the performance of financial analysts?

Results from the existing literature on financial analysts show that some of them are better than the others; (see Stickel, 1992, and Sinha et al., 1997 among others). Moreover, differences in analysts' performance have been shown to be partly explained by factors such as analysts' experience, portfolio complexity and resources.

Although extensive research has been made in the United States, work on analysts' forecasts in Europe is in a more nascent stage. There are at least three reasons why the characteristics of earnings' forecasts for European companies are worth to be more deeply analysed. First, not much is known about the way the European labour market for financial analysis works. More precisely, one does not know how financial analysts' compensation is related to the quality of their output (e.g. earnings forecasts or recommendations). In the U.S., analysts' compensation is generally related to the investment banking deals (mainly IPOs) to which they take part and to their external reputation. External reputation is influenced by annual polls such as the Institutional Investor's All-American Research Team poll (see Stickel, 1992). Since two of the most important criteria to obtain a high ranking in these polls are the perceived quality of earnings forecasts and stock-picking ability, US analysts have strong incentives to produce accurate earnings forecasts. In Europe, the IPO activity is lower

---

[8] For example, in an article entitled "Analysts, even worse than weatherfrogs", the German magazine "Der Spiegel" compares financial analysts' accuracy to the accuracy of weather forecasts made by frogs (see Spiegel Online, 2000).

than in the U.S. Therefore, the information generated by analysts is delivered mainly to the bank's investing customers. As research reports and recommendations are usually provided free to investor clients, analysts' activity generate little direct profit. Consequently, analysts' compensation is lower[9]. External reputation is also less important for analysts in Europe than in the U.S. Analyst rankings are in a nascent stage and far less popular than in the U.S[10]. Furthermore, existing rankings tend to focus on sell-side analysts who work for the largest Anglo-Saxon investment banks[11]. Therefore, it is hard to know whether European analysts really derive benefits from producing accurate earnings forecasts.

Second, there are still major differences in accounting practices across European countries[12] which have two important consequences on European financial analysts' activity. First, as reported by Morgan Stanley Dean Witter (1998), this constitutes a major obstacle in cross-border equity valuation. European research department being now organised by industry, most of the European analysts have to follow companies located in distinct countries which report under different accounting rules. Second, as documented by Alford et al. (1993), differences in accounting practices lead to differences in the value-relevance and the timeliness of earnings across countries. Earnings forecasts are usually used as input for valuation models by analysts and investors. Capstaff et al. (2001) argue that if earnings are weakly relevant for future returns, analysts may devote only few efforts and resources to earnings forecasting. In the same vein, if investors can not use earnings forecasts as a reliable input in their valuation models, they may attribute little importance to their accuracy in valuing the quality of their research analysts. Overall, the differences in the accounting practices under which European companies report may complicate the task of European financial analysts and influence the incentives for European financial analysts to produce accurate earnings forecasts.

---

[9] Rielle (2001) documents strong differences between remunerations of financial analysts and of portfolio managers in favor of portfolio managers. She also reports strong differences in salaries between Swiss and US financial analysts.

[10] The first Thomson – Extel ranking was published in 1997 whilst the first Institutional Investor European ranking was published in 1998.

[11] This is corroborated by an article in Le Point by Golliau (2000). About existing analysts' rankings, she writes: "Anglo-Saxon rankings have a tendency to select only… Anglo-Saxons".

[12] European listed companies of the European Union (EU) will have to adopt IAS for their group account by 2005 due to EU regulation. But, as of today, European companies are still free to report under domestic accounting rules.

Third, even if there is a trend toward the integration of European markets, stock prices still respond predominantly to domestic factors; see Isakov and Sonney (2003) and Baca et al. (2000). For U.S. stocks, Guay et al. (2003) show that analysts encounter difficulty incorporating the effects of interest rates, foreign exchange and commodity price shocks in their estimates. One can suspect that industry-specialised analysts covering stocks across different European countries face an even more complicated task. Not only are the economic shocks difficult to integrate in their estimates but, to a certain extent, these shocks differ across countries.

This paper seeks to identify the determinants of financial analysts' forecasts accuracy for 14 European financial markets. I test whether European financial analysts' forecast accuracy is linked with their experience. I investigate how portfolio complexity affects the forecast error of financial analysts in a context of increasing industry specialisation. Finally, I examine whether analysts working for prestigious brokerage houses produce more accurate forecasts than their peers.

Important differences are documented with respect to concurrent studies performed on the US market. Controlling for firm specific experience, no evidence is found about a learning effects in the financial analyst profession in Europe. I observe a negative link between forecast accuracy and the degree of international diversification of analysts' portfolios. This suggests that the synergy gains from the industry-structured research departments in Europe may be altered by the decrease in forecast accuracy due to increasing country diversification. I provide evidence that analysts employed by large brokerage houses covering Europe do not produce more accurate forecasts than their peers.

In a second set of analysis, I test whether there is a relationship between analysts' accuracy and their career prospects. I find that there is a high number of analysts who leave the profession each year and that analysts positive career development is not linked with their relative forecast accuracy. However, analysts with bad track-records are more likely to leave the profession. Thus, one can reasonably conclude that the labour market does not reward analysts who produce accurate earnings forecasts.

The paper is structured as follows. Section 2 reports the main results from previous researches. Section 3 describes the work hypothesis and empirical methodology. Section 4 gives a description of the data set. Section 5 presents the empirical results and Section 6 concludes.

3.2 Prior research

3.2.1 Differential forecast accuracy among security analysts

Stickel (1992) shows that Institutional Investor All-American Research Team analysts forecast EPS more accurately than non-All-American analysts. Their forecast bias is smaller, they produce forecasts more frequently and their forecast revisions have a greater impact on security prices. Sinha et al. (1997) document superior performance in subsequent periods for analysts who are identified as superior in a previous period. Desai et al. (2000) observe that companies recommended by Wall Street Journal All-Star analysts outperform the market. They also document a superior forecasting ability for analyst who focus on a single industry. Conversely, Jacquillat and Grandin (1994) find no evidence of differential ability among research department in France.

3.2.2 The determinants of financial analysts' forecast accuracy

Several factors have been identified as determinants of financial analysts' forecast accuracy. Examining quarterly earnings forecasts and stock recommendations, Mikhail et al. (1997) show that more experienced analysts issue more accurate forecasts and that stock prices react more strongly to their forecast revisions. Clement (1999) documents a positive relationship between analysts' relative forecast accuracy and analysts' firm-specific and general experience. Brokerage houses' research operation structure and resources are found to be related to forecast accuracy. Indeed, the author observes a positive relationship between brokerage houses' size (number of analysts employed) and forecast accuracy. He shows that forecast error increases with the number of industries and firms followed by individual analysts. Finally, he notes a negative relationship between forecast age and forecast accuracy. Brown (2001) reaches the same conclusions. In addition, he confirms the persistence in financial analysts' forecast accuracy; see also Sinha et al. (1997) for previous evidence. Jacob et al. (2000) examine the impacts of analysts' aptitude, learning-by-doing and the internal environment of the brokerage house on forecast accuracy. They find that brokerage house's characteristics and analysts' aptitude are positively correlated with forecast accuracy.

However, experience ("learning-by-doing") is no longer positively correlated with forecast accuracy once specific company-analyst alignment has been controlled for. They argue that the small but statistically significant learning effect documented by Clement (1999) may result from the survival of more clever analysts within the profession or from analysts for which the optimal company-alignment has been found. In line with Clement (1999) and Brown (2001), they find that the higher the forecast horizon, the less accurate the forecasts are. Hong et al. (2000) notice a deterioration of forecast accuracy as financial analysts age. Lim (2001) examines the relationship between analysts' characteristics and the forecast bias. He argues that more experienced analysts and analysts employed by large brokerage houses need less to cultivate management access. Consistent with this hypothesis, he finds that more experienced analysts working for important brokerage houses issue less biased forecasts. On the other hand, less experienced analysts issue rationally biased forecasts to gain management access and consideration.

Clement et al. (2000) are the first to investigate the characteristics of financial analysts' relative performance outside the US market. They document important differences between Canadian, British, Japanese, German stocks and US ones. Indeed, they show that for Japanese and German stocks, after controlling for firm-specific experience, analysts do not produce more accurate forecasts as they age. They explain their finding by the fact that the Japanese and German societies consider the employer-employee relationship like a family link in which employees do not need demonstrate a superior ability to keep their job. However, they also fail to find a link between relative accuracy and general experience on the British and Canadian markets where the employer-employee relationship is supposed to be closer to the US one. Moreover, their approach does not make a clear-cut split between local versus foreign analysts. A positive link between the size of the brokerage house and forecast accuracy is reported for Canadian and British markets but not for German and Japanese markets where analysts employed by large institutions have no advantage relative to their peers. They justify this finding by differences in corporate governance procedures between common-law countries (Canada and UK) and civil-law countries (Japan and Germany). In common-law countries, where equity is more extensively used as a source of capital, financial analysts of important brokerage houses have an advantage relative to their peers due to an extensive access to private communication with management. On the other hand, in civil-law countries, where the reliance to public external capital is more restricted, analysts who work for important brokers have less influence on stock prices and, therefore, a limited access to private communication with the management. This explanation neglects the fact that most of the big European (and Japanese) banks are universal banks. They may provide corporations with less investment banking services but they provide commercial credit facilities and other services. As such, they also have a private access to management.

As shown above, the relationship between financial analysts' experience and forecast accuracy is subject to controversial results and is highly sensitive to the methodology used to measure experience. As mentioned in the introduction, previous research shows that the findings of similar studies conducted on US stocks cannot be generalized to other countries. Although the differences between these markets have been highlighted, no credible explanation has been given yet to explain them. The present research is designed to fill, at least partly, this gap.

3.3 Hypotheses and empirical design

3.3.1 Hypotheses

- *Effects of experience on forecast accuracy*

In agreement with previous research, two measures of experience are retained: company-specific (task-specific) and general experience. Analysts' company-specific experience is measured by the accumulation of firm-specific skills over time. General experience represents the general forecasting skills and knowledge accumulated by analysts through time.

At least three reasons favour the positive relation between experience and forecast accuracy. First, "learning-by-doing" suggests a positive relationship between experience and task performance. Financial analysts' forecasting skills should improve with repetition and feedback. As mentioned by Jacob et al. (1999), the more experienced the analysts become, the more capable they should be to identify the relevant sources of information and the factors that drive a company's earnings. They must also be able to use their past forecast errors to improve their future forecasts.

Second, Lim (2001) suggests that less experienced analysts are likely to be more reliant on management relations than seasoned analysts. As a consequence, they issue more optimistic forecasts in order to cultivate management relations.

Third, if the labour market is efficient, the best performing analysts should be rewarded for their efforts and the poorest performer should be forced out of the profession. Consequently, one could expect more experienced analysts to be more accurate. Hong and Kubik (2003) show that US analysts work in an environment where their forecasting performance affects their career prospects.

Nevertheless, previous research and the context of this study also suggest some reasons to believe that analysts' forecast accuracy may not increase with forecasting experience. A primary and necessary condition for analysts to improve their forecasting skills as they age (learning effect) is that they devote sufficient effort to forecasting earnings. For this condition to be met, at least two requirements have to be satisfied. First, analysts must derive personal benefits from producing more accurate forecasts than their peers (see Holmström, 1999). Personal benefits can be either monetary or social (e.g. reputation or personal recognition). As mentioned in the introduction, little is known about the level of analysts compensation packages in the different European countries and about the relationship between their salaries and forecast accuracy. The second necessary requirement to motivate analysts to spend time and efforts on forecasting earnings is the value relevance of earnings. If earnings are only weakly related to future returns their accuracy will not be important in the eyes of investors. Consequently, the resources devoted by analysts to forecasting earnings may be less important than in the U.S.. Alford et al. (1993) and Ball et al. (2000) underline differences in the size of the relationship between security returns and annual earnings across European countries[13]. Therefore, the effort devoted by analysts to forecasting earnings may differ from those devoted by U.S. analysts and they may differ across European countries as well.

- *Effects of portfolio complexity on forecast accuracy*

Previous research show a negative association between portfolio complexity and forecast accuracy. In single-country studies, the number of companies and industries followed are used as proxies for portfolio complexity. Consistent with previous studies, a negative relationship between forecast accuracy and these two variables is expected. In this multi-country framework, the number of different countries for which financial analysts provide forecasts is added as a third proxy for portfolio complexity. A negative relationship between

[13] In both studies, the correlation between returns and earnings changes appears to be high in France and the U.K. and low in Germany. Alford et al. (1993) also document strong correlation in Netherlands whilst for other European countries correlations are relatively low.

forecast accuracy and the number of countries followed is assumed for two reasons. First, despite the increasing importance of industry effects, country effects are still the main determinant of stock returns in Europe (see Isakov and Sonney, 2003 and Baca et al., 2000 among others). This still imperfect market integration in Europe means that, nowadays, analysing a Dutch bank still differs from analysing a German one. We conjecture that it may prove difficult for an analyst following companies in many European countries to take these different country effects into account. As a consequence, its relative performance should decrease with the number of countries in which he follows stocks. The recent transition in Europe from country to industry organised research departments may exacerbate the influence of multiple-country-following on forecast accuracy.

Second, as outlined by Hope (2003), institutional factors such as disclosure levels, degree of accounting standards' flexibility and degree of accrual accounting vary across European countries. Again, these differences, that have been shown to impact forecast accuracy, may alter the performance of analysts following companies in multiple countries since it may prove difficult for them to get familiar with each different reporting environment.

- *Effects of brokerage house's size on forecast accuracy*

There are several reasons to believe that analysts employed by prestigious brokerage houses should issue more accurate forecasts than their peers. First, large brokerage houses have the opportunity to provide their analysts with superior resources, such as information tools and administrative support, than medium and small-sized brokerage houses. Second, we expect top-tier brokerage houses to have the prestige and financial resources to attract the best analysts. Important brokerage houses are ready to pay more to hire influential financial analysts. Third, as Hong and Kubik (2003) show, poor performing analysts working for top-tier brokerage houses are more likely to be penalized by the labour market. Consequently, only the best analysts should stay in place in big brokerage houses. Fourth, Phillips and Zuckermann (2001) show that analysts who work for prestigious brokerage houses (high-status analysts) enjoy a greater degree of immunity to pressure than middle status analysts (analysts working for less prestigious brokerage houses) who have to cultivate ties with corporate executives. Indeed, they show that high-status analysts are more likely to issue SELL recommendations than financial analysts who work for less prestigious brokerage houses. Lim (2001) draws the same conclusions for earnings forecasts as he shows that analysts who work for big brokerage houses tend to issue less biased earning forecasts.

3.3.2 Measurement of dependent and independent variables

The definition of variables are similar to those used in previous research. Therefore, I only provide the reader with a short description of each variable and place in brackets the study that first suggested it.

PMAFE [Clement (1999)]: The ratio of the current year individual analyst's forecast error for a particular firm divided by the mean current-year forecast error of all analysts for the firm, minus one. It measures relative forecast accuracy.

GEXP [Lim (2001)]: The logarithm of one plus the number of consecutive years (up to the current year) during which the analyst has been supplying at least one forecast. It measures analysts' general forecasting skills.

CEXP [Lim (2001)]: The logarithm of one plus the number of consecutive years (up to the current year) during which the analyst has been supplying at least one forecast for a specific firm. It measures company-specific (task-specific) experience[14].

NCOMP [Clement (1999)]: The number of firms for which the analyst supplied at least one forecast during the current year. It measures portfolio complexity.

NSIC [Clement (1999)]: The number of two-digit SICs for which the analyst supplied at least one forecast during the current year. This variable measures industry specialisation.

NCOU [Clement et al. (2000)] : The number of two-digit I/B/E/S country codes for which the analyst supplied at least one forecast during the current year. It measures analysts portfolio's geographical diversification.

*TOP*10 [Clement (1999)]: A dummy variable set to one if the analyst is employed by a firm ranked in the top 10% during the current year and set to zero otherwise. Brokerage houses are ranked yearly with respect to the number of analysts employed. In the multiple-

[14] Clement (1999) and Jacob et al. (1999) measure job and company experience as the number of years (not the logarithm of one plus the number of years) for which the analyst has been supplying forecasts to I/B/E/S. Our empirical results are not sensitive to the choice operated for this measure.

country regressions, $TOP10$ is computed by ranking brokerage houses on an European basis whereas for the country regression they are ranked on a country basis. It proxies for the resources available to the financial analyst.

$FAGE$ [Lim (2001)]: The logarithm[15] of one plus the fraction of year separating the current-year earnings forecast made by the analyst on a specific firm from the end of fiscal year. The variable controls for forecasts' staleness.

3.3.3 Estimation methodology

The methodology described in Baltagi (2002, pp. 12-15) is applied to control for firm and year effects. Differences across firms and years can be captured by regressing each observation on the dependent variables and a dummy variable for each firm-year observation. Doing this, we control for any difference in the difficulty of forecasting earnings among firms and for changes that may affect analysts' forecasting task over time (e.g. changes in forecast technology over time). This methodology is equivalent to estimating the model with all variables adjusted by their related firm-year means. Due to the size of the sample, I use the latter approach. The estimated model is the following:

$$\begin{aligned} PMAFE_{i,j,t} = & \beta_1 \cdot DCEXP_{i,j,t} + \beta_2 \cdot DGEXP_{i,j,t} + \beta_3 \cdot DNCOMP_{i,j,t} \\ & + \beta_4 \cdot DNCOU_{i,j,t} + \beta_5 \cdot DNSIC_{i,t,t} + \beta_6 \cdot DTOP10_{i,j,t} \\ & + \beta_7 \cdot DFAGE_{i,j,t} + \varepsilon_{i,j,t} \end{aligned} \qquad (1)$$

with all variables firm-year mean adjusted (*D* stands for cross-sectionally centered). I do not include a constant term since the respective means have been subtracted from each variable. A positive (negative) value for the centered variable means that the forecast error or characteristic of analyst *i* for stock *j* is above (below) average on year *t*.

[15] Using a linear relationship between forecast age and relative forecast error in the regressions yields to the same result.

3.4 Sample selection

The individual analysts' forecasts are provided by Institutional Broker Estimate System (I/B/E/S). The Detail History File for European markets covers the period from 1987 to 1999. Since forecasts for 1987 are scarce, the sample is restricted to the 1988-1999 period. Ranked by the number of individual analyst's forecasts, I include the 14 major European markets: France, United-Kingdom, Netherlands, Germany, Sweden, Spain, Switzerland, Italy, Norway, Denmark, Finland, Belgium, Ireland and Austria. The Detail History tape also contains a Broker - Analyst file in which each individual analyst and broker is identified by a personal code valid all through the period. Thus, the analyst can still be tracked as she moves to another brokerage company. I also use the realised yearly EPS provided with the database[16]. The initial sample contains all individual analyst forecasts[17] issued between 1988 and 1999 for the above mentioned countries. Consistent with previous research, I apply the following filters to this initial sample:

1. Each forecast must be issued between the end of previous fiscal year and the current fiscal year end.[18]

2. The last forecast issued by each analyst for a given firm a given year is taken into account.

3. Analysts who appear in the database in the two initial years (1988 and 1989) are dropped from the database as well as all forecasts issued in 1988 and 1989.

4. The company for which the forecast is issued must be followed by at least three analysts.

5. Realised Earning Per Share has to be listed in the I/B/E/S Actual File.

The first requirement attempts to limit the impact of expectation management by companies' executives on our empirical results. Recent research show that managers have an

[16] Actual File lists historical reported earnings. These are entered into the database on the same basis as analyst's forecasts.

[17] It is impossible to determine the identity or experience of team members' analysts. However, our empirical results are the same if we include teams of analysts in the sample. They are available upon request by the author.

increasing tendency to manipulate analysts' expectations downward as the earning announcement date narrows (see, e.g., Aboody and Kasznik, 2000). We use the most recent forecasts before the end of current fiscal year to evaluate the analysts because we need a common time frame to compare their performance[19] (see Crichfield et al., 1978) among others. The third filter is attributable to the fact that the I/B/E/S data set is left censored. Indeed, it is impossible to compute how much experience analysts who appear in the database in 1988 have. The deletion of all forecasts issued during 1988 and 1989 enables the *CEXP* and *GEXP* to present some variability during the initial year of the final sample (1990). With fewer than three forecasts for a company, comparisons may not be meaningful, hence the fourth restriction. The final requirement is made to avoid heterogeneous data[20].

As shown in Panel B of Table 3.1, the final sample contains a total of 99'063 forecasts provided by 5'605 analysts for 2'812 different companies. The major part of the forecasts (89%) is concentrated in the last five years of the period (1995-1999). Panel C of Table 3.1 shows that more than 40% of the forecasts are produced for French and English companies. The smallest countries have few observations during the initial years. The exclusion of analysts' teams produces a strong reduction in the number of observations for the English market which is the most important in terms of forecasts number (individual analysts and teams undistinguished) in the I/B/E/S European Detail File.

---

[18] In Clement (1999), earnings forecasts are required to be issued between the end of previous fiscal year and 30 days before current fiscal year end. An additional proportion of 17.35% of the observations should be excluded by applying this more restrictive criteria. Note that our empirical results are insensitive to this restriction.

[19] Note that the obtained results are not sensitive to the chosen cut-off date.

[20] Earnings per share provided in the I/B/E/S Actual File differ slightly from the reported earnings per share, in the sense that some one-time items such as write-offs are excluded from the I/B/E/S numbers. Liu and Thomas (2000) show that the deletion of some one-time items in actual earnings as reported by I/B/E/S increases the value-relevance of earnings relative to reported earnings taken from Compustat.

Table 3.1: Sample statistics

	No. Forecasts	No. Analysts	No. Brokers	No. Firms
Panel A: Number of observations lost due to data filtering				
Initial sample of annual earnings forecasts	343'553	6'167	374	5'310
Lost observations due to:				
- Imposing 365 days and minimum forecast horizon	80'216	316	10	306
- Taking the last forecast issued by each analyst	142'847	0	0	0
- Controlling for left censoring	5'357	123	8	227
- Requiring a minimum coverage of three analysts per year	12'356	100	4	1'896
- Missing fiscal year-end earnings	3'714	23	1	69
Final sample	99'063	5'605	351	2'812
Panel B: Sample by year				
1990	703	110	30	193
1991	771	138	31	206
1992	1'525	194	38	334
1993	2'223	357	69	415
1994	5'411	700	114	669
1995	10'791	1'456	168	1'111
1996	15'701	2'113	215	1'556
1997	19'608	2'705	242	1'828
1998	20'840	3'004	253	1'974
1999	21'490	3'481	237	1'936

Table 3.1 (continued)

	No. Forecasts	No. Analysts	No. Brokers	No. Firms
Panel C: Sample by country				
France	23’872	1’418	102	442
U.K.	19’604	1’465	100	870
Netherlands	10’616	868	92	185
Germany	10’263	1’073	85	231
Sweden	6’037	815	76	181
Spain	5’768	567	75	120
Switzerland	5’476	555	74	156
Italy	4’401	617	84	135
Norway	3’119	511	57	111
Finland	2’945	450	70	104
Denmark	2’838	361	54	106
Belgium	2’790	370	60	82
Ireland	887	141	38	53
Austria	447	126	38	36

This table summarizes the number of forecasts, analysts, brokers and firms included in the sample during the period under review. Panel A presents the number of observations lost due to: maximum and minimum forecast horizon requirement; considering only the last forecast issued by each analyst; the deletion of the forecast issued by analysts who appear in the database in the two initial years (1988-1989) and the deletion of forecasts issued during the 1988-1989 period (left censoring); the elimination of the forecasts issued for companies which are followed by less than three analysts during a year; and the deletion of companies for which no fiscal year-end earnings data was available in the database. Last row of Panel A reports the total number of forecasts, total number of different analysts, brokerage houses and companies appearing in the sample. Panel B details the sample by year. *No. Forecasts* represents the number of annual earnings forecasts made each year. *No Analyst* represents the number of analyst who produced a forecast during the fiscal year *t*. *No Brokers* represents the number of banks (or brokerage companies) for which analysts work each year. *No. Firms* is the number of firms in the sample.

3.5 Empirical results

3.5.1 Descriptive statistics

- *Raw variables*

Table 3.2 shows descriptive statistics for the raw (non centered) variables[21]. Similar to the US feature, European financial analysts present an optimistic bias. On average, financial analysts stay in the sample for about two years (2.34). This is about half of what Hong et al. (2000) observe for US financial analysts. Therefore, the turnover in the profession is higher in Europe than in the US. On average, European financial analysts follow a stock during 1.75 years. This is one year less than what Hong et al. (2000) observe for US analysts. The turnover in European financial analysts' stock portfolios is yet also higher than for US analysts. This result may be related to the higher turnover in the profession but also to the restructuring of European research departments. European financial analysts cover an average of 1.5 different countries with some of them (99% percentile of the distribution) providing forecasts on seven different countries. On average, brokerage houses employ slightly more than ten analysts per year while some of the biggest employ 85 of them. There seems to be important discrepancies between the size of the brokerage houses in Europe. On one side, there are large brokerage houses that tend to employ many analysts because they do business in all types of industries and in all countries. On the other side, there are smaller brokerage houses that tend to be more numerous and more regionally focused although they also provide a diversified industry and international coverage to their clients. The number and average size of brokerage houses are in line with what Hong and Kubik (2003) document for the US, suggesting that the size of the financial analysis labour market is almost similar in these two regions.

[21] The objective is to compare the mean values with those obtained in similar studies conducted on the US market. The differenced variables used in the regressions are difficult to interpret since they represent differences from their respective means. Descriptive statistics for the differenced variables used in the regressions are available upon request by the author.

Table 3.2: Descriptive statistics for the raw variables

			Percentile				
Variable	N	Mean	1	25	50	75	99
Forecast error (%)	99'063	-2.48	-28.61	-2.79	-0.28	0.28	7.91
Company experience (years)	99'063	1.75	1.00	1.00	1.00	2.00	5.00
General experience (years)	14'258	2.34	1.00	1.00	2.00	3.00	8.00
Number of companies	14'258	6.95	1.00	2.00	5.00	10.00	31.00
Number of countries	14'258	1.48	1.00	1.00	1.00	1.00	7.00
Number of 2 digit codes	14'258	2.36	1.00	1.00	2.00	3.00	8.00
Forecast age (days)	99'063	105.47	2.00	43.00	85.00	152.00	302.00
Number of analysts by brokerage firm	1'420	10.36	1.00	2.00	6.00	11.00	84.81

This table shows descriptive statistics for the raw (not demeaned) variables. *Forecast error* represents the spread between realised earning per share for stock *j* and forecasts forecasted earning per share in year *t* deflated by the stock price at the end of year *t*. *Company experience* represents the number of years through year *t* for which an analyst provides estimates for company *j*. *General experience* represents the number of year through year *t* for which an analyst provides at least one forecast to I/B/E/S. *Number of companies* is the number of different firms for which analyst *i* provides forecasts during year t. *Number of countries* is the number of different countries for which each analyst provides forecasts during year *t. Number of 2 digit codes* is the number of different SICs codes for which each analyst provides forecasts during year *t*. *Forecast age* represents the number of days between fiscal year end and forecast date for company *j* in year *t*. *Number of analysts by brokerage firm* is the number of analysts employed by each brokerage firm during year *t*.
All mean values are statistically significant at 1% level.

On average, European financial analysts are following seven companies per year against more than nine for their US counterparts. The average number of days separating the last forecast from the end of the fiscal year exceeds 100 days; which is surprisingly high. This lack of forecasting activity could mirror the low frequency of accounting disclosures in some European countries[22]. Finally, each company is followed by an average of 9.65 analysts each year (not shown) and 28% of the analysts are employed by large brokerage houses (not shown). In summary, the turnover in the financial analysis labour market in Europe is higher than in the US. Though, the structure of the labour market does not seem to be different in these two regions. Furthermore, European financial analysts do not revise their forecasts frequently during the year.

[22] For instance, quarterly accounts are required only in Norway. French companies have to issue quarterly revenue statements whereas in other countries half year accounts are issued.

Table 3.3: Spearman rank correlation among the regression variables

	DCEXP	*DGEXP*	*DNCOMP*	*DNCOU*	*DNSIC*	*DTOP10*	*DFAGE*
PMAFE	0.011 ***	0.024 ***	-0.014 ***	0.016 ***	-0.001	0.009 ***	0.183 ***
DCEXP		0.615 ***	0.175 ***	0.036 ***	0.123 ***	-0.002	0.110 ***
DGEXP			0.273 ***	0.120 ***	0.196 ***	0.043 ***	0.117 ***
DNCOMP				0.088 ***	0.687 ***	-0.149 ***	-0.034 ***
DNCOU					-0.138 ***	0.313 ***	0.004
DNSIC						-0.201 ***	0.001
DTOP10							0.000

Table 3.3 presents the Spearman rank correlation coefficients for the differenced variables used in the regressions. *PMAFE* = difference between the absolute forecast error for analyst *i* for firm *j* at time *t* and the mean absolute forecast error for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. *DCEXP* = the number of years (including *t*) that analyst *i* supplied a forecast for firm *j* minus the average number of years analysts following firm *j* had supplied forecasts. *DGEXP* = number of years (including *t*) that analyst *i* appeared in the data set minus the average number of years analysts following firm *j* at time *t* appeared in the data set. *DNCOMP* = the number of companies followed by analyst *i* at time *t* minus the average number of companies followed by an analyst following firm *j* at time *t*. *DNCOU* = the number of different countries for which analyst *i* provided forecasts during year *t* minus the average number of countries for which analysts following firm *j* during year *t* provided forecasts. *DNSIC2* = the number of different 2 digit SICs for which analyst *i* provided forecasts during year *t* minus the average number of 2 digit SICs for which analysts following firm *j* during year *t* provided forecasts. *DBIG5* = dummy variable with value of 1 (0 otherwise) if analyst works at a brokerage house ranked among the top 5% minus the mean value of dummy variable for analysts following firm *j* at time *t*. *DFAGE* = the age of analyst *i*'s forecast minus the age of the average analysts' forecast following firm *j* at time *t*, where age is the difference in days between forecast year end date and estimation date.

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

- *Regression variables*

Table 3.3 presents the Spearman rank correlation coefficient for the regression variables. It comes out that forecast error is positively correlated with both experience variables (*DCEXP* and *DGEXP*). Forecast accuracy decreases as the number of companies (*DNCOMP*) and number of countries (*DNCOU*) increase. There is no statistically significant relationship between industry specialisation (*DNSIC*) and forecast accuracy.

Surprisingly, a positive relation is found between the size of the brokerage house (*DTOP10*) and forecast error. The lower the number of industries followed, the higher is the number of countries. This is consistent with the argument that a higher industry specialisation leads to a higher degree of geographical diversification in the portfolio. Analysts employed by large brokerage houses tend to follow a smaller number of companies and industries but in a higher number of countries. Because some variables present a high degree of correlation, the robustness of the regression results has to be carefully checked.

3.5.2 Analysts' characteristics and relative forecast bias

The coefficient estimates for equation (1) are shown in Table 3.4. Since almost 90% of the observations are concentrated within the last five years of the sample, only the 1995-1999 coefficient estimates are reported. The conclusions are only slightly modified after including the observations of the first sub-period's (1990-1994). The results, not presented here, are available upon request by the author.

Panel A of Table 3.4 reports individual annual regressions' results[23]. Three out of seven variables have coefficients that display the same sign over the whole period. Consistent with concurrent research, *DFAGE* and *DNCOU* are positive while *DCEXP* is negative; *DFAGE* being significant each year, *DNCOU* and *DCEXP* in three out of five years. Surprisingly, *DTOP10* and *DNSIC* display changing signs' coefficients over the period.

[23] The adjusted R-squared are significantly lower than they would be with classical OLS estimation since we eliminate a large source of variation by removing firm-year effects.

Table 3.4: Relative forecast error and individual analysts' characteristics

Year	*DCEXP*	*DGEXP*	*DNCOMP*	*DNCOU*	*DNSIC*	*DTOP10*	*DFAGE*	Adj. R^2	*N*
Panel A: Annual regressions									
1995	-2.26	-0.43	-0.24 *	0.84	1.50 **	9.23 ***	123.54 ***	4.17%	10'791
	-0.84	-0.20	-1.66	1.12	1.98	4.45	19.76		
1996	-4.34 **	-0.72	0.04	1.29 **	0.61	0.61 ***	4.07 ***	4.74%	15'701
	-2.12	-0.47	0.35	2.45	1.07	2.63	24.16		
1997	-1.84	1.17	0.01	0.19	-0.31	-0.69	50.55 ***	1.76%	19'608
	-1.59	1.16	0.15	0.55	-0.91	-0.67	15.99		
1998	-3.12 ***	0.66	-0.04	0.53 *	-0.23	-2.00 **	65.88 ***	3.20%	20'840
	-2.79	0.62	-0.74	1.72	-0.75	-2.12	21.50		
1999	-4.83 ***	3.54 ***	-0.19 *	1.00 **	0.94 *	1.69	110.47 ***	4.17%	21'490
	-3.25	2.70	-1.83	2.22	1.79	1.34	25.21		
Panel B: Pooled regressions									
1995-1999	-3.22 ***	1.19 **	-0.07 *	0.76 ***	0.44 **	1.63 ***	89.29 ***	3.40%	88'430
	-4.64	1.98	-1.84	3.82	2.08	2.78	47.56		
Panel C: Fama-McBeth regressions									
1995-1999	-3.28 ***	0.84	-0.08	0.77 ***	0.50	2.46	94.84 ***		5
	-5.67	1.11	-1.46	4.04	1.44	1.24	6.18		

Table 3.4 presents the regression coefficients with t-statistics below. In Panel A and B, t-statistics are based on White (1980). The t-statistics in panel C are calculated as in Fama and McBeth (1973). Panel A presents results of annual regressions. Panel B presents pooled regression coefficients estimated from 1995 to 1999. Panel C presents Fama and McBeth (1973) regression coefficients and t-statistics. All variables are defined as in Table 3.3. *PMAFE* is the independent variable. All coefficients have been multiplied by 100.
***, **, * denote significance at the 1%, 5%, and 10% levels respectively.

Panel B of Table 3.4 reports the results of the pooled regressions whilst Panel C reports time-series averages and t-statistics of the yearly coefficients computed in the style of Fama and MacBeth (1973) [24]. Consistent with Hong et al. (2000) and Jacob et al. (1999), no learning effect is detected after controlling for company-specific experience (*DCEXP*). Indeed, the coefficient associated with *DGEXP* is either positive (Panel B) or zero (Panel C).

This finding may have three origins. First, as suggested by Capstaff et al. (2001), the low value-relevance of earnings in some countries (e.g. Germany and Switzerland) may discourage analysts to spend time on earnings forecasting. This argument will be further investigated in the next sub-section. Second, the good performing analysts may be insufficiently rewarded by the labour market. This issue will be addressed more deeply in sub-section 5.4. Finally, the turnover in the profession may be so high that European analysts simply do not have time to accumulate significant experience during their careers.

Contrary to what is expected, portfolio complexity has no influence on the forecast error as the coefficient associated with the number of followed firms (*DNCOMP*) is not significant at conventional levels. This result contradicts the US evidence. One explanation could be that more skilled analysts are assigned a greater number of companies. As expected, *DNCOU* is positive and significant. This finding denotes two aspects. First, analysts active on many European markets still encounter difficulties to integrate the impact of country-factors on companies' earnings. Second, these analysts have difficulties to manage the different reporting environments that prevail across European countries. Moreover, the negative impact of country-diversification on forecast accuracy increases significantly over the period. Indeed, regressing the yearly coefficients associated to *DNCOU* on a constant term and the logarithm of a trend variable gives a positive and statistically significant value (at 1% level) for the slope coefficient. As shown in Panel C, there is no relationship between the relative forecast error and the number of industries followed by the analysts (*DNSIC*) once potential yearly correlations among residuals have been controlled for. Overall, this result is challenging for brokerage houses covering Europe that seek to optimise the structure of their research department. Actually, industry-organised research department increases the number of covered countries and, hence the forecast error. In this context, one optimal solution could consist in keeping a staff of country-specialised analysts in order to support the industry-specialised ones.

Forecast error does not decrease with the size of the brokerage house. Panel B reports a significant positive relation between forecast error and the size of the brokerage house whereas in Panel C no relationship is detected. This result is very different from those documented for the US market. Furthermore, it is inconsistent with the hypothesis that

[24] The standard error of our pooled regressions' estimates may be downwardly (upwardly) biased if regressions' residuals are positively (negatively) correlated across years. By using Fama and MacBeth (1973) regressions, we

analysts at larger firms have more resources, an easier access to managers' private information and that the largest brokerage houses employ the best analysts. Two explanations can be suggested.

First, the largest investment banks may simply not hire the most accurate analysts. This issue is investigated in sub-section 5.4. Second, for marketing reasons, smaller banks must provide international research even if they have limited resources to do it. The practical evidence suggests that, for international research, they may simply act as buy-side analysts and rely on the earnings forecasts provided by the largest banks' sell-side analysts[25]. Consequently, as suggested by Cooper et al. (2001), looking only at forecast accuracy to assess analysts' relative quality, may not be sufficient to distinguish between the performance of both groups of analysts.

Finally, potential multi-collinearity effects are examined[26]. For this purpose, I compute the variance inflation ratio (see Kennedy, 2000) and arbitrarily remove the variable with the highest score. This operation does not change the inferences associated with the explanatory variables[27]. I also remove company experience (*DCEXP*) from equation (1) since it is highly

are able to overcome this bias.

[25] This is corroborated by an article in Bilan by Vial (2002). Quoting the CEO of a Swiss private bank where the size of the team of analysts was strongly reduced, he writes: "Before, we were covering all markets. But now, we provide primary research only for the Swiss market and a limited number of European ones. For the rest, we select external research".

[26] Note that by estimating fixed effects regressions as we do, potential problems due to multi-collinearity are already partly addressed (Baltagi, 2002, pp. 5-9).

[27] I also estimate equation (1) using Generalized Method of Moments. The standard errors associated to the regression coefficients are only marginally altered by this operation and the conclusions remain the same.

correlated with general experience (*DGEXP*). Again, this operation does not alter our conclusions[28].

3.5.3 Country regressions

In order to check if there are major differences between the determinants of analysts' relative performance across European countries, I estimate equation (1) for each of the 14 countries of the sample.

[28] The coefficient associated with *DGEXP* is negative in three out of five years but its average is not statistically significant over the period.

Table 3.5: Mean value for the raw variables by country

	Mean													
Variable	France	UK	Netherlands	Germany	Sweden	Spain	Switzerland	Italy	Norway	Finland	Denmark	Belgium	Ireland	Austria
Relative forecast error (%)	-2.14	-0.56	-2.22	-2.24	-0.53	-3.77	-0.85	-7.26	-1.55	-2.81	-1.41	-3.94	-34.43	-3.49
Company experience (years)	1.31	1.66	1.80	1.43	1.76	1.85	1.80	1.59	1.74	1.67	1.69	1.70	1.79	1.51
General experience (years)	2.64	2.45	2.58	2.48	2.54	2.57	2.64	2.52	2.38	2.54	2.49	2.42	2.85	2.66
Number of companies	8.63	7.17	9.03	7.50	7.27	8.03	8.49	7.65	7.36	8.17	7.71	8.39	9.61	7.54
Number of countries	2.14	1.80	2.58	2.45	2.67	2.51	2.73	2.78	2.73	2.95	2.76	2.99	2.37	3.64
Number of 2 digit codes	2.47	1.83	2.68	2.28	2.35	2.30	2.27	2.40	2.31	2.71	2.48	2.44	2.31	2.28
Forecast age (days)	98.29	111.61	110.89	86.17	101.83	110.91	99.12	100.63	101.91	102.15	109.72	101.00	125.11	99.79
Number of analysts by brokerage firm	9.55	10.83	6.14	7.55	6.99	4.96	4.62	4.49	5.22	4.31	3.79	3.46	2.61	2.15

This table shows the mean value for the raw (not demeaned) variables for each country. All variables are defined as in Table 3.2.
All mean values are statistically significant at 1% level.

Table 3.5 reports the mean values of the raw regression variables for each country. The reported mean values are not homogeneous across European countries. Analysts following UK and Swedish shares appear to be the most accurate and those following Irish and German shares the least accurate ones[29]. Portfolio complexity and brokerage house size are negatively related to the size of the different stock markets. Analysts covering smaller countries generally follow a higher number of companies and a higher number of countries. This is consistent with the view that banks in smaller countries employ a smaller number of analysts who have to provide global European coverage for their clients. No differences can be noticed across countries for analyst' experience; figures of all countries are smaller than the US ones. Analysts following German shares appear to be the most active (the average forecast age equals 86 days) whilst those following UK and Dutch shares are the least active ones.

We run pooled regressions for each separate country separately over the 1995-1999 period[30]. The explanatory variables are the same as those used in the multi-country analysis excepting the brokerage house's size dummy variable. It is replaced by a country-based measure instead of a Europe-based one. Results for the pooled regressions are presented in Table 3.6. Consistent with the multi-country results, the coefficient associated with *DFAGE* is positive and significant for all countries. We report a significant relationship between firm-specific experience (*DCEXP*) and forecast error in France and UK as well as a marginally significant one for the Netherlands. Knowing that these countries' earnings display a high correlation with future returns, our result suggests that analysts may devote more resources to earning forecasting than those active in other countries. Unfortunately, excepting for Ireland, general forecasting experience is not significant. The relationship between the number of followed companies and relative analysts' performance is negative and significant for UK and Swedish shares whilst it is significantly positive (as expected) for Danish shares only. As expected, the signs associated to *DNCOU* and *DNSIC* are positive for almost all countries, though only marginally or not significant. Differences across countries are noticed for the coefficients associated with brokerage house's size. Analysts following UK, Swedish, Irish,

---

[29] Since I do not attempt to investigate differences in forecast accuracy among countries but rather among analysts, I let the reader refer to Hope (2003), Chang et al. (2000) and Basu et al. (1998) who examine several variables which be at the origin of differences among countries.

[30] In order to save space, results for Fama and McBeth (1973) regressions are not tabulated. The main conclusions remain the same although the statistical significance of the variables is generally weaker. Results are available upon request by the author.

and Austrian shares employed by large brokerage houses seem to produce more accurate forecasts than those employed by small- and medium-sized brokerage houses.

Table 3.6: Country regressions

Country	*DCEXP*	*DGEXP*	*DNCOMP*	*DNCOU*	*DNSIC*	*DTOP10*	*DFAGE*	Adj. R^2	*N*
France	-3.34 ***	0.76	0.08	0.81 **	0.08	-0.79	85.66 ***	3.05%	20'661
	-2.65	0.66	0.86	2.12	0.19	-0.67	23.41		
UK	-9.33 ***	2.75 *	-0.28 ***	0.80	0.62	-3.83 ***	105.34 ***	4.14%	18'907
	-5.24	1.89	-2.99	1.59	1.10	-2.98	23.49		
Netherlands	-4.07 *	3.27	0.03	1.75 ***	0.20	3.56	96.01 ***	4.10%	8'997
	-1.95	1.63	0.32	2.99	0.36	1.54	16.08		
Germany	0.04	-0.42	-0.29 *	0.86	1.07	2.52	57.58 ***	1.27%	9'159
	0.02	-0.24	-1.86	1.53	1.27	1.06	10.37		
Sweden	1.24	-0.53	-0.56 **	0.44	2.01 *	-10.35 ***	146.27 ***	8.87%	5’389
	0.39	-0.20	-2.04	0.52	1.95	-4.22	18.68		
Spain	-2.33	2.44	-0.22	1.78 **	0.40	0.92	53.62 ***	1.72%	4’859
	-0.89	1.02	-1.18	2.39	0.46	0.35	8.63		
Switzerland	-4.17	6.62 **	-0.21	0.82	0.70	3.44	88.38 ***	2.35%	4'691
	-1.21	2.15	-0.72	0.79	0.59	1.20	9.35		
Italy	-0.65	-0.08	-0.28 **	-0.16	-0.01	-0.86	20.97 ***	0.29%	3’873
	-0.26	-0.04	-2.02	-0.27	-0.02	-0.34	2.89		
Norway	-4.88	3.10	-0.18	1.63	-0.32	1.45	148.15 ***	10.69%	2’799
	-1.13	0.83	-0.47	1.46	-0.23	0.43	15.84		
Finland	-2.04	-0.53	0.33	0.40	-0.04	3.62	90.03 ***	5.84%	2’768
	-0.61	-0.18	1.20	0.48	-0.04	1.49	10.55		
Denmark	3.64	1.82	0.42	-0.80	-1.22	-0.04	90.30 ***	3.92%	2’684
	0.93	0.53	1.39	-0.69	-1.08	-0.01	9.47		
Belgium	3.05	1.64	0.01	0.83	0.21	3.08	35.09 ***	0.66%	2’427
	0.81	0.43	0.07	0.88	0.21	0.89	3.54		
Ireland	1.04	-14.67 ***	0.67	0.40	-1.63	-10.05 *	149.60 ***	10.75%	863
	0.16	-2.75	1.37	0.21	-0.91	-1.68	7.36		
Austria	-7.11	3.70	-0.19	-0.23	1.04	-13.22 *	63.33 **	1.63%	381
	-0.68	0.53	-0.12	-0.08	0.32	-1.76	2.56		

Table 3.6 presents the regression coefficients with t-statistics below for equation (1). Pooled regression coefficients estimated from 1995 to 1999 for each separate country. t-statistics are based on White (1980). All variables are defined as in Table 3.3. All coefficients have been multiplied by 100.

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

Overall, our results show that there are some differences throughout countries. Regression estimates for U.K. and Ireland present some similarities with those obtained in the U.S. This is not surprising since the UK market is the European market which is probably the most similar to the US one in terms of corporate governance system, accounting rules and job market for financial analysts. The coefficients associated with the size of the brokerage house display differences with those obtained in the multi-country regression. However, these differences across countries can not be attributed by differences in corporate governance procedures as suggested by Clement et al. (2000). U.K. and Ireland are common-law countries but Sweden and Austria are code-law ones. Other results are generally close to and consistent with the multiple-country results. However, their statistical significance is weak.

3.5.4 Are accurate forecasters rewarded?

This subsection addresses to the potential relation between the low effort devoted to earnings forecasting and the compensation system of European analysts. In other words, similar to Hong and Kubik (2003) for US analysts, I test whether analyst's career development depends on their forecast accuracy. Descriptive statistics about financial analysts' turnover and career developments are commented in order to characterize the European labour market for financial analysis. In a second step, I investigate whether this market rewards (punishes) very good (bad) performing analysts. Career concerns are measured in four ways: (1) The number of analysts who change brokerage house during a year, (2) the number of analysts who move from a low-tier brokerage house to a top-tier house during a year[31], (3) the number of analysts who move from a high status brokerage house to a low status one during a year and (4) the number of analysts who move out of the profession during a year. The first three measures are taken from Hong and Kubik (2003) whilst the fourth one is taken from Hong et al. (2000). Each year, top-tier brokerage houses are defined as a the brokerage houses which stand in the top 10% percentile with respect to the number of analysts they employ during a year[32].

[31] As underlined by Hong and Kubik (2003) and Phillips and Zuckermann (2001), there are substantial advantages from being hired by an elite brokerage house: wages are substantially higher and analysts' reputation increases due to higher media attention than in lower status houses.

[32] Hong and Kubik (2003) use two additional measures of brokerage house status: the Institutional Investor brokerage house yearly ranking and Carter-Manaster measure of investment banking hierarchy. Their results are robust to the measure employed.

- *European financial analysts' job separation measures*

Table 3.7 shows the movements in the European financial analysts business during the 1990-1999 period. About 4.14% of the analysts change brokerage houses each year. This is less than in the US where Hong and Kubik (2003) document an average of 14.32% per year. Only 1.3% of the analysts move to top-tier brokerage houses in a given year and about the same proportion move to lower status brokerage houses. This is much lower than for the U.S. where 23.73% of analysts move to high-status houses and 25.74% to low-status houses each year. These numbers suggest that movements along the brokerage houses hierarchy are much lower in Europe than in the U.S. The average number of analysts who leave the profession each year exceeds 13% with peaks at over 20% during the most recent years[33]. This explains the low level of experience documented in Table 3.2.

Table 3.7: Yearly movements of financial analysts

Year	N	Movements (%)	Up Movements (%)	Down Movements (%)	Exits (%)
1990	110	5.45	1.82	1.82	11.82
1991	139	2.17	0.72	2.17	15.94
1992	194	2.58	0.00	0.52	13.92
1993	357	2.24	0.84	0.84	9.24
1994	700	3.71	0.71	1.29	8.14
1995	1456	9.75	2.88	2.27	5.36
1996	2113	8.00	3.60	2.27	11.31
1997	2705	2.88	1.07	1.00	13.31
1998	3004	2.93	0.67	0.63	21.60
1999	3481	1.69	0.52	0.43	22.69
Average		4.14	1.28	1.32	13.33

Table 3.7 presents the percentage of analysts who move each year. *N* is the total number of analysts who produce a forecast during year *t*. *Movements* represents the percentage of analysts who changed brokerage house during year *t*. *Up Movements* represents the percentage of analysts who move from a low-status brokerage house to a high-status brokerage house during year t. *Down Movements* represents the percentage of analysts who move from a high-status brokerage house to a low-status brokerage house during year *t*. *Exits* represents the percentage of analysts who leave the profession during year *t*. The last row presents the yearly averages.

[33] Despite the fact that virtually all analysts report to I/B/E/S, I can't infer with certainty that all analysts who stop submitting forecasts to I/B/E/S leave the profession. Some of them may join a team of analysts or cover another geographic region.

Table 3.8 depicts the relationship between analysts' movements and their experience. The objective is to investigate the relationship between analysts career concerns and experience. Consistent with Hong and Kubik (2003), the percentage of analysts who move from low status to high status brokerage houses increases as financial analysts become more seasoned. The percentage of analysts who move from a top-tier brokerage house to a low-tier house also increases with experience but remains very low across all experience years. Analysts are more inclined to quit the profession during their four initial years in the business.

Table 3.8: Financial analysts movements and experience

Experience (years)	No. Analysts	Movements (%)	Up Movements (%)	Down Movements (%)	Exits (%)
1	5'553	2.22	0.77	0.56	13.67
2	3'633	4.38	1.54	1.27	17.34
3	2'353	5.44	1.32	1.27	18.40
4	1'357	5.53	2.06	1.62	14.59
5	718	6.13	2.23	1.67	12.67
6	326	7.67	2.76	2.76	15.34
7	165	5.45	3.64	3.03	9.70
8	79	8.86	3.80	2.53	22.78
9	41	4.88	2.44	2.44	9.76

Table 3.8 depicts the percentage of analysts who move during the 1990-1999 sample years with respect to their experience in the business. *Experience* is measured as the number of years through year *t* for which an analyst provides forecasts to I/B/E/S. *No. Analysts* is the total number of analysts with the corresponding years of experience in our sample. The analysts' job separation measures are defined as in Table 3.7.

- *The link between analysts' track-records and career concerns*

In order to formally test if the labour market rewards analysts for providing accurate forecasts, I investigate the relationship between the two job separation measures and forecast track-record. For that purpose, the two following probit models are estimated:

$$Prob\left[Up\ Movement_{i,t+1}=1\right]=\alpha+\beta_1\cdot TrackRec_{i,t}+\beta_2\cdot Experience_{i,t} +Control\ variables_{i,t} \tag{2}$$

$$Prob\left[Exit_{i,t+1}=1\right]=\alpha+\beta_1\cdot TrackRec_{i,t}+\beta_2\cdot Experience_{i,t} +Control\ variables_{i,t} \tag{3}$$

where:

$Up\ Movement_{i,t+1}$ = dummy variable that takes a value of one if financial analyst *i* moves to a top-tier brokerage house during year *t+1* and zero otherwise.

$Exit_{i,t+1}$ = dummy variable that takes a value of one if financial analyst *i* leaves the profession during year *t+1* and zero otherwise.

$TrackRec_{i,t}$ = dummy variable that takes a value of one if financial analyst *i*'s historical relative forecast error ranks in the top (bottom) 10% percentile during year *t* and zero otherwise. Historical relative forecast error is measured for each analyst as the average relative forecast error (*PMAFE*) during the 3 years preceding financial analyst *i*'s movement.[34]

$Experience_{i,t}$ = Number of years through *t* for which analyst *i* has been supplying at least one forecast during a year.

Following Hong and Kubik (2003), I control for the type and number of firms followed by the analyst as well as for year effects. Consequently, three *Control Variables* are added to the regression: (1) the number of firms the analyst follows during the three-year period, (2) the average coverage of the portfolio of firms that the analyst follows during the three-year period, and (3) year dummies[35]. In order to calculate each analyst's historical track-record, the sample is restricted to financial analysts with a minimum of 3 years of experience (e.g. an analyst's track-record for 1995 is its average *PMFAE* computed between 1992 and 1994). Therefore, I estimate equation (2) for 4'557 analyst/year units between 1995 and 1999 and equation (3) for 3'800 analyst/year units on the same period.

---

[34] Hong and Kubik (2003) also use a relative measure of accuracy in their study. However, they compute the average rank (in terms of forecast accuracy) of each analyst over all the shares he follows.

[35] Hong and Kubik (2003) add Brokerage house effects (dummy variable for each brokerage house) as an additional control variable. With this additional variable, the variance-covariance matrix is almost singular. For the same reason, excepting for year effects, the link between job separation and the control variables is assumed to be linear.

Rows 1 and 2 of Table 3.9 present the results for equation (2) whereas rows 3 and 4 exhibit the results for equation (3)[36]. Coefficients for equation (2) indicate that there is no link between financial analysts forecast track record and the probability of being hired by a top-tier brokerage house. High-status brokerage houses do not seem to value financial analysts' historical track-record when they hire new analysts[37]. The coefficient associated with *Experience* is significantly different from zero. Consequently, analysts who have been in the business for a longer time are more likely to be hired by a top-tier brokerage house albeit no link with forecasting skills is established. The second set of results indicate that financial analysts who produce bad forecast track-records are significantly more likely to leave the profession. Moreover, the probability of leaving the business does not decreases as financial analysts become more seasoned.

Table 3.9: Measuring the link between analysts' movements and track-record

	Track-Record			
	Top 10%	Bottom 10%	Experience	N
Up Movement	-0.07		0.15 ***	3'800
	0.17		0.03	
Exit		0.38 ***	-0.02	4'557
		0.08	0.02	

Table 3.9 presents results of logistic regressions (3) and (4). Coefficients are estimated from a sample of 4'556 analyst/year pairs between 1995 and 1999. *Up Movement* = 1 if analyst *i* moves to a top-tier brokerage house during year *t+1*, 0 otherwise. *Exit* = 1 if analyst *i* leaves the profession during year *t+1*, 0 otherwise. *Top 10%* = 1 if financial analyst *i* historical relative forecast accuracy lies in the top 10% of the distribution, 0 otherwise. *Bottom 10%* = 1 if financial analyst *i* historical relative forecast accuracy lies in the bottom 10% of the distribution, 0 otherwise. Historical relative forecast accuracy is the mean *PMAFE* for each analyst computed from year *t-2* to *t*. *Experience* = number of years (including *t*) that analyst *i* appeared in the data set. Standard-errors are shown below the coefficients. ***, **, * denote significance at the 1%, 5%, and 10% levels respectively.

In summary, only a small number of analysts who start at less prestigious brokerage houses are able to move up to prestigious ones. Top-tier brokerage houses do not value the track-record that analysts have developed in their previous positions but they consider other

[36] In agreement with Hong and Kubik (2003), we have also estimated both equations for other forecast accuracy ranks (10-25%, 25-50%, etc.). Our results show that the probability that an analyst leaves the profession decreases homogeneously with his forecast accuracy. Inversely, whatever analysts' forecast accuracy rank used, there is no relationship between analysts' track-record and the probability of being hired by a top-tier brokerage house.

[37] Note that, as suggested by an anonymous referee, the small number of analysts who move to higher-status brokerage houses each (*Up Movement = 1)* may impact on the reliability of our results.

factors related to financial analysts' experience (e.g. the network they have built during their tenure). Consequently, there is no incentive for financial analysts who seek for positive career developments to produce more accurate earnings' forecasts. This result is consistent with the US evidence documented by Hong and Kubik (2003) on their 1996-2000 sub-period. They show that accuracy matters less for analysts' career development over this period. Indeed, during the stock mania of the late 1990s, analysts may have faced pressure to promote stocks in order to generate underwriting business and trading commissions at the expense of their objectivity. The number of analysts who leave the profession each year is very important and remains important as financial analysts gain experience. Lower performing analysts are more likely to leave the market than better ones.

Collectively, the findings suggest that the labour market for financial analysis in Europe reacts asymmetrically to forecast accuracy. On one hand, it sanctions financial analysts with too bad forecast track-records. On the other hand, it does not reward analysts with excellent track-records. These results may explain two of the previous findings. First, since analysts derive no benefits from forecasting more accurately than their peers, they do not devote much effort to earnings forecasting; hence the absence of learning effects. Second, the largest banks do not hire the best analysts in terms of forecast accuracy. Consequently, despite the additional resources available to them, they do not outperform their colleagues working for smaller firms in terms of forecasting accuracy.

3.6 Conclusion

This paper investigates whether the differences in analysts' forecast accuracy can be associated with analysts' experience, task complexity, and resources availability. It focuses on yearly EPS forecasts provided by financial analysts for 2812 different European companies between 1990 and 1999. Three main factors drive the relative performance of analysts active on European markets. First, the most recent forecasts appear to be the most accurate ones. Consequently, investors using consensus forecasts or financial researchers who intend to test asset pricing and cost-of-capital models involving earnings expectations variables will get a better quality consensus and a better proxy for earnings expectations by giving higher (lower) weight to the most recent (oldest) forecasts. Second, the lower the number of countries followed by an analyst, the more accurate she is. Therefore, a research department where company coverage is organised by industry may actually not be optimal in the European context since synergies gained from covering stocks in the same industry may be more than offset by the difficulty to produce forecasts for a portfolio of firms from different countries. Finally, a positive relationship is reported between analysts' relative performance and the number of years he follows a firm. However, this result is mainly driven by analysts following UK shares suggesting that low effort may be devoted to earnings forecasting in countries where earnings display low relevance for stock returns.

Beside this, this study documents important differences relative to concurrent researches that have been performed on the US market. No relationship is found between forecast accuracy and the seniority of financial analysts. This result could be attributed to the lack of implicit incentives for analysts to produce good forecast track records in Europe during the period. No difference is noticed between the relative performance of analysts working for large brokerage houses and other analysts. This is not consistent with common wisdom that attributes more resources, more private access to management and more ability to the analysts who work for the largest banks.

This study also raises several questions which are worth to be investigated by further research. There is a need to investigate the career concerns of European financial analysts in more details. More precisely, it would be interesting to examine whether there are other factors that impact on European analysts career development and whether these factors differ across the European countries. The important turnover detected in the European investment research community is an other important source of investigation. Why are European analysts moving out of the profession so quickly? A better understanding of the reasons which move analysts out of the profession would enable banks to give analysts the right incentives to stay. In turn, this would certainly increase the quality of the output produced by European financial analysts. Finally, it would be very interesting to complete the kind of investigation presented in this paper with additional performance criterion; for instance analysts' timeliness (see Cooper et al., 2001) or price impact of forecast revisions (see Stickel, 1992)

.

Chapter 4: Who are the best? Local versus foreign analysts on Latin American emerging markets

(*In collaboration with Jean-François Bacmann*)

4.1 Introduction

Past research suggests that geographic proximity is related to information flow. However, the empirical evidence on the impact of geographic proximity on the quality of investors' information is mixed. Brennan and Cao (1997) report that US investors are less informed about foreign markets conditions than are local investors. Kang and Stulz (1997) find no evidence that foreign investors outperform in Japan. Using US mutual fund holdings, Coval and Moskowitz (2001) show that investors located near potential investments have significant informational advantages relative to the rest of the market. Choe et al. (2000) show that foreign investors on the Korean market are disadvantaged relative to domestic individual investors. Inversely, Seasholes (2000) reports that foreigners act like informed traders in emerging markets. He finds that foreign investors profits come from trading stocks of large firms with low leverage and liquid shares. Similarly, Grinblatt and Keloharju (2000) find that foreign investors on the Finnish stock market generate superior performance than local investors.

The objective of the present paper is to investigate the relative performance of local and foreign analysts on Latin American emerging markets. As such, our research directly contributes to the debate on the impact of geographic proximity on the quality of information since practical evidence suggests that foreign analysts are more distant from the firms they follow than their local counterparts. However, our investigation differs from previous research since we do not focus on the relative performance of investors but on the relative performance of individuals located at the upstream side of them.

Ex-ante, it is difficult to foresee which group of analysts is better at analyzing Latin American market companies. On one hand, foreign analysts may have superior resources and better international expertise that provide them an advantage on their local counterparts. Moreover, being more distant from the analyzed firms, they may be less subject to agency problems such as conflict of interest. On the other hand, residence may give local analysts a better access to private information. Furthermore, a better knowledge of the institutional context in which companies evolve as well as the low cultural, geographical, and lingual distance between local analysts and the firms may induce an informational advantage for local analysts.

We measure analysts' relative performance with three dimensions: (1) forecast timeliness, (2) forecast accuracy and (3) impact of forecast revisions on security prices. Latin American markets were chosen for three reasons. First, for geographical considerations, Latin American markets have always presented a great interest for US institutional investors. As a consequence, they create an important demand for financial analysts services on these markets. Second, Latin American countries are in the same time zone as the United States. Consequently, the information set available to most of the foreign analysts at a given time is the same as that available to local analysts. Finally, as underlined by Choe et al. (2002), private information is likely to be more important on emerging stock markets than on developed ones.

Our results can be summarized as follows. First, although local financial analysts appear to be more active than foreign ones, there is a strong evidence that analysts who work for foreign brokerage houses supply timelier forecasts than their local counterparts. Using Cooper, Day and Lewis. (2001, CDL thereafter) leader to follower ratio in order to distinguish between timely analysts (leaders) and less timely ones (followers), we detect a greater number of leaders among foreign analysts than among local analysts. This finding suggests that local analysts have a tendency to revise their earnings forecasts in order to accommodate the opinions of foreign analysts.

Second, we find strong evidence that foreign analysts produce less biased forecasts than local analysts. This result holds for almost all Latin American countries and is robust to the size of the companies under study. We find that lead analysts, whatever their origin, produce more accurate forecasts than other analysts suggesting that leaders have an important informational advantage over other analysts.

Finally, abnormal returns following earnings forecasts revisions suggest that foreign analysts' revisions impact prices more than local analysts' revisions. We find that foreign financial analysts' downward revisions have a significant impact on stock returns while local analysts' revisions have no impact on stock returns. This suggests that the market considers forecast revisions provided by foreign analysts as more informative than the revisions provided by their local counterparts.

Our paper complements previous research in three ways. First, we contribute to the literature on the importance of geography in economics by showing that location has an impact on the quality of the information provided by analysts. If foreign (local) investors rely mostly on foreign (local) analysts' research in order to take their investment decisions, our results may explain the superior performance of foreign investors on some markets; see Seasholes (2000) and Grinblatt and Keloharju (2000). Second, by showing that analysts' location/affiliation has a significant impact on their forecast accuracy, we contribute to the large amount of literature which investigates the origins of financial analysts forecasts' bias. Third, we provide a contribution to the research that investigates agency problems in financial analysis; see Michaely and Womack (1999) and Lin and McNichols (1998). If local banks have more commercial and investment banking relationship with local companies, the higher optimistic bias documented for local analysts may partly be caused by the conflict of interest they face. Beside their contribution to past research, our results have an important practical implication: Investors should better rely on the research produced by analysts working for foreign brokerage houses when they invest in Latin American emerging markets.

The paper proceeds as follows: Section 2 presents the data used in this study; Section 3 investigates the relative timeliness of financial analysts; Section 4 tests for differences in forecast accuracy; Section 5 investigates the impact of forecast revisions on security prices; and Section 6 concludes.

4.2 Data and overview statistics

The analysts' forecasts[38] are provided by Institutional Broker Estimate System (I/B/E/S) for 7 Latin American emerging markets: Argentina, Brazil, Chile, Colombia, Mexico, Peru

[38] Note that we make no distinction between individual analysts and team of analysts.

and Venezuela. One year earning per share (EPS) forecasts are used from 1993 to 1999. Brokers are classified as local or foreign according to their country of origin. All brokerage houses with headquarters located in one of the 7 countries under study are classified as local. Other brokerage houses are classified as foreign. Stock prices are extracted from Datastream. To be included in the sample, a forecast should meet the following conditions:

1. Realized EPS has to figure in the I/B/E/S Actual File.
2. The forecast must be issued between the end of previous fiscal year and current year earning reporting date.
3. The company for which the forecast is issued must be followed by at least 3 foreign and 3 local analysts.

Table 4.1 : Summary statistics by year

Year	No. of Forecasts		No. of Analysts		No. of Brokers		No. of Stocks
	Local	Foreign	Local	Foreign	Local	Foreign	
1993	3246	1410	158	99	44	22	151
1994	7257	3393	214	142	59	37	265
1995	7144	3664	354	206	59	41	260
1996	6709	4599	384	298	63	44	264
1997	7016	5977	341	376	59	38	295
1998	6034	5915	328	377	53	31	291
1999	4810	4423	251	287	45	21	216
Total	42216	29381	872	782	105	65	450

This table reports yearly statistics for the data. *No. of Forecasts* represents the number of annual earnings forecasts made each year. *No. of Analyst* represents the number of analysts who produced a forecast during the fiscal year *t*. The total number of analysts who produced an earning forecast during the entire period is indicated in the last row. *No. of Brokers* represents the number of banks (or brokerage companies) for which analysts work each year. The total number of brokers identified during the entire period is indicated in the last row. *No. of Stocks* is the number of firms in the sample. The total number of firms for which forecasts were produced during the period is indicated in the last row.

The last condition restricts the sample to big and medium-sized companies. The final sample includes 71'597 EPS forecasts. Table 4.1 shows that local analysts have produced 44% more forecasts than their foreign counterparts. The number of analysts and brokerage houses active on Latin American markets has sensibly increased between 1993 and 1999. This is due to the increasing coverage of the I/B/E/S database but also to the increasing attractiveness of these markets for foreign investors.

Table 4.2: Summary statistics by country and industry

Panel A: sample by country

	No. of Forecasts		No. of Analysts		No. of Brokers		No. of Stocks
	Local	Foreign	Local	Foreign	Local	Foreign	
Argentina	6060	4469	165	275	27	41	56
Brazil	16530	10193	346	394	34	47	185
Chile	3156	2373	78	191	13	29	46
Colombia	171	428	6	53	2	17	16
Mexico	15116	10320	277	384	25	44	102
Peru	1042	1237	37	139	12	34	33
Venezuela	141	361	1	81	1	20	12

Panel B: sample by industry

	No. of Forecasts		No. of Analysts		No. of Brokers		No. of Stocks
	Local	Foreign	Local	Foreign	Local	Foreign	
Finance	4822	4589	335	295	93	53	63
Consumer non-durables	6646	4020	380	242	99	50	81
Consumer services	5809	3957	324	233	87	48	54
Consumer durables	1085	559	158	84	68	28	9
Energy	1335	1041	155	116	59	37	11
Transportation	327	223	76	54	42	27	6
Technology	153	63	45	22	26	12	2
Basic industries	9'243	5758	481	348	101	54	89
Capital goods	5739	3591	389	251	87	50	66
Utilities	7057	5580	349	293	103	53	69

This table reports statistics by country and by industry. The variables are defined as in Table 4.1.

Table 4.2 shows that most of the forecasts (73%) are concentrated on Brazil and Mexico. In addition, in each country, foreign analysts tend to be more numerous than local ones. However, from Table 4.1, we see that this finding is reversed at the aggregated level. Thus, foreign analysts tend to follow several different markets while local analysts are more focused on their respective local markets. Firms from 10 different industries are represented in the sample[39]. The most important industrial sectors in terms of number of forecasts are Basic Industries with 21% of the forecasts, Utilities and Consumer Non-Durables with 18%, and

[39] The industry classification is based on the I/B/E/S industry grouping codes.

15% of the forecasts, respectively. There is no evidence that a particular industrial sector is more followed by a given group of analysts.

Non-tabulated results indicate that the average number of analysts employed by foreign brokerage houses amounts to 7.9 while it amounts to 5.5 for local ones suggesting that, on average, foreign brokerage houses are bigger than local ones[40]. Foreign analysts follow higher market value companies than local analysts. The average market value of a company followed by a foreign analyst is approximately USD 2.2 billion while it amounts to USD 1.9 billion for local analysts. This evidence is observed for each individual year. It is consistent with the hypothesis that foreign investors favor bigger companies when they invest in emerging markets. Finally, 91 different companies out of 450 have quoted American Depositary Receipts (ADR). Lang et al. (2002) show that non-U.S. companies listed on U.S. exchanges have different characteristics than other non-U.S. firms: they display greater analyst coverage and increased forecast.

Table 4.3: Frequency of forecast issuance and revision

Panel A: number of calendar days elapsed between forecasts				
	Mean	Min	Median	Max
Local analysts	76.87	1.00	65.00	358.00
Foreign analysts	79.24	1.00	66.00	372.00
Panel B: number of revisions per analyst				
	Mean	Min	Median	Max
Local analysts	1.41	0.00	1.00	23.00
Foreign analysts	1.16	0.00	1.00	11.00

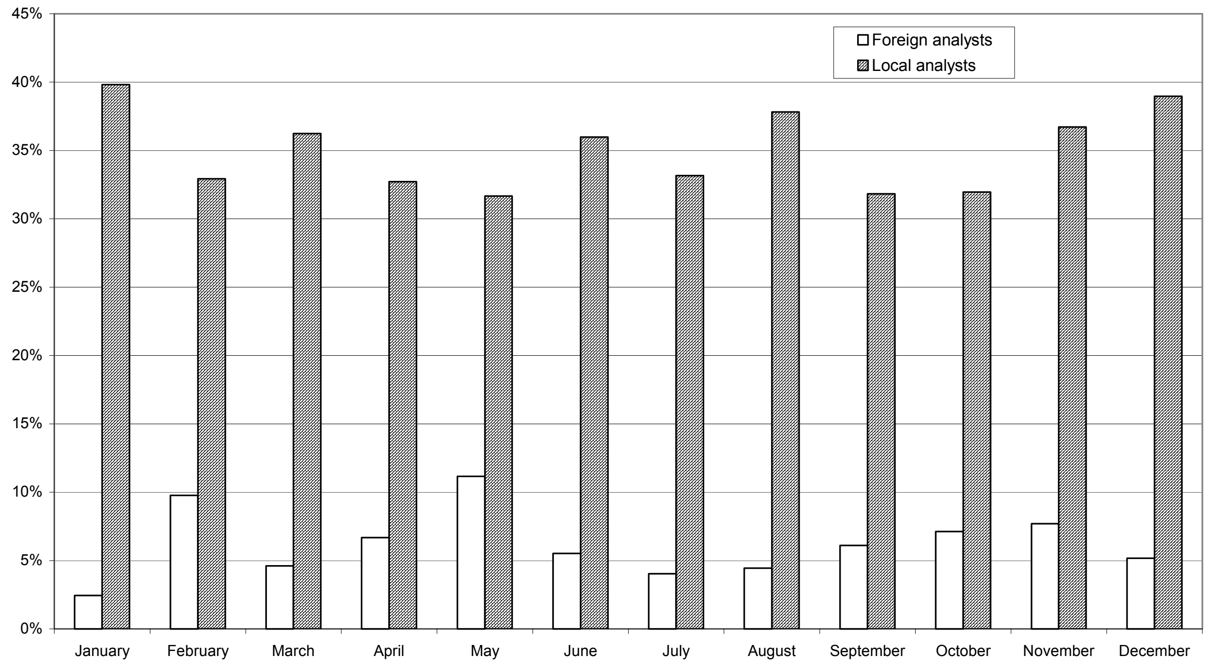
This table reports summary statistics on financial analysts' activity. Panel A presents statistics about the number of calendar days that separate two consecutive forecasts by analyst for a particular company in a given year. Panel B reports statistics on the number of revisions by analyst for a particular company in a given year.

Table 4.3 shows that local analysts are slightly more active than foreign ones. On average, they produce a forecast every 76 day while their foreign peers do it every 71 day.

[40] Previous research shows that the number of analysts is a good proxy for the size of the brokerage house; see Stickel (1995).

Local analysts revise more often than their foreign counterparts: on average 1.41 times per firm each year against 1.16 times.

Figure 4.1: Analysts' activity across the year



This figure illustrates financial analysts' average portfolio turnover by month of the year. The dashed part measures local analysts' portfolio turnover for each month of the year. The white part measures the difference between local and foreign analysts' portfolio turnover. The months of the year are represented on the *X*-axis. Portfolio turnover for a given analyst is the sum of all forecast revisions done during the month divided by the total number of companies followed.

Figure 4.1 shows financial analysts' average portfolio turnover by month of the year. The portfolio turnover for a given analyst is the sum of all forecast revisions done during the month divided by the total number of companies he follows. The turnover of local analysts is rather regular through the year. Moreover, it is greater than the turnover of foreign analysts during all months of the year. Foreign financial analyst revisions seem to follow a cyclical pattern. Analysts tend to revise more frequently during the months of January, March and July. Although the frequency of forecast revisions gives an insight on the activity of financial analysts, this does not indicate that more active analysts have advantages in collecting and processing information. They may simply change their mind several times to accommodate the opinions of others. Therefore, in the subsequent section, we propose to measure analysts' relative activity with their timeliness.

4.3 Analysts' timeliness

4.3.1 Empirical design

CDL show that timely analysts' (leaders) forecast revisions provide greater value to investors than other analysts' (followers) forecasts. They argue that timeliness is an important and necessary indicator of financial analysts' relative performance. Using forecast accuracy alone to assess the relative performance of financial analysts can lead to misclassification errors because less informed analysts can improve the accuracy of their forecasts by simply mimicking timely skilled analysts.

The leader to follower ratio developed by CDL is used to distinguish leaders from followers. This ratio is computed for each analyst/firm/year unit. It is distributed as $F_{(2KH,2KH)}$[41], where H is the number of other analysts following a particular firm in a given year and K is the total number of forecasts provided by the analyst during the year for that firm. Similar to CDL, analysts having LFR significantly greater than 1 at the 10% level are considered as leaders. Moreover, each analyst is required to produce at least 3 forecasts per year for the firm under consideration. As mentioned CDL, this restriction minimizes the possibility for an analyst to be classified as leader thanks to a single lucky forecast.

In order to test whether a group (local or foreign) tends to lead the other one, we compare the number of local leaders to the foreign ones. However, since the total number of analysts is different between the 2 groups, such a comparison is not directly possible. Thus, the proportion of leaders in a given group g, L_g, is compared to the proportion of analysts in group g in the sample, P_g. In order to determine whether a group of analysts has significantly more (less) leaders than its proportion in the population suggests, we test the following hypothesis:

$$H_0 : L_g = P_g \ vs \ H_1 : L_g \neq P_g .$$

Consequently, the following normally distributed statistic is computed:

$$Time_g = \frac{\left(L_g - P_g\right)}{\sqrt{P_g \cdot \left(1 - P_g\right)}} \cdot \sqrt{N} ,$$

[41] CDL derive the distribution of the *LFR* by assuming that the time elapsed between the arrival of two subsequent revisions follows an exponential distribution.

where:

$$L_g = \frac{Number\ of\ leaders\ in\ group\ g}{Total\ number\ of\ leaders},$$

$$P_g = \frac{Number\ of\ analysts\ from\ group\ g}{N},$$

$$N = Total\ number\ of\ analysts\ .$$

4.3.2 Results for analysts' timeliness

According to the LFR statistic, 172 leaders out of 2'203 observations are detected. This represents 118 different analysts from 52 different brokerage houses. One analyst is classified 8 times as leader whereas two analysts are classified 5 times. There are 91 out of 203 different companies for which a leader is identified.

Table 4.4 shows the breakdown of the leaders according to their origin. The proportion of local analysts within the leaders is significantly smaller than their proportion within the full sample[42]. This result suggests that, on average, foreign analysts lead while local analysts herd. Even if local analysts supply forecasts more often, their forecasts revisions do not induce other analysts to revise their own forecasts and local analysts have a tendency to issue their forecasts shortly after lead foreign analysts have issued forecast revisions.

Panel B of Table 4.4 identifies the country of origin of the leaders. Foreign analysts working for US, Dutch and German brokerage houses have a significant tendency to produce timely forecasts. On the other hand, Swiss brokerage houses' analysts have a greater tendency to herd than their peers. The more timely local analysts are from Brazil while the less timely ones are working for Mexican, Argentinean, and Chilean brokerage houses.

[42] The inverse is automatically true for foreign leaders.

Table 4.4: Financial analysts' timeliness

Panel A: local analysts' LFR vs. foreign analysts' LFR

	No. of analysts N	No. of leaders	% leaders L_g	% observations P_g	Difference
Local	1334	90	52.3	60.6	-8.2 ***
Foreign	869	82	47.7	39.4	8.2 ***
	2203	172	100.0	100.0	0.0

Panel B: LFR by analysts' country of origin

Country of origin	No. of analysts N	No. of leaders	% leaders L_g	% observations P_g	Difference
USA	399	50	29.1	18.1	11.0 ***
Mexico	705	45	26.2	32.0	-5.8 ***
Brazil	316	27	15.7	14.3	1.4 *
Netherlands	71	12	7.0	3.2	3.8 ***
Germany	73	7	4.1	3.3	0.8 **
Switzerland	240	7	4.1	10.9	-6.8 ***
Argentina	112	7	4.1	5.1	-1.0 **
Chile	154	5	2.9	7.0	-4.1 ***
	2203	172	100.0	100.0	0.0

This table reports the number of analysts identified as leaders as well as the test of the null hypothesis, which is stating that the proportion of leaders in a given group equals the proportion of analysts from the given group in the total sample. The last column represents the difference between the percentage of leaders in a given group, L_g, and the percentage of analysts from the given group, P_g. The significance of this difference is determined by the following normally distributed statistic: $Time_g = \left(\left(L_g - P_g\right) / \sqrt{P_g \cdot \left(1 - P_g\right)}\right) \cdot \sqrt{N}$. Panel A reports results for all Latin American markets. Panel B reports results by analysts' country of origin. Results for countries with less than 50 observations are not shown.
***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4.5 reports the joint distribution of local and foreign lead analysts across companies. There are some segments of the market where only leaders from a particular group can be found. Indeed, there are 37 companies out of 203 (18%) for which only local leaders are identified. Among these firms, 16 are Brazilian. The number of companies for which only foreign leaders are detected equals 24 (12%). Only a few companies (30 out of 203) exhibit leaders from both groups.

Table 4.5: Foreign and local leaders distribution across firms

	No. of local leaders					
No. of foreign leaders	0	1	2	3	4	5
0	112	33	3	0	0	1
1	17	13	4	0	0	0
2	6	3	2	2	1	0
3	1	2	0	1	0	0
4	0	1	1	0	0	0

This table reports the number of different firms for which a given number of leaders was identified. Column headers are the number of local leaders, whereas row headers corresponds to the number of foreign leaders. The elements of the table are the number of different firms for which a given number of foreign leaders is identified conditional on the fact that a given number of local leaders is identified.

In summary, the above results indicate that foreign analysts have a greater tendency to lead than local analysts. This is particularly true for U.S., Dutch and German analysts. Moreover, there are segments in the market where one category of analysts systematically leads other analysts. The implications of these findings in terms of forecast accuracy and earnings forecasts' informativeness are investigated in the following two sections.

4.4 Forecast accuracy

4.4.1 Empirical design

Forecast accuracy is the most widely used measure of the quality of an analyst's research. Indeed, the more accurate earnings forecast is, the more accurate the price extracted from any valuation model will be. Forecast accuracy is measured using the average percentage forecast error adjusted for the horizon bias[43]. Analyst i's percentage forecast error at date t is,

$$FE_{ijt} = \frac{FEPS_{it} - EPS}{|EPS|},$$

[43] Prior studies such as Kang, O'Brien and Sivaramkarishnan (1994) show that forecast bias increases with forecast horizon.

where:

$FEPS_{it} =$ analyst i's EPS forecast for company j at date t,

$EPS =$ reported earning per share at the end of the forecast horizon.

In order to correct for the horizon bias, CDL forecast accuracy regression is used. Compared to the matching forecasts methodology used by Stickel (1992), this operation is much less data-consuming and better suited for our study. Each FE_{ijt} is regressed on the length of time from forecast release to earning announcement date. The residuals from this regression are used to measure forecast accuracy. Formally,

$$FE_{ijt} = \alpha + \beta \cdot T + \varepsilon_{ijt}, \qquad (1)$$

where:

$T =$ number of days until the earnings announcement date,

$\varepsilon_{ijt} =$ residual forecast error for analyst i on firm j at date t.

The relative accuracy of each group of analysts is computed in three successive steps. First, for a given firm, the average residual forecast error is computed for each analyst,

$$MFE_{ij} = \sum_{t=1}^{K} \left| \varepsilon_{ijt} \right| \Big/ K,$$

where:

$MFE_{ij} =$ mean forecast error by analyst i for firm j,

$K =$ number of forecasts issued by analyst i for firm j during a given year.

Second, for each firm/year, individual analysts' mean forecast errors are averaged over all analysts of a given group g,

$$MGFE_{gj} = \sum_{i \in g} MFE_{ij} \Big/ N_j^g,$$

where:

$MGFE_{gj} =$ mean group forecast error for firm j,

$N =$ number of analysts from group g following firm j during a given year.

Finally, the mean difference forecast error between 2 groups is computed as

$$MDFE = \sum_{j=1}^{J} \left[MGFE_{Fj} - MGFE_{Lj} \right] \Big/ J$$

where J is the number of company/year units. In order to assess whether one group of analysts produces more (less) accurate forecasts than the other, the following hypothesis is tested:

$$H_0 : MDFE = 0 \text{ } vs \text{ } H_1 : MDFE \neq 0 .$$

A parametric mean test, a Wilcoxon sign rank test of equality of medians as well as a non-parametric binomial sign test are performed to test the hypothesis.

4.4.2 Results for forecast accuracy

Table 4.6 reports the descriptive statistics for the absolute value of percentage forecast errors. These numbers are not corrected for the horizon bias[44]. Consequently, no statistical test is run on them since it would not be accurate to compare forecasts issued at different horizons. Despite this limitation, some interesting conclusions can be drawn from this table. First, their magnitude and variability are larger than those obtained by previous studies on developed markets. This reflects the difficulty for analysts to issue forecasts in countries characterized by important potential information asymmetries and unrestrictive corporate disclosure requirements. The lower means and standard deviations obtained for American Depositary Receipts are consistent with this explanation. Second, considering the median

[44] A clear economic interpretation of horizon bias-corrected forecast errors remains so far an open question in the litterature.

forecast error across countries, there does not seem to be particular countries for which analysts produce significant more accurate forecasts.

Table 4.6: Mean absolute forecast errors

Sample	N	Analysts	Mean	Stdev	Min	Median	Max
Panel A: Forecast accuracy for Latin America							
Latin America	1741	Local	1.61	12.93	0.00	0.28	387.99
		Foreign	1.54	10.96	0.00	0.29	355.71
Panel B: Forecast accuracy by country							
Argentina	260	Local	1.47	8.32	0.00	0.23	119.01
		Foreign	1.40	7.89	0.00	0.22	112.54
Brazil	667	Local	1.52	10.87	0.00	0.30	250.22
		Foreign	1.48	7.84	0.00	0.35	141.75
Chile	180	Local	0.94	3.07	0.00	0.26	32.76
		Foreign	0.88	3.28	0.00	0.18	38.87
Mexico	461	Local	1.54	9.58	0.00	0.29	170.05
		Foreign	1.47	7.17	0.00	0.30	108.90
Peru	113	Local	1.04	2.87	0.01	0.29	23.47
		Foreign	0.98	2.50	0.00	0.32	18.74
Colombia	39	Local	0.25	0.40	0.01	0.14	2.22
		Foreign	0.33	0.62	0.00	0.15	3.75
Venezuela	20	Local	0.59	1.13	0.02	0.21	5.19
		Foreign	0.58	0.96	0.00	0.30	4.40
Panel C: Forecast accuracy by company characteristics							
High MV	594	Local	1.34	16.25	0.00	0.19	387.99
		Foreign	1.44	15.50	0.00	0.21	355.71
Small MV	576	Local	2.26	13.33	0.00	0.43	250.22
		Foreign	2.02	9.39	0.00	0.51	141.75
ADR	330	Local	0.87	1.93	0.00	0.22	16.58
		Foreign	0.83	1.90	0.00	0.21	17.64
Panel D: Forecast accuracy for leaders							
Leaders	84	Local	0.77	1.94	0.00	0.20	15.45
	77	Foreign	0.78	1.81	0.00	0.20	10.62

This table reports descriptive statistics for the absolute forecast errors (abs[*FEPS*]). Panel A presents descriptive statistics on absolute forecast error for all Latin American countries. Panel B reports statistics for individual countries. Panel C reports statistics on forecast errors for different companies' characteristics while Panel D presents descriptive statistics for companies for which a leader is identified. Market values are computed in USD. High market value (MV) companies are companies with fiscal year end market capitalization located in the top 33% of the distribution. Small market value (MV) companies are companies with fiscal year end market capitalization located in the bottom 33% of the distribution. The identity of the companies with American Depositary Receipts as well as their first quotation date were taken from the New York Stock Exchange web site (http//www.nyse.com/listed). Note that the forecast errors are not corrected for the horizon bias.

Third, consistent with previous research on developed markets (see Brown, 1997), financial analysts seem to produce more accurate forecasts for higher market capitalization companies. Finally, leaders' earnings forecasts are more precise and display less dispersion.

The slope coefficient of equation (1) equals 0.01 and is significantly different from zero[45]. Emerging market analysts' bias decreases significantly with the distance between forecast release date and earnings announcement date. The intercept is not statistically different from zero.

Hypothesis tests and descriptive statistics for the mean difference forecast errors ($MDFE$) are reported in Table 4.7. Panel A reports the differences in $MDFE$ between local and foreign analysts for the whole sample as well as for each country. Except for Brazil and Venezuela, the average $MDFE$'s are positive implying that foreign analysts outperform local analysts. This average is statistically significant in Columbia and only marginally in Mexico. However, looking at the distribution of $MDFE$'s, we see that some extreme observations may bias the results of our parametric test. Therefore, a non-parametric approach appears much more appropriate. In this case, excepting for Venezuela, the null hypothesis is rejected for all countries, at conventional statistical levels. Thus, there is a strong evidence that foreign analysts are more accurate than local analysts on Latin American emerging markets. Panel B indicates that the superior ability of foreign analysts to predict firms earnings does not depend on size. Surprisingly, this superior ability is the lowest for American Depositary Receipts, which have a richer information environment and are the least distant firms for foreign analysts. Conflicts of interest due to increased investment and commercial banking relationship with foreign banks following U.S. exchange listing may explain this finding.

As reported in panel C, there is a strong evidence that leaders produce more accurate forecasts than follower analysts. The leader-follower criterion appears more important than the geographical one. However, no comparison is performed between local and foreign leaders as the number of firm/year units for which leaders of both types are simultaneously identified is very low. Two important conclusions can be drawn about the behavior of financial analysts on Latin American markets. First, contrary to what has been documented by CDL, leader analysts do not "trade accuracy for timeliness". Indeed, they are able to release timelier and more accurate forecasts. Second, follower analysts do not exactly reproduce the

---

[45] Results are not shown. They are available on request by the authors.

earnings per share forecasts issued by leader analysts. Even if their forecast releases closely follow leader analysts' ones, they avoid to reproduce exactly the information released by leader analysts.

Table 4.7: Financial analysts relative forecast accuracy

	Distribution of the Mean Difference Forecast Errors (*MDFE*)						Sign of *MDFE*
	N	Mean	Stdev	Min	Median	Max	% Local > Foreign
Panel A: Difference in forecast accuracy by companies' country of origin							
Latin America	1741	0.14	4.16	-97.38	0.08 ***	110.70	58.07 ***
Argentina	260	3.30	16.55	0.25	1.72 **	251.78	57.69 **
Brazil	668	-0.03	4.30	-97.38	0.07 **	31.65	56.59 ***
Chile	180	0.06	2.07	-26.16	0.15 ***	3.43	63.89 ***
Mexico	461	0.24 *	3.07	-8.49	0.06 **	60.77	55.75 **
Peru	113	0.02	1.37	-11.98	0.16 **	3.29	62.83 ***
Colombia	39	0.44 ***	0.77	-1.35	0.40 ***	3.10	76.92 ***
Venezuela	20	-0.09	0.83	-1.98	0.04	1.60	50.00
Panel B: Differences in forecast accuracy by companies' characteristics							
High Market Value	594	-0.02	4.27	-97.38	0.10 ***	31.65	59.43 ***
Small Market Value	576	0.28	5.1	-26.16	0.08 ***	110.70	56.60 ***
ADR	330	0.06	0.86	-8.10	0.06 **	7.73	55.15 *
Panel C: Differences in forecast accuracy by analysts' timeliness							
							% Leaders > Others
Local leaders vs. local followers	82	-0.38 ***	0.77	-5.23	-0.44 ***	1.11	0.24 ***
Foreign leaders vs. foreign followers	75	-0.44 ***	0.67	-2.11	-0.41 ***	1.65	0.27 ***
Local leaders vs. foreign followers	84	-0.33 ***	1.11	-6.13	-0.27 ***	4.70	0.30 ***
Foreign leaders vs. local followers	77	-0.67 ***	1.08	-6.55	-0.54 ***	0.88	0.21 ***

This table presents descriptive statistics as well as hypothesis tests for the Mean Difference in Forecast Errors (*MDFE*). In Panel A, the third column reports the average difference between local analysts' forecast errors and foreign analysts' forecast errors. Column 6 reports the median difference between local analysts' forecast errors and foreign analysts' forecast errors. Column 8 reports the percentage of firm/year units for which the average forecast error of local analysts was greater than the average forecast error of foreign ones. A parametric mean test is performed on column 3 numbers, a Wilcoxon signed rank test of equality of medians is performed on column 6 numbers, and a non-parametric sign test is performed on column 8 numbers. Panel B reports the same statistics for different companies' characteristics. In Panel C, the third column reports the mean difference in forecast error between leaders and followers. Column 6 reports the median difference between lead analysts' forecast errors and follower analysts' forecast errors. Column 8 reports the percentage of firm/year units for which the average forecast error of lead analysts was greater than the average forecast error of follower ones. The same statistical tests as in Panel A and B are performed.
***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Overall, this section shows that emerging market companies' fundamentals are predicted with a great amount of noise. In this context, foreign analysts have a better ability to analyze Latin American firms' earnings potential than their local peers. This finding shows that the information asymmetries that can arise due to the distance (geographical, cultural or lingual) between the foreign analysts and the companies is more than compensated by their resources, expertise and/or talent. These results also show that the group of analysts that revises more frequently is the less accurate one. Finally, timely analysts are the most accurate ones. Consequently, lead analysts do not give up forecast accuracy when releasing more timely forecasts.

4.5 Impact of forecast revisions on security prices

4.5.1 Empirical design

This section investigates whether one group of analysts' revisions provides more information to investors. The objective is to determine whether the stock price reaction following forecast revisions differs between the different groups of analysts. The reaction around forecast revisions for a given firm is proxied by the cumulative excess return during the forecast release period (days 0 and +1). This cumulative excess return is computed as the difference between the buy-and-hold returns for the firm's common stock and the value-weighted Datastream country index.

The incremental information content of each revision is measured by the scaled distance relative to the consensus forecast[46]. More precisely:

$$FSUR_{ijt} = \frac{FEPS_{ijt} - CF_{jt-1}}{\sigma(CF_{jt-1})}$$

where:

$FSUR_{ijt} =$ forecast surprise following analyst i's revision for firm j at date t,

$CF_{jt-1} =$ consensus EPS forecast for firm j at date $t-1$,

[46] Our results are not sensitive to the choice of the scaling factor.

$\sigma(CF_{jt-1}) =$ standard deviation of the consensus forecast[47] at date $t-1$.

The consensus forecast is based on the average of the forecasts issued by analysts (excluding analyst i) during the 2 months preceding date t. Each analyst is required to provide at least 3 forecasts per year for the firm and each consensus forecast is required to contain at least 3 individual forecasts.

The impact of forecast revisions on security prices is measured by the following cross-sectional regression equations:

$$CAR_{jt} = \beta_0 + \beta_1 FSUR_{ijt} + \beta_2 LNSIZE_{jt} + \beta_3 LOC_i + \varepsilon_{jt}\,, \tag{2}$$

$$CAR_{jt} = \beta_0 + \beta_1 FSUR_{ijt} + \beta_2 LNSIZE_{jt} + \beta_3 LEAD_i + \varepsilon_{jt}\,, \tag{3}$$

$$CAR_{jt} = \beta_0 + \beta_1 LOC_i \times FSUR_{ijt} + \beta_2 FOR_i \times FSUR_{ijt} + \beta_3 LNSIZE_{jt} + \varepsilon_{jt}\,, \tag{4}$$

where:

$CAR_{jt} =$ cumulative excess return for firm j during the forecast release period (days 0 and +1),

$LNSIZE_j =$ logarithm of the market value (in USD) of common stock at fiscal year end,

$LOC_i =$ dummy variable set to 1 if analyst i is a local one and 0 otherwise,

$LEAD_i =$ dummy variable set to 1 if analyst i is a leader and 0 otherwise,

$FOR_i =$ dummy variable set to 1 if analyst i is foreign and 0 otherwise.

Equations (2) and (3) measure the abnormal return associated with the different groups of analysts' forecast revisions. Equation (4) measures the proportion of abnormal return explained by local and foreign analysts' forecast revisions. The size variable is a proxy for the

[47] Similar to Stickel (1992), a standard deviation less than 0.25 is arbitrarily set to 0.25 to mitigate small denominators. Our results are not affected by this operation.

differences in firms' information environment[48] but also for foreign investors' ownership since they tend to concentrate their investments on high-capitalization liquid firms.

4.5.2 Results for the impact of forecast revisions on security prices

Table 4.8 reports the mean cumulative abnormal return during the forecast release period. The price reaction depends on the size of the revision. Strong downward revisions as well as bottom 50% revisions display statistically significant price reactions. Conversely, top 50% and strong upward revisions do not impact on prices. This is consistent with Stickel (1992, 1995) who documents a non-linear relation between forecast revisions and price reactions. Therefore, the regressions are restricted to revisions of a given magnitude.

Table 4.8: Stock price reactions following forecast surprises

	All FSUR	Bottom 10%	Bottom 50%	Top 50%	Top 10%
Mean (%)	-0.06 **	-0.24 **	-0.11 ***	0.00	-0.01
Standard deviation (%)	4.69	5.08	4.74	4.65	4.63
N	26027	2603	13019	13019	2603

This table reports some descriptive statistics about the cumulative abnormal returns (CARs) following forecasts' revisions. Cumulative abnormal returns are computed as the difference between the buy-and-hold return for the firm's common stock and the value-weighted Datastream country index during the forecast release period (days 0 and 1). The column All FSUR reports statistics on CARs for all forecast surprise level. Bottom 10% reports CARs for forecast surprises located in the top 10% of the distribution. Bottom 50% reports statistics for CAR's located in the bottom 50% of the distribution. In the column Top 50%, statistics are reported for CAR's located in the top 50% of the distribution. Top 10% reports statistics for CAR's located in the top 10% of the distribution.
***, **, * denote significance at the 1%, 5%, and 10% levels respectively.

Results for the cross-sectional regressions (2), (3) and (4) are reported in Table 4.9. First, the impact of revisions on prices is larger for bigger firms. This differs from what has been found on developed markets. Small firms are probably characterized by low foreign investor

48 Stickel (1995), among others, reports that buy and sell recommendations induces a greater price reaction for smaller companies than for larger ones.

following and low liquidity. This may prevent prices from integrating new information releases quickly[49].

[49] The same analysis was conducted using days 0 to 5 cumulative excess returns. The main conclusions remain the same.

Table 4.9: The relation between stock price reactions and analysts' origin

Panel A: $CAR_{jt} = \beta_0 + \beta_1 FSUR_{ijt} + \beta_2 LNSIZE_{jt} + \beta_3 LOC_i + \varepsilon_{jt}$

FSUR Cut-off	β_0	β_1	β_2	β_3	N
Bottom 10%	-1.626 ***	0.096 **	0.237 ***	-0.011	2603
	(-2.966)	(1.968)	(3.236)	(-0.054)	
Bottom 50%	-0.943 ***	0.093 ***	0.142 ***	-0.102	13019
	(-4.387)	(2.756)	(4.780)	(-1.208)	
Top 50%	-0.336	-0.009	0.059 **	-0.111	13019
	(-1.590)	(-0.370)	(2.053)	(-1.333)	
Top 10%	-1.225 **	-0.003	0.189 ***	-0.143	2603
	(-2.439)	(-0.103)	(2.778)	(-0.777)	

Panel B: $CAR_{jt} = \beta_0 + \beta_1 FSUR_{ijt} + \beta_2 LNSIZE_{jt} + \beta_3 LEAD_i + \varepsilon_{jt}$

FSUR Cut-off	β_0	β_1	β_2	β_3	N
Bottom 10%	-1.641 ***	0.096 **	0.238 ***	0.125	2603
	(-3.114)	(1.963)	(3.253)	(0.223)	
Bottom 50%	-1.008 ***	0.093 ***	0.144 ***	-0.236	13019
	(-4.857)	(2.750)	(4.846)	(-1.016)	
Top 50%	-0.419 **	-0.008	0.062 **	-0.165	13019
	(-2.068)	(-0.318)	(2.150)	(-0.681)	
Top 10%	-1.326 ***	-0.002	0.193 ***	-0.497	2603
	(-2.749)	(-0.056)	(2.844)	(-0.953)	

Panel C: $CAR_{jt} = \beta_0 + \beta_1 LOC_i \times FSUR_{ijt} + \beta_2 FOR_i \times FSUR_{ijt} + \beta_3 LNSIZE_{jt} + \varepsilon_{jt}$

FSUR Cut-off	β_0	β_1	β_2	β_3	$\beta_1 = \beta_2$	N
Bottom 10%	-1.657 ***	0.065	0.169 **	0.246 ***	2.396	2603
	(-3.149)	(1.244)	(2.491)	(3.355)		
Bottom 50%	-1.017 ***	0.068 *	0.138 ***	0.144 ***	1.417	13019
	(-4.901)	(1.711)	(2.715)	(4.870)		
Top 50%	-0.405 **	-0.036	0.002	0.061 **	0.622	13019
	(-1.992)	(-0.831)	(0.085)	(2.102)		
Top 10%	-1.309 ***	-0.015	0.001	0.191 ***	0.089	2603
	(-2.672)	(-0.280)	(0.031)	(2.802)		

This table presents the coefficients obtained by regressing the cumulative abnormal returns following forecast revisions on the magnitude of the revision, firm size, and dummy variables indicating analysts' status. Revisions are dated within the firm's current fiscal year over the 1993-1999 period. CAR_{jt} is the cumulative abnormal return to security i during the release period (days 0 and +1). $FSUR_{ijt}$ is the forecast surprise following analyst i's revision at date t. $LNSIZE_{jt}$ is the natural logarithm of the market value (in USD) of common stock at fiscal year end. FOR_i is a dummy variable that takes a value of 1 if analyst i is employed by a foreign brokerage house and 0 otherwise. LOC_i is a dummy variable that takes a value of 1 if analyst i is employed by a local brokerage house and 0 otherwise. $LEAD_i$ is a dummy variable that takes a value of 1 if analyst i is a leader and 0 otherwise. In the fifth column of panel C, a F test is performed to test the equality of β_1 and β_2. All coefficients are multiplied by 100. T-statistics are based on White (1980). For each regression the adjusted R^2 are less than 0.01.
***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Second, there is a statistically significant relation between forecast surprise and price reaction for large downward and bottom 50% revisions (see panel A and B). Third, panel A shows that the intercept of cross-sectional equation (2) does not differ between local and foreign analysts. This is also the case for leader and follower analysts (see panel B). Fourth, panel C reports that there is a strong link between downward revisions (bottom 10% and bottom 50%) by foreign analysts and cumulative abnormal returns. This link is not found when looking at local analysts. Moreover, the regression coefficient for large downward foreign analysts' revisions is 2.6 times larger than for local analysts. The market incorporates the information embedded in foreign analysts' revisions. Conversely, the information included in local analysts' forecasts is not taken into account by the market. However, the equality of the coefficients cannot be rejected by the F-tests. Finally, for the top 50% as well as for the top 10% (large upward revisions) cut-offs, there is no price reaction at all. For all revision levels, cumulative excess returns following forecast releases are bigger for larger firms.

Overall, this section shows that the incremental information contained in large downward and bottom 50% forecasts revisions by foreign analysts has a significant impact on stock prices. On the other hand, prices do not react to forecasts revisions issued by local analysts. This result is consistent with the findings of the two previous sections: foreign analysts produce more accurate and timelier forecasts than local ones. As a consequence, the unexpected component of their forecasts, measured by the forecast surprises, has a greater impact on excess stock return than the corresponding forecast surprises for local analysts. The market does not seem to consider forecasts issued by leader analysts as being more informative than those issued by other analysts. However, the scarcity of the observations for which a leader could be identified (972 revisions out of 31'439) may be at the origin of this finding. Finally, there is evidence that emerging market investors take into account financial analysts' tendency for overconfidence. Indeed, prices do not react to large upward revisions at all.

4.6 Conclusions

Foreign financial analysts' EPS forecasts are more timely and more accurate than local financial analysts' forecasts. Building on CDL methodology, 172 leader analysts are identified. Out of these 172 leaders, 82 are foreign. This is significantly greater than the proportion of foreign analysts' forecasts in the sample. Conversely, local analysts display a significant tendency to follow the “crowd”. The fact that only a few local and foreign leaders are identified simultaneously for a given firm indicates that local and foreign leaders leads other analysts on specific segments of the market. This is particularly true for local analysts on the Brazilian market. Except for Venezuela, foreign analysts are more accurate in each individual country. Considering all countries, foreign financial analysts’ forecasts are more precise in 58% of the cases.

In terms of security price, stocks react negatively to downward revisions released by foreign analysts. There is no price reaction following local financial analysts’ revisions. Nevertheless, the evidence is mixed to the extent that the coefficients associated to foreign and local analysts’ forecast surprises are not statistically different. Forecasts issued by leaders do not have any significant additional impact on security prices. However, this finding may be due to the low weighting of leaders’ revisions in the whole sample.

Overall, the consistency between the results given by the various performance measures indicates that there is no reason to question the superior performance of foreign financial analysts. This superiority may be linked to the superior resources available to analysts who work for important international brokerage houses, to the better international expertise of these analysts, to their greater talent, and to conflicts of interest faced by analysts employed by local banks, which offer commercial or investment banking activities. The present results are consistent with a better information and greater sophistication on the part of foreign investors. Indeed, foreigners’ portfolio profits on emerging markets, such as those documented by Seasholes (2000), may be driven by the better ability of foreign analysts at analyzing firms’ situation for their clients. However, further research is needed to understand which category of investors (foreign or domestic) trade around foreign and local analysts’ revisions. Moreover, this study shows that financial analysts’ forecasts on Latin American emerging markets share some common properties with forecasts issued on developed markets: On average, they are too optimistic, their bias decreases as the result’s release date narrows and the forecast errors are influenced by some firm characteristics such as size, and information environment (ADR’s). Finally, the practical implication of this investigation is that investors should rely more heavily on foreign financial analysts’ forecasts than on local ones when they invest in Latin American markets.

Chapter 5: Executive Compensation and Analyst Guidance: The Link between CEO Compensation and Expectations Management

(*In collaboration with Manuel Kast*)

5.1 Introduction

Over the last decade, companies have tried particularly hard to meet analyst expectations. There has been a strong decrease in the tendency of managers to report earnings falling short of analyst estimates (Brown 2001a, Burgstahler and Eames 2001). Reporting earnings that do not fall short of analyst expectations can be achieved by two principal mechanisms. First, through the manipulation of discretionary accruals, executives are able to manage earnings in order to meet or beat analyst expectations. The second method is the induction of pessimism in analyst forecasts by providing analysts with negative clues leading to downward revisions in the consensus estimates. As a result, firms can more easily meet or beat analyst expectations. The business press is replete with articles referring to this latest practice. In a December 1998 Fortune Magazine article entitled "The Guidance Game", E. Schonfeld writes:

> *"… a company is allowed to provide the analysts with clues, or so-called guidance, about what it thinks earnings will be. The guidance number usually shows up as the consensus estimate among analysts. If the company meets or just beats the consensus, both that company and the analyst win: The stock goes up and everyone looks smart."*

Fuller and Jensen (2002) attribute the increasing tendency of managers engaging in analyst manipulation strategies to a shift in the nature of executive compensation structure. As stock options have become an increasingly important component of executive compensation, the preservation or enhancement of short term stock value around the earnings announcement has become a priority for managers. In the Business Week edition of May 24, 1998, M. Vickers corroborates this explanation:

> *"Companies need to generate positive surprises to keep not only stockholders but also stock-option holders happy – and that group is growing…"*

In this paper, we investigate whether the tendency of executives to manage analyst forecasts downward is related to the incentives provided by their compensation packages. Although past research and financial media have claimed that executives' expectations management practices are due to the increasing dependence of their compensation to the evolution of short term stock prices, to date no direct empirical tests of this relationship have been performed, taking explicitly into account the degree and nature of management's compensation and ownership exposure to their firm's stock performance.

We conduct two distinct sets of investigations. First, we identify the key components of CEO compensation contracts together with stock and option ownership, which influence the extent of analyst guidance, taking into account other firm-specific factors. We tackle this problem by considering the characteristic components of the CEO compensation package due to their differing risk and incentive profiles. We find that CEO compensation components strongly influence the propensity of managers to engage in expectations management strategies. Consistent with common wisdom, we report a strong positive relationship between the practice of analyst guidance and the value of the CEO's in-the-money exercisable options as well as one between the sensitivity of the option portfolios to stock price movements and analyst guidance. Moreover, we document a positive relationship between the percentage of shares held by CEOs and analyst guidance. Furthermore, there is a strong positive relationship between analyst guidance and the bonuses paid annually to CEOs suggesting that meeting or beating analyst expectations constitutes an important determinant of CEO performance assessment. Finally, we document a negative link between CEO base salary and analyst guidance.

Second, we examine the extent to which the stock market is able to discern any pessimistic bias in analyst consensus forecasts induced by expectations management strategies. We conduct an event study around the earnings announcement dates to measure the valuation effects induced by expectations management strategies and we investigate whether these valuation effects are related to the factors that explain the extent of analyst guidance. Similar to previous research, we find that firms which meet of beat analyst consensus forecasts display strong positive cumulative abnormal returns during the period surrounding the announcement date. However, for these firms, the market is partially able to discern analyst guidance strategies: companies that are suspected of managing analyst expectations in order to report a positive earnings surprise display a lower abnormal return at the earnings announcement than those not suspected of guiding analysts downward. Further analysis shows that this discount is significantly and positively related to the options held by the CEOs.

Our findings complement previous research in several ways. For the first time the crucial role of executive compensation in explaining analyst guidance is demonstrated. Secondly, we complement Matsumoto's (2002) analysis in which she shows that specific firm characteristics explain managerial incentives to avoid negative earnings surprises, although without including executive compensation components. In addition we provide the evidence that managers actually profit from taking actions to avoid negative earnings surprises. We also complement the results of Aboody and Kaznik (2000), who show that executives manipulate analyst expectations by rushing bad news reports in order to decrease the strike prices of their awarded options. While they consider only the impact of newly awarded options as incentives to manipulate analyst expectations we take into account explicitly the impact of all exercisable in-the-money options and share ownership. Finally, our investigation contributes to the earnings surprise literature by showing that the positive cumulative abnormal returns for firms that meet or beat analyst forecast is smaller if the firms are likely to achieve this through expectations management. This complements the results of Bartov et al. (2002), who draw identical conclusions, by using a different method to measure expectations management.

The remainder of the paper is organized as follows. In Section 2, we review the literature related to expectations management. In Section 3, we develop hypotheses concerning the cross-sectional relationship between expectations management and CEO compensation components as well as CEO stock and option ownership. Section 4 presents the sample and the empirical design. Results are provided in Section 5. The paper is concluded in Section 6.

5.2 Literature review

Three important conclusions for expectations management stand out from past research. First, reported earnings impact stock prices. Bartov et al. (2002) show that stocks of firms which meet or beat analyst forecasts command a significantly higher return at the announcement date than those with unfavorable surprises. Furthermore, they show that the cost of managing analyst expectations downward before the announcement date, is more than compensated by the stock price reaction to positive earnings surprises at the announcement date. More specifically, the stock price response to earnings announcement is 1.5 times stronger than the response to analysts' downward revisions before the announcement date in their sample. Lopez and Rees (2000) show that the firms that beat or meet analyst estimates over multiple subsequent quarters experience positive cumulative abnormal returns at the announcement date. Skinner and Sloan (2001) document that firms reporting negative surprises suffer large asymmetric market reactions compared to those reporting positive surprises; this applies in particular to growth firms.

Second, management is concerned about the evolution of short term stock prices for several reasons. As underlined by Richardson et al. (2001), managers of companies that intend to issue new equity are preoccupied with the current price level of their company as it directly impacts the amount of capital raised in the issue. Since many equity issues occur in the period following the public earnings announcement, a sharp price increase at the earnings release is particularly important for the success of such issues. Richardson et al. (2001) show that forecast pessimism prior to an earnings announcement is more common for firms that are about to issue new equity. The structure of management compensation packages is another reason why executives care about their firms' near term stock prices. Murphy (1999) documents a strong increase in option compensation for U.S. CEOs between 1991 and 1996 across all industrial sectors. He also reports a strong increase in the value of stocks held by S&P 500 CEOs over the nineties. Yermack (1997) investigates CEO timing ability with respect to corporate news announcements and finds that CEOs receive stock option awards in advance of good earnings news boosting stock prices. By the same token, earnings announcements before CEO stock option awards are less favorable on average. Yermack concludes that CEOs exert influence on the compensation committee and are therefore able to manage the timing of their awards. Aboody and Kaznik (2000) find that CEOs make opportunistic voluntary disclosure decisions that increase the value of their stock option compensation. In particular, they investigate the timing of voluntary disclosures around option awards to the CEOs of firms with fixed award schedules, and find that managers of such firms manage investor expectations downward prior to the award date, by delaying good news and rushing forward bad news. Richardson et al. (2001) show that analyst forecasts are more pessimistic for firms whose insiders are net sellers of the firm's stock in the period following earnings announcement. Managers may as well be concerned that a negative earnings surprise will affect their performance evaluation. Puffer and Weintrop (1991) find an increased probability of CEO turnover when earnings fall short of analyst expectations. In the same vein, Matsumoto (2002) shows that managers of firms with high institutional ownership are more likely to take actions to avoid negative earnings surprises. She attributes her finding to the pressure for near-term performance characterizing institutional investors. Moreover, she finds that firms relying on implicit claims with stakeholders and companies in industries with high litigation risk are more likely to take actions to avoid negative earnings surprises.

Finally, prior research concludes that managers have the ability to manage analyst forecasts. This is achieved by using numerous mechanisms, including public disclosures and non-formal communications (Rao and Sivakumar 2000) or by pressure on analysts to adjust their forecasts away from their true beliefs. A crucial input to the analyst is timely access to new information about the covered companies and, most of the time, this information is obtained from the companies themselves. Consequently, analysts have to cooperate with firms to achieve less restricted access to company management (Boni and Womack 2002). Lim (2001) argues that analysts rationally issue biased forecasts in order to obtain valuable future information from management, which is one of their key sources of information. To the extent that the analyst's employer holds large positions or maintains an investment banking relationship with the company covered, the analyst is likely subject to additional pressures regarding his forecasts. Michaely and Womack (1999) and Lin and McNichols (1998) document a systematic bias in recommendations for companies underwritten by the analyst's institution.

Overall, past research shows that there is a strong relationship between the sign of the earnings surprise and the stock price reaction at the earnings announcement, that managers have strong incentives to avoid negative surprises, and that they have the possibility to manage analysts through various information channels or by exerting pressure on analysts to issue forecasts that are compatible with managements' own objectives.

5.3 Hypothesis development

In this section, we provide a description of the various components that constitute most executive compensation packages: base salary, annual bonus, long term incentive plans, restricted stock plans, and stock option plans. Then, we develop hypotheses about the relationship between expectations management and these compensation components as an integral part of the CEO's total firm-related financial exposure.

Base salary represents the fixed component in executive contracts. Salaries are typically based on general industry salary surveys, and supplemented by detailed analysis of selected industry peers. Gao and Shrieves (2002) show that high CEO base salary decreases the incentive to engage in earnings management strategies. Since the total compensation of managers with a high base salary component is less dependent on the evolution of short term stock price, we expect managers with large base salary components to be less likely to engage in expectations management strategies. This leads to our first hypothesis.

Hypothesis 1: The relationship between the salaries paid to CEOs and expectations management is negative.

Bonus plans awarded to top executives are generally based on a single-year performance measure. Murphy (1999) reports that most companies use two or more performance measures to pay the annual bonus to top executives and almost all companies rely on some measure of accounting profits to assess performance. Previous research suggests that the difference between analysts' earnings forecasts and realized earnings serves as a measure for the board to assess management performance (Puffer and Weintrop 1991) and that analysts' earnings forecasts reflect the board of directors' expectations about future performance for their organizations (Imhoff and Lobo 1984, Fuller and Jensen 2002). Therefore, executives receiving bonus plans have an interest to keep the directors' expectations moderate (via analyst forecasts) in order to set performance thresholds relatively low. Accordingly our second hypothesis is as follows:

Hypothesis 2: The relationship between the annual bonus plans awarded to CEOs and expectations management is positive.

The structure of common long term incentive plans is similar to the structure of bonus plans, with the exception that long term incentive plans are typically based on rolling-averages of three or five-year cumulative performance. As a consequence, we expect the relationship between long term incentive plans and expectations management to be similar, but weaker than that between bonus plans and expectations management. This leads to our third hypothesis.

Hypothesis 3: The relationship between long term incentive plans awarded to CEOs and expectations management is positive.

CEO stock positions have a linear payoff with respect to the share price. As a result, we expect a positive relationship between the total value of stocks held by managers and analyst guidance. Restricted stocks are "restricted" because shares are forfeited under certain conditions typically related to employment retention. We also expect a positive relationship between restricted stocks awarded to managers and analyst guidance. However, this latter relation is expected to be weaker as our data contains the restricted stocks granted in the current fiscal year only, which may also not be at the CEO's free disposal yet.[50] Hence the fourth hypothesis states the following:

Hypothesis 4: There is a positive relationship between the stocks held by CEOs and expectations management.

Stock options provide a direct link between managerial rewards and share price appreciation. Awarded stock options are usually non-tradable, and are typically forfeited if the executive leaves the firm before vesting. Murphy (1999) documents that most options expire after ten years and are granted with strike prices equal to the "fair market value" on the date of the grant. Given the convexity of option value with respect to stock price, executives will have a strong incentive to guide analysts, particularly when the sensitivity of granted options value with respect to stock price is relatively high. This leads to the fifth hypothesis.

Hypothesis 5: There is a positive relationship between expectations management and the options held by the CEO (and their sensitivity with respect to stock price).

5.4 Sample and methodology

[50] The detailed description of the compensation variables is contained in Section 4.3.

In this section, we first describe our sample selection process. Then, we present the measurement of the variables used in this paper and report their summary statistics. Finally, we describe the methodology used to test our hypotheses.

5.4.1 Sample selection

We use data from four sources. The CEO compensation information is taken from Standard and Poor's Execucomp database. Execucomp reports components of executive compensation for approximately 1500 U.S. firms (S&P 500, S&P 400 Mid Cap, S&P 600 Small Cap) between 1992 and 2001. We obtain annual earnings forecasts from Thomson Financial's I/B/E/S historical database. Accounting data is taken from Standard and Poor's Compustat. Daily stock returns and market capitalization data are obtained from the Center of Research in Security Prices (CRSP). The initial sample contains 14'873 observations for 3'956 different firms in the Execucomp database. Firms are excluded from this initial sample if they are financial institutions (SIC codes 6000-6999), utilities (SIC codes 4800-4999), quasi-regulated industries (SIC codes 8000 and above), or if the firms have missing data in I/B/E/S, CRSP, or Compustat. We also exclude firm-year observations in which a company has incomplete or inconsistent details concerning the options granted to its CEO (e.g. missing maturity date, missing exercise price or a maturity date smaller than the grant date). We exclude as well firm-years in which a company belongs to an industry (defined by its two-digit SIC code) that contains less than 8 other companies for that year.

Finally, we exclude all observations for the years 1992 and 2001.[51] In 1992, Execucomp reports compensation data for 433 CEOs only.[52] As a result, after having filtered the data as described above, only 174 observations remain for this year. Another reason to delete this year from our sample is the fact that it was the first year in which executive compensation information had to be published in the present form and we do not want to introduce any self-selection biases in case the characteristics of the firms (not) reporting are correlated with the firm characteristics used in the construction of our explanatory variables. The final sample contains 7'787 firm-year observations.

[51] The exclusion of the observations for the year 2001 is due to the fact that we still have not received the latest update of the CRSP daily database. As soon as this is done, we will add these observations to our sample.

[52] In 1992 only S&P500 companies were included in the database.

5.4.2 Measuring expectations management

In order to measure expectations management, we adapt Matsumoto's (2002) methodology to yearly data. She defines expectations management as the difference between the last analyst consensus earnings forecast and the expected earnings per share based on a model of prior earnings and stock price changes. More formally, for each firm *i* in industry *j* during year *t*, the yearly change in earnings is modeled as a function of prior yearly change in earnings and returns cumulated over the current year:[53]

$$\frac{\Delta EPS_{ijt}}{P_{ijt-1}} = \alpha_{jt} + \beta_{1jt} \cdot \frac{\Delta EPS_{ijt-1}}{P_{ijt-2}} + \beta_{2jt} \cdot CUMRET_{ijt} + \varepsilon_{ijt}, \qquad (5)$$

where:

ΔEPS_{ijt} = earnings per share for firm *i* in two-digit SIC code *j* in year *t*, less earnings per share for the same firm one year prior, as reported by I/B/E/S.

P_{ijt} = price per share for firm *i* in two-digit SIC code *j* at the end of year *t*.

$CUMRET_{ijt}$ = cumulative daily excess return for firm *i* in four-digit SIC code *j* during year *t*. Returns are cumulated from three days after year *t-1* earnings announcement to 20 days before year *t* earnings announcement.

The model is estimated for each firm-year using all firms in that year that belong to the same two-digit SIC code. In a year, there must be at least 8 companies in a particular industry for the equation to be estimated. The parameter estimates from the prior firm-year are used to determine the expected change in earnings per share ($E[\Delta EPS]$):

$$E\left[\Delta EPS_{ijt}\right] = \left[\hat{\alpha}_{jt-1} + \hat{\beta}_{1jt-1} \cdot \frac{\Delta EPS_{ijt-1}}{P_{ijt-2}} + \hat{\beta}_{2jt-1} \cdot CUMRET_{ijt}\right] \cdot P_{ijt-1}. \qquad (6)$$

This value is then added to the previous year's earnings to obtain an estimate of the expected analyst forecast ($E[FEPS]$) for the current year's earnings:

$$E\left[FEPS_{ijt}\right] = EPS_{ijt-1} + E\left[\Delta EPS_{ijt}\right]. \qquad (7)$$

---

[53] Returns are intended to capture additional value-relevant information that an analyst might use to estimate earnings.

Finally, we compute the unexpected earnings forecast as the difference between the last consensus forecast released by analysts prior to the earnings announcement date ($FEPS$) and the expected analyst forecast computed from the model:

$$UEF_{ijt} = FEPS_{ijt} - E\left[FEPS_{ijt}\right]. \tag{8}$$

Similar to Matsumoto (2002), we define a dichotomous variable *DOWN*=1 if $UEF < 0$ indicating that analyst expectations have been managed downward, and *DOWN*=0 if $UEF \geq 0$ indicating that analyst expectations have *not* been managed downward.

In Table 5.1, we report the average value of the coefficients obtained from the industrial regressions described in equation (5) as well as the average value of their associated *t*-statistics, together with regression *R*-squareds.

Table 5.1:Summary statistics for the expectations management proxy

	Mean	Std. dev.	Average t-stat.	Q1	Median	Q3
α	0.043	0.247	1.320	-0.014	0.037	0.100
β_1	0.854	10.578	1.756	-1.700	0.178	2.231
β_2	0.543	0.631	1.988	0.283	0.393	0.542
Adj. R^2	0.292	0.211	n.a.	0.165	0.254	0.342

Reported average parameter estimates, standard deviations, and average *t*-statistics from the regression of changes in earnings per share on past changes in earnings per share and cumulative excess stock returns. The regression is estimated each year using data for all firms in the same two-digit SIC code. Altogether 269 regressions are performed for 36 different two-digit SIC code groups from 1992 to 1999.

On average, changes in earnings per share are positively and significantly associated with cumulative excess returns. Earnings per share changes are also positively associated with past changes in earnings. However, the average significance level is weaker.

5.4.3 Measuring CEO compensation components and ownership variables

We obtain the dollar value of each CEO's annual base salary, the dollar value of the CEO's annual bonus, the amount paid out to the CEO according to the company's long term incentive plans (*LTIP*), and the value of restricted shares (*RSG*) awarded during the year directly from the Execucomp database. In addition, we include the total percentage of the firm's shares held by the CEO at the end of the fiscal year ($SHARE$) to assess the impact of the total share position (as opposed to the stock grants awarded in the present year only) on expectations management. In addition we use the value of in-the-money and exercisable options (*INMONEX*) held by the CEO to measure the impact of the entire relevant option position. This item is provided by Execucomp and includes all in-the-money exercisable options from prior years' grants.

Considering the convexity of the relationship between share and option price, we should ideally compute a sensitivity measure of the INMONEX options to price movements in order to assess the exact impact of share price changes on CEO option portfolios. However, we cannot achieve this since Execucomp reports detailed characteristics (e.g. maturity, strike price) only for the options that have been granted during the current fiscal year. Therefore we compute a variable based on the average sensitivity of the latter options in the CEO's portfolio to price changes of the underlying company stock (OPTSENS) to use it as a proxy for the sensitivity of the *INMONEX* options. The sensitivity of options that have been granted to CEOs during the current fiscal year, is measured as in Core and Guay (2001). We define the sensitivity of granted options awarded to CEOs as the change in the dollar value of the holder's option for a 1% change in the stock price. We estimate the sensitivity of stock option value to stock price as the partial derivative of the option value with respect to stock price ("delta"). The option deltas are based on the Black-Scholes (1973) formula, as modified by Merton (1973) to account for dividend payments.[54] The detailed methodology as well as the parameters used to compute the value of the options awarded annually to CEOs are presented in the appendix.

[54] We are aware that the Black-Scholes approach has many limitations for executive stock options: executives are limited by institutional restrictions to hedge or arbitrage their option values in the secondary market, their options are subject to forfeiture if they leave the company, and they are not free to trade or sell their options. In addition, company executives are undiversified, with their financial as well as human capital invested disproportionately in their company. As a result, CEOs tend to exercise their options much earlier than outside investors would. However, as underlined by Core and Guay (2001), the Black-Scholes model can be considered as an accurate method to produce an instrumental variable to capture cross-sectional variation in option plan deltas.

Table 5.2: Summary statistics for CEO compensation components

	Mean	Std. dev.	Min	Q1	Median	Q3	Max
SALARY	559.552	315.819	0.000	396.677	500.000	625.000	3'654.849
BONUS	504.575	787.798	0.000	149.500	298.000	500.000	14'276.000
LTIP	127.083	649.007	0.000	0.000	0.000	0.000	15'105.000
RSG	289.089	7'446.258	0.000	0.000	0.000	0.000	650'812.050
SHARE	3.346	7.097	0.000	0.195	0.483	1.379	63.230
INMONEX	8'312.227	44'984.672	0.000	162.299	891.250	2'737.279	1'959'915.445
OPTSENS	40.892	180.398	0.000	2.974	9.491	20.742	9'993.093

SALARY is the annual base salary paid to CEOs. BONUS denotes the annual bonus paid to CEOs. LTIP is the sum paid to CEOs in a given year according to the long term incentive plan. RSG is the value of restricted shares awarded to CEOs in a given fiscal year. SHARE is the percentage of shares held by CEOs at the end of a given fiscal year. INMONEX is the value of in-the-money exercisable options held by CEOs at the end of a given fiscal year. Option sensitivity (OPTSENS) is the dollar amount of option value change if the underlying stock price moves up 1%. Except for SHR, which is expressed in percent, all variables are expressed in thousands of dollars. The total number of observations is 7'787.

Table 5.2 summarizes the CEO compensation components. The average annual base salary paid to CEOs equals 559'552 dollars. The distribution for base salary is highly skewed, some CEOs receiving nil base annual salary. The mean annual bonus paid to CEOs equals approximately 0.50 million of dollars, with a range from just 0 to more than 14 million dollars. The average value of the long term incentive plans paid to CEOs equals 127'083 dollars. Less than 33% of CEOs receive long term incentive plans. The average (median) amount of in-the-money exercisable options held by CEOs equals 8.31 (0.89) million dollars, with a range from 0 to almost 2 billion dollars. An increase in the share price by 1% leads to an average value increase of the stock options awarded annually to CEOs of 40'892 dollars. Again, this amount varies substantially across the sample observations, with a standard deviation of 180'398 dollars. The average amount of restricted stocks granted to CEOs is relatively small compared to other compensation components. Its mean is 289'089 dollars and, similar to long term incentive plans, less than 33% of CEOs receive restricted stocks. Finally, the mean (median) percentage of shares held by CEOs equals 3.35% (0.48%), with a range from 0% to 63.23%.

5.4.4 Measuring control variables

We include additional explanatory variables to control for earnings thresholds, information environment, growth prospects, and further firm-specifics that are potentially related to expectations management. Degeorge et al. (1999) suggest that executives acting in self interest and being subject to outside monitoring have strong incentives to manipulate behavioral thresholds. In their analysis of earnings per share and forecast error distributions, Degeorge et al. find evidence consistent with earnings management in order to exceed zero earnings, past earnings, and analyst expectations. We include three control variables to capture these thresholds. The indicator variable *LOSS* equals one if a particular firm reports a loss in the current fiscal year (annual Compustat item A18). *MEET* is a dummy variable that equals one if the firm's reported EPS at the announcement date meets or beats analyst expectations, as measured by the last consensus estimate prior to the announcement date. The indicator variable *INCEPS* equals one if the firm reports a positive earnings variation relative to the previous year (Compustat item A18).

A priori, the direction of these threshold variables' influence on the probability of expectations management is not unambiguous. On the one hand, meeting or beating analyst expectations leads to a significant stock price rise at the earnings announcement. Furthermore, Lopez and Rees (2000), show that this appreciation is much lower for firms that report a loss. Accordingly, the same argument could apply to firms (not) reaching positive earnings changes. Therefore, one can expect managers of firms that report a loss, that will not meet analyst expectations, or that report a fall in earnings per share to have less incentives to manage analysts. On the other hand, if managers already use *earnings* management to reach one or several of these behavioral thresholds, then the probability of executives making use of *analyst* management might decrease. Hence, the relationship between analyst guidance and *LOSS* might be positive and negative for *INCEPS* and *MEET*.

Brown and Higgins (2002) find that guidance increases with the richness of the firm's information environment. They characterize information environment as the availability and effectiveness of communication between managers and analysts and document a positive relationship between a firm's analyst coverage and the probability of expectations management. In addition they use the absolute value of the *final* forecast error as an alternative proxy for information environment and document a negative relationship between forecast error magnitude and expectations management. However, this finding is to a certain extent tautological, since forecast errors will be smaller almost by construction for firms that manage analyst expectations downward. Typically, firms that beat analyst forecasts do so by a very small amount, whereas firms whose earnings fall short of the consensus frequently do so by much larger numbers ("big baths"). We measure a firm's informational environment by using two related proxies. First, we include residual analyst coverage (*RCOV*) as proposed by

Hong et al. (2000). Residual analyst coverage is the residual from the regression of the logarithm of one plus the number of analysts following the firm on the logarithm of the market value of the company taken at the beginning of the fiscal year. The number of analysts for a particular firm-year corresponds to the number of estimates which constitute the last consensus forecast released before the earnings announcement date. Using residual coverage instead of the number of analysts following the firm provides a measure that does not serve as proxy for a firm's market capitalization. As shown by Hong et al. (2000), market value is the most important determinant of analyst coverage. Consistent with Brown and Higgins (2002), we expect a positive relationship between expectations management and analyst coverage. Our second proxy for informational environment is the absolute value of the *initial* forecast error (*IFE*). We compute it as: $|FEPS_{it}^{ini} - EPS_{it}|/P_{it}$, where $FEPS_{it}^{ini}$ is the first consensus forecast released by analysts for company *i* in year *t*, EPS_{it} is the company's actual earnings per share, and P_{it} is the company's share price at the beginning of the fiscal year. Matsumoto (2002) documents a strong negative relationship between the initial forecast error and the probability that a firm meets or beats analyst expectations.[55]

We include the market-to-book ratio (*MB*) as a proxy for the growth prospects of the firm. It is computed as the market capitalization of the company divided by its book value of assets, both taken at the beginning of the fiscal year. Prior research has found growth firms (high market-to-book ratio) to suffer large and asymmetric reactions to negative earnings surprises (Skinner and Sloan 1999). Brown (2001b) shows that growth firms have a higher probability of managing analysts compared to value firms. He accounts for this by the increase in managerial compensation in stocks and options. Due to the asymmetric market reaction to bad news, growth firm managers' portfolios will suffer a higher loss following a negative earnings surprise than those of value firm managers. Thus, if this explanation is valid, by including stock-based compensation and a proxy for growth jointly as explanatory variables for expectations management, there should not be any difference between the propensity of growth and value firms to engage in expectations management strategies. However, if the motives for growth firm managements to avoid negative surprises are not exclusively due to the structure of their management compensation, the growth proxy should remain positive and

[55] Note that Matsumoto (2002) also uses the logarithm of the firm market value as control variable for the firm information environment. Due to potential multi-collinearity problems between market capitalization and most of the compensation variables, we do not include this proxy for the informational environment. However, including the logarithm of the market value does not change any main conclusions.

significant in explaining earnings management. Matsumoto (2002) reports that firms with high growth prospects (measured by the analyst long term EPS growth consensus forecast for the firm) are more likely to take actions to avoid negative surprises.[56] Alternatively, firms in distress (with very low market-to-book) might depend particularly on short-term earnings surprises in order to obtain additional financing or signal recovery to stakeholders, which suggests a negative relationship between analyst guidance and market-to-book.

We include three additional variables to control for the value-relevance of earnings, reliance on implicit claims with stakeholders, and litigation risk. Matsumoto (2002) shows that firms with low value-relevance of earnings (i.e., firms whose future cash flows are predicted poorly by current earnings) are less likely to avoid negative earnings surprises, since market reactions are expected to be relatively moderate. We use *EARNRET* to control for the value-relevance of earnings. It is computed as the decile rank of the *R*-squared from yearly industry-specific regressions of cumulative excess returns on yearly changes in earnings.[57] Matsumoto (2002) finds that firms depending particularly on implicit claims with stakeholders are more likely to take actions to avoid negative earnings surprises. She argues that avoiding negative surprises at the earnings announcement yields more favorable terms of trade with stakeholders, such as suppliers, clients, and employees. These groups are likely to limit their assessment of a company's financial performance to reported earnings, since the financial press focuses its attention primarily on earnings announcements rather than initial analyst forecasts. We use the proxies *LABOR*, *DUR*, and *R&D*, developed by Bowen et al. (1995) to measure reliance on implicit claims. *LABOR* is a measure of labor intensity, defined as one minus the ratio of total gross property, plant, and equipment (Compustat item A7) divided by firm size, measured as total gross assets (total assets plus accumulated depreciation, depletion, and amortization with Compustat items A6 and A196 respectively). The indicator variable DUR denotes membership in the durable goods industry sectors and equals one for firms with primary (three-digit) SIC codes 150-179, 245, 250-259, 283, 301, and 324-399. *R&D* denotes research intensity, computed as annual research and development

[56] We also estimate our regression with the firm consensus long term EPS growth forecast supplied by I/B/E/S instead of *MB*. Our results are insensitive to this modification.

[57] Firms are grouped according to their two-digit SIC code. Every year, for each industry group, we regress cumulated daily excess returns (cumulated from three days after the fiscal year *t-1* earnings announcement date to 20 days before fiscal year *t* earnings announcement) on the change in earnings per share from fiscal year *t-1* to fiscal year *t,* scaled by the share price at the end of fiscal year *t-1*. We require each industry group to contain at least 8 firms. The firms with R^2s in the highest (lowest) 10% of the distribution are assigned a value of 1 (10).

expenditures (Compustat item A46) divided by total assets (Compustat item A6). Employing factor analysis with principal component factors we transform *LABOR*, *DUR*, and *R&D* into the single variable *ICLAIM*, representing reliance on implicit claims.[58]

Furthermore, a strong price drop at the earnings announcement can give rise to shareholder litigation. Therefore, firms with a higher risk of shareholders filing lawsuits may take more actions to avoid negative earnings surprises. Consistent with Francis et al. (1994), Soffer et al. (2000), Ali and Kallapur (2001), and Matsumoto (2002), we control for litigation risk by including the dummy variable *LIT* indicating whether a firm belongs an industry classified as litigious. *LIT* equals one for firms with primary SIC codes 2833-2836, 3570-3577, 3600-3674, 5200-5961, and 7370-7374 (biotechnology, electronics, retailing, and computers).

Table 5.3 displays descriptive statistics of the control variables. The mean and median of *EARNRET* with values of 6.2 and 7.0 respectively are relatively high since the industry portfolios with low *R*-squareds contain more firms on average than the industry groups with high *R*-squareds from the regressions of cumulative excess returns on annual changes in earnings. Only 8.8% of the firm-year observations are loss reporting firms. The thresholds of meeting or beating analyst forecasts and reporting increased EPS have been reached in 65% and 69% of firm-years respectively. Firms in the durable goods industries account for 42.5% of the firm-year observations, firms in litigious industries account for 34.8%. Residual analyst coverage ranges from -1.9 to 1.4 with the mean (median) of 0.003 (0.022) close to zero. Both *IFE* and *MB* display very large positive outliers. Due to the replacement of missing values with zeros, *R&D* is highly skewed as well, with about 30% of the values being zero. We use it together with *LABOR* and *DUR* to generate *ICLAIM*, which has zero mean and variance one by construction.

---

[58] Almost one third of the observations for R&D are missing. Following Bowen et al. (1995) and Matsumoto (2002) we replace missing values by the value zero. The results do not depend on this ad-hoc assumption. We also perform all regressions with *LABOR*, *DUR*, and *R&D* jointly and individually included as additional explanatory variables. The coefficients of *DUR* and *R&D* are never significantly different from zero. Only *LABOR* is (highly) significant and positive, thus behaving identically as *ICLAIM*.

Table 5.3: Summary statistics for control variables

	Mean	Std. dev.	Min	Q1	Median	Q3	Max
EARNRET	6.231	2.710	1.000	4.000	7.000	9.000	10.000
LOSS	0.088	0.284	0.000	0.000	0.000	0.000	1.000
MEET	0.653	0.476	0.000	0.000	1.000	1.000	1.000
INCEPS	0.692	0.462	0.000	0.000	1.000	1.000	1.000
IFE	0.055	1.118	0.000	0.002	0.006	0.021	90.944
RCOV	0.003	0.446	-1.918	-0.285	0.022	0.295	1.388
MB	4.146	12.540	0.123	1.716	2.612	4.250	678.094
LABOR	0.574	0.216	0.024	0.429	0.600	0.742	0.995
DUR	0.425	0.494	0.000	0.000	0.000	1.000	1.000
R&D	0.040	0.077	0.000	0.000	0.006	0.051	1.395
ICLAIM	0.000	1.000	-1.755	-0.758	-0.099	0.711	9.131
LIT	0.348	0.476	0.000	0.000	0.000	1.000	1.000

Returns on earnings EARNRET is the decile rank from industry specific regressions of cumulative excess returns on yearly changes in earnings. LOSS is an indicator variable which equals one if a loss is reported in the current fiscal year. MEET is an indicator variable which equals one if reported earnings meet or beat the last consensus estimate prior to the announcement. Increasing earnings per share INCEPS is an indicator variable that equals one if reported earnings per share exceed the previous year's earnings per share. Initial forecast error IFE is the absolute value of the difference between the first consensus estimate in the fiscal year and reported earnings per share, scaled by share price at the beginning of the fiscal year. Residual analyst coverage RCOV is the residual from a regression of the log of one plus the number of analysts contributing to the last consensus estimate prior to the announcement on the log market value of the company at the beginning of the fiscal year. Market-to-book ratio MB is market value of equity divided by book value of assets at the beginning of the fiscal year. Labor intensity LABOR is defined as one minus the ratio of gross property, plant, and equipment to total gross assets. DUR is a dummy variable indicating membership in durable goods industries (SIC codes 150-179, 245, 250-259, 283, 301, 324-399). R&D is annual research expenses divided by total assets. Missing values for R&D are set to zero. ICLAIM is the score of the factor analysis combining LABOR, DUR, and R&D into a single variable measuring reliance on implicit claims. LIT is a dummy variable indicating membership in litigious industries (SIC codes 2833-2836, 3570-3577, 3600-3674, 5200-5961, 7370-7374). The total number of observations is 7'787.

For the regression analysis, we measure all compensation and ownership variables as well as *IFE* and *MB* with the values of their cumulative distribution functions (hereafter referred to as cdf) for three reasons. Firstly, all these variables are highly skewed. The cdf transformation generates a uniform distribution of the transformed variables, which enhances the speed of conversion of the parameter estimates to the true population parameters. Secondly, the effect of outliers is mitigated without discarding this information completely as done in censoring the sample. Finally, this transformation is consistent with imposing decreasing marginal effects as the variables increase. Intuitively, this postulates that the first 1000 Dollars of any compensation component have higher importance than a 1000 Dollar variation at high income or ownership levels. The cdf transformation is similar to the log transformation commonly applied to firm size. However, the log transformation is less appropriate for the compensation and ownership variables, since there is a large number of observations with value zero, which would yield infinitely large negative values. Moreover, the use of the cdf transformation is not problematic for this study, since we are mainly interested whether distinct components of executive compensation increase or decrease the probability of expectations management (i.e. we are after the sign of the estimated coefficients), rather than estimating precisely the marginal effect of a 1000 Dollar increase in executive remuneration on the probability to manage analysts.

In Table 5.4, we report Pearson correlation coefficients between *DOWN* and the exogenous variables, where *SALARY*, *BONUS*, *LTIP*, *RSG*, *SHARE*, *INMONEX*, *OPTSENS*, *IFE*, and *MB* are expressed as the values of their cumulative distribution functions. Except for *SALARY*, the signs of the correlation coefficients are consistent with those predicted by our hypotheses. The compensation components and ownership variables are generally significantly positively correlated,[59] except for the percentage of shares owned by CEOs which is negatively correlated with the compensation components and option ownership. The annual bonus awarded to CEOs is positively related to *MEET* and *INCEPS* and negatively related to *LOSS*. The signs of the correlation coefficients between *DOWN* and the firm-specific control variables are consistent with previous research.

5.4.5 Measuring the impact of CEO compensation on expectations management

To test whether executive compensation components are associated with expectations management as postulated in our hypotheses, we first perform a logit regression, modeling the probability that analyst expectations have been managed downward.

For the limited dependent variable model, the existence of a latent variable D^* is assumed such that:

$$DOWN_i = \begin{cases} 1 & \text{if } D^* > 0 \\ 0 & \text{if } D^* < 0 \end{cases}$$

with $D^* = x_i'\beta + \nu_i$, $\nu_i \sim \text{logistic}(0, \pi^2/3)$.

---

[59] We conduct multi-collinearity diagnostic tests computing the variance inflation ratios (Kennedy 2000) for all variables used in the regression analysis. None of these ratios displays a value greater than 10, thus indicating that multi-collinearity does not cause any concern.

Table 5.4: Correlation coefficients for regression variables

	SALARY	BONUS	LTIP	RSG	SHARE	INMONEX	OPTSENS	EARNRET	LOSS	MEET	INCEPS	IFE	RCOV	MB	ICLAIM	LIT
DOWN	*0.020*	**0.142**	**0.059**	0.009	0.016	**0.169**	**0.085**	0.003	**-0.062**	**0.105**	**0.112**	**-0.214**	*0.024*	*0.021*	**0.046**	0.002
SALARY		**0.503**	**0.141**	**0.134**	**-0.233**	**0.273**	**0.317**	**-0.059**	**-0.144**	**0.038**	**0.037**	**-0.107**	-0.016	0.003	**-0.128**	**-0.102**
BONUS			**0.166**	**0.138**	**-0.209**	**0.398**	**0.341**	*-0.019*	**-0.264**	**0.183**	**0.340**	**-0.349**	0.005	**0.114**	*0.022*	**-0.101**
LTIP				**0.041**	**-0.087**	**0.097**	**0.073**	-0.010	**-0.089**	**0.044**	**0.080**	**-0.148**	**-0.033**	**0.057**	-0.007	**-0.076**
RSG					**-0.072**	**0.043**	**0.074**	-0.019	**-0.067**	**0.029**	**0.064**	**-0.086**	0.006	-0.015	**-0.045**	**-0.082**
SHARE						**-0.152**	**-0.267**	**-0.046**	-0.018	-0.002	0.004	0.009	**-0.023**	0.007	**-0.044**	*0.020*
INMONEX							**0.417**	**0.036**	**-0.155**	**0.170**	**0.248**	**-0.357**	**0.113**	**0.322**	**0.133**	**0.104**
OPTSENS								0.042	**-0.087**	**0.109**	**0.103**	**-0.193**	**0.122**	**0.202**	**0.115**	**0.082**
EARNRET									**0.032**	**0.031**	0.027	*-0.034*	-0.002	**0.096**	**0.197**	**0.129**
LOSS										**-0.173**	**-0.286**	**0.376**	**-0.031**	**-0.111**	**0.088**	**0.117**
MEET											**0.278**	**-0.242**	**0.081**	**0.100**	**0.058**	**0.055**
INCEPS												**-0.571**	**0.075**	**0.177**	**0.031**	**0.021**
IFE													**-0.073**	**-0.330**	**-0.076**	**-0.068**
RCOV														-0.008	**-0.101**	**0.112**
MB															**0.214**	**0.201**
ICLAIM																**0.216**

Summary of the correlation coefficients for the variables used in the regression analysis. SALARY, BONUS, LTIP, RSG, SHARE, INMONEX, OPTSENS, IFE, and MB are measured as the values of their cumulative distribution functions. The other variables are measured as described in Table 5.3. The total number of observations is 7’787. Bold figures denote significance at the 1% level. Figures in italic denote significance at the 5% level.

This corresponds to:

$$\Pr ob(DOWN_i = 1) = \Lambda(x_i'\beta) = \frac{e^{x_i'\beta}}{1+e^{x_i'\beta}},$$

where Λ is the cdf of the logistic distribution and

$$\begin{aligned} x_i'\beta = \beta_0 &+ \beta_1 SALARY_i + \beta_2 BONUS_i + \beta_3 LTIP_i + \beta_4 RSG_i \\ &+ \beta_5 SHARE_i + \beta_6 INMONEX_i + \beta_7 OPTSENS_i + \beta_8 I_{93} + ... + \beta_{14} I_{99}) \end{aligned} \tag{9}$$

Consistent with prior research on earnings management and forecast guidance (Matsumoto 2002, Brown 2002) we pool the observations from 1993 to 2000 performing the logit regression for the entire sample.[60] In all regressions indicator variables I_{93} to I_{99} control for year effects (relative to the base year 2000, represented by the constant β_0), which are not captured by the compensation (and control) variables.

In order to evaluate the compensation and ownership hypotheses jointly with the various alternative explanations for forecast guidance, we extend the above specification by including the full set of control variables:

$$\begin{aligned} \Pr ob(DOWN_i = 1) = \Lambda(&\beta_0 + \beta_1 SALARY_i + \beta_2 BONUS_i + \beta_3 LTIP_i + \beta_4 RSG_i \\ &+ \beta_5 SHARE_i + \beta_6 INMONEX_i + \beta_7 OPTSENS_i + \beta_8 LOSS_i + \beta_9 INCEPS_i + \\ &\beta_{10} MEET_i + \beta_{11} IFE_i + \beta_{12} EARNRET + \beta_{13} MB_i + \beta_{14} RCOV_i + \beta_{15} ICLAIM_i \\ &+ \beta_{16} LIT_i + \beta_{17} I_{93} + ... + \beta_{23} I_{99}) \end{aligned} \tag{10}$$

A potential drawback of the pooled logit specification is unobserved heterogeneity. For instance, the CEO's ability to guide or manipulate analysts is hard to measure, but might be correlated with other explanatory variables, thus causing biased coefficient estimates. The executive's skill to negotiate his or her compensation components with the compensation committee, for example, is likely to be correlated with the skill to deal with analysts, and will be reflected in the compensation variables. Moreover, differing attitudes toward business ethics or moral standards are just as hard to observe, but undeniably play a role in the CEO's

[60] This implies the assumption that observations $i = 1,...,N$ are independent, including consecutive observations of the same firm. In order to correct for firm clustering we compute robust standard errors adjusted for clustering. However, these differ only in the order of three digits after the comma, so we do not report them (available upon request).

propensity to manage analysts. Therefore we estimate a fixed effects logit model, allowing for unobserved heterogeneity at the firm level:

$$\begin{aligned}\Pr ob(DOWN_{it}=1)=\Lambda(&\beta_0+\beta_1 SALARY_{it}+\beta_2 BONUS_{it}+\beta_3 LTIP_{it}+\beta_4 RSG_{it}+\beta_5 SHARE_{it}\\&+\beta_6 INMONEX_{it}+\beta_7 OPTSENS_{it}+\beta_8 LOSS_{it}+\beta_9 INCEPS_{it}\\&+\beta_{10} MEET_{it}+\beta_{11} IFE_{it}+\beta_{12} EARNRET_{it}+\beta_{13} MB_{it}+\beta_{14} RCOV_{it}\\&+\beta_{15} ICLAIM_{it}+\beta_{16} LIT_{it}+\beta_{17} I_{93}+\ldots+\beta_{23} I_{99}+\alpha_i)\end{aligned} \qquad (11)$$

with: $\Lambda(\beta' X)=\frac{e^{(\alpha_i+\beta' X)}}{1+e^{(\alpha_i+\beta' X)}}$ and α_i the firm-specific fixed effect.

Since the estimation of the conditional logit model restricts the sample to firms with temporal variation in the endogenous variable, all the firms which are found to manage expectations throughout the entire sample period have to be excluded from the regression as well as the firms for which the *DOWN* variable is 0 throughout. Moreover, the conditional logit estimator requires at least two years of observations for each firm. Since the exclusion of these "extreme" observations may diminish the significance of explanatory variables due to sample restriction, as opposed to correcting for unobserved heterogeneity, we estimate the random effects probit model, which is an alternative panel specification that takes unobserved heterogeneity into account without losing the firms deleted with the fixed effects logit method. The model is specified as follows.

$$\begin{aligned}D_{it}^{P*}=&\beta_0+\beta_1 SALARY_{it}+\beta_2 BONUS_{it}+\beta_3 LTIP_{it}+\beta_4 RSG_{it}+\beta_5 SHARE_{it}\\&+\beta_6 INMONEX_{it}+\beta_7 OPTSENS_{it}+\beta_8 LOSS_{it}+\beta_9 INCEPS_{it}+\beta_{10} MEET_{it}+\\&\beta_{11} IFE_{it}+\beta_{12} EARNRET_{it}+\beta_{13} MB_{it}+\beta_{14} RCOV_{it}+\beta_{15} ICLAIM_{it}+\beta_{16} LIT_{it}\\&+\beta_{17} I_{93}+\ldots+\beta_{23} I_{99}+\alpha_i+\eta_{it}\end{aligned} \qquad (12)$$

with η_{it} ~ i.i.d. N(0,1) and α_i ~ N(0, σ_α^2).

In addition we perform further sensitivity analyses relating to variable measurement and conditioning the sample on behavioral thresholds.

5.5 Results

5.5.1 CEO compensation and expectations management

Table 5.5 displays the results of the pooled logit regression of *DOWN* on the compensation and ownership variables, controlling for year effects (coefficients on the year dummies are not reported) [61].

Table 5.5: Downward guidance and CEO compensation components

Variable	Predicted sign	Coefficient	p-value	Marginal Effect
SALARY	-	-0.613	0.000	-0.139
BONUS	+	0.987	0.000	0.224
LTIP	+	0.304	0.000	0.069
RSG	+	-0.017	0.842	-0.004
SHARE	+	0.439	0.000	0.100
INMONEX	+	1.006	0.000	0.228
OPTSENS	+	0.257	0.011	0.058
Wald chi2(14)	614.140		N	7787
Prob > chi2	0.000		Pseudo R2	0.068

Pooled logit regression results including compensation variables only; year effects are included but not reported. Except for time dummies, all exogenous variables (defined in Table 5.2) are expressed in terms of the values assigned by their cumulative distribution functions. *p*-values are computed with robust standard errors. Marginal effects are computed as $e^{\beta' X}/(1+e^{\beta' X})^2$, evaluated at the means of X. The chi2 statistic and the corresponding *p*-value are given for the joint test of significance of the model coefficients. *N* is the number of firm-year observations. Pseudo R2 is McFadden's measure of goodness of fit, computed as $1-(L_u/L_c)$, where L_u denotes the unconstrained Log-Likelihood of the (full) model and L_c denotes the constrained Log-Likelihood of the constrained (intercept only) model.

Consistent with our first hypothesis salary has a negative influence on the probability of expectations management. With a *p*-value <0.000 it is highly significant. Consistent with our second hypothesis, the relationship between bonus and analyst guidance is positive. As with salary, the *p*-value <0.000 indicates high significance. Consistent with our third hypothesis, long term incentive plans increase the probability of expectations management. Again, with a *p*-value <0.000 the variable is highly significant. Not supporting our fourth hypothesis, the variable *RSG* (restricted stock grants) is not significantly different from zero and has a

[61] The dummy coefficients are all highly significant, individually and jointly.

negative sign. We attribute this result to the failure of the variable (in the raw form) to measure the value of stock at the disposal of the executive for short term transactions. However, our fourth hypothesis is strongly supported by the high significance of *SHARE* (*p*-value <0.000) which is positively related to expectations management. *SHARE* is likely a much better proxy to measure the CEO's incentive from stock ownership than *RSG*, which measures the value of the restricted stocks awarded in the current year only, during which, for many the vesting period has not yet ended. Consistent with our fifth hypothesis, both option value and sensitivity are positive and (highly) significant with *p*-values <0.000 and 0.011 respectively. *INMONEX* and *BONUS* display the largest coefficients.

In summary, the pooled regression with year effects strongly supports our hypotheses about the relationship between expectations management and CEO compensation, stock and option ownership.

Table 5.6 shows the results of the pooled logit regression of the analyst guidance measure *DOWN* on the compensation and ownership variables, controlling for year effects and further firm-specific control variables.

Again, with only the exception of restricted stock grants all CEO compensation and ownership variables lend strong support to our five hypotheses. The coefficient of *SALARY* is negative and highly significant (*p*-value <0.000). The coefficients of *BONUS, SHARE*, and *INMONEX* are positive and highly significant (*p*-values <0.000), while the coefficients on *LTIP* and *OPTSENS* remain positive and significant at conventional levels.

The three threshold variables *LOSS*, *INCEPS*, and *MEET* are all significant, with *INCEPS* having a negative coefficient. Consistent with prior research (Matsumoto 2002), the variable proxying for forecasting uncertainty *IFE*, is negative and highly significant. In contrast to Matsumoto (2002) *EARNRET* is not significant. Nor is residual analyst coverage *RCOV*, which also does not explain analyst guidance. In sharp contrast to previous research *MB* is negative and highly significant. Likely, as conjectured by Brown (2001b), market-to-book was found positive and significant in explaining analyst management due to growth firms' pronounced stock and option remuneration practices. In our sample we control for these effects and find *MB* to have the opposite sign, possibly because it proxies for distress. Again, consistent with prior research there is a positive relation between reliance on implicit claims (*ICLAIM*) and analyst guidance. As in Matsumoto (2002), *LIT* is negative, but not significant at conventional levels.[62]

Table 5.6: Downward guidance, CEO compensation components, and control variables

Variable	Predicted sign	Coefficient	p-value	Marginal Effect
SALARY	-	-0.477	0.000	-0.108
BONUS	+	0.652	0.000	0.147
LTIP	+	0.200	0.024	0.045
RSG	+	-0.098	0.265	-0.022
SHARE	+	0.379	0.000	0.086
INMONEX	+	0.814	0.000	0.184
OPTSENS	+	0.210	0.044	0.047
LOSS	+/-	0.207	0.031	0.045
INCEPS	+/-	-0.230	0.001	-0.051
MEET	+/-	0.255	0.000	0.058
IFE	-	-1.574	0.000	-0.355
EARNRET	-	0.000	0.992	0.000
MB	+/-	-0.635	0.000	-0.143
RCOV	+	-0.008	0.892	-0.002
ICLAIM	+	0.092	0.001	0.021
LIT	+	-0.101	0.078	-0.023
Chi2(23)	786.471		N	7787
Prob > chi2	0.000		Pseudo R2	0.0919

Pooled logit regression estimates of *DOWN* on all explanatory variables; year effects are included but not reported. All exogenous variables are defined in Table 5.2 and Table 5.3. SALARY, BONUS, LTIP, RSG, SHARE, INMONEX, OPTSENS, IFE, and MB are expressed in terms of the values assigned by their cumulative distribution functions. All reported items are defined as in Table 5.5.

[62] We also investigate the relationship between expectations management and earnings management. We estimate discretionary accruals as the difference between actual accruals reported by the firms and an estimate of total accruals given by the modified Jones model (Jones 1991) described in Dechow et al. (1995). In order to control for earnings management, we run regression (10) with an additional dichotomous variable that takes a value of 1 when the estimate of discretionary accruals is positive and zero otherwise. This variable is not statistically significant and its inclusion does not impact the signs or the statistical significance of the coefficients associated with the other variables. Detailed results are available upon request.

Overall, the inclusion of additional firm-specific control variables corroborates the importance of executive compensation with stock and option ownership in order to explain expectations management.

Table 5.7: Fixed and random effects estimations

Variable	Predicted sign	Panel A: Fixed effects logit regression Coeff.	p-value	Marginal Effect	Panel B: Random effects probit regression Coeff.	p-value	Marginal Effect
SALARY	-	-0.300	0.280	-0.075	-0.285	0.000	-0.105
BONUS	+	1.146	0.000	0.285	0.392	0.000	0.145
LTIP	+	0.171	0.127	0.043	0.123	0.022	0.046
RSG	+	-0.025	0.825	-0.006	-0.057	0.286	-0.021
SHARE	+	0.024	0.905	0.006	0.223	0.000	0.082
INMONEX	+	1.492	0.000	0.371	0.493	0.000	0.182
OPTSENS	+	0.440	0.001	0.110	0.124	0.049	0.046
LOSS	+/-	0.209	0.128	0.052	0.123	0.039	0.044
INCEPS	+/-	-0.291	0.000	-0.073	-0.137	0.001	-0.050
MEET	+/-	0.196	0.002	0.049	0.155	0.000	0.058
IFE	-	-1.221	0.000	-0.304	-0.945	0.000	-0.349
EARNRET	-	0.003	0.816	0.001	0.000	0.986	0.000
MB	+/-	-2.183	0.000	-0.543	-0.380	0.000	-0.140
RCOV	+	0.071	0.531	0.018	-0.004	0.906	-0.002
ICLAIM	+	0.051	0.677	0.013	0.058	0.001	0.021
LIT	+	-0.769	0.027	-0.187	-0.063	0.070	-0.023
Chi2(23)		825.931	N	6844	855.812	N	7’787
Prob > chi2		0.000	Pseudo R2	0.140	0.000	Pseudo R2	0.092

Conditional logit (fixed effects) and random effects probit estimates of *DOWN* on all explanatory variables; year effects are included but not reported. All exogenous variables are defined in Table 5.2 and Table 5.3. SALARY, BONUS, LTIP, RSG, SHARE, INMONEX, OPTSENS, IFE, and MB are expressed in terms of the values assigned by their cumulative distribution functions. All reported items are defined as in Table 5.5.

5.5.2 Sensitivity tests

The results of modeling the dependence across units in a panel framework are presented in Table 5.7. The fixed effects logit regression of *DOWN* on the compensation, ownership, and control variables is displayed in Panel A.

All compensation and ownership components keep their predicted sign, but compared to the pooled logit regression, the marginal effects of the variables *BONUS*, *INMONEX*, and *OPTSENS* are now about twice as large and still highly significant. No longer significant however, are the compensation and ownership variables *SALARY*, *LTIP*, and *SHARE*. The coefficients of the threshold variables *LOSS*, *INCEPS*, and *MEET* stay at about the same level, but with *LOSS* being no more significant. Like *BONUS* and the option variables, the marginal effect of MB is changing remarkably, now being almost four times as large as before and still highly significant and negative. *LIT* becomes significant, but in opposition to the prediction, whereas *ICLAIM* loses significance. *IFE* is still negative and highly significant, *EARNRET* and *RCOV* remain insignificant.

The strong changes in the magnitudes of *BONUS*, *INMONEX*, and *OPTSENS* are possibly a sign of unobserved heterogeneity at the firm or equivalently CEO level, relating to skill and ethical standards. However, the conditional logit approach is flawed with the deletion of all firms with the endogenous variable indicating expectations management in all years as well as the firms without expectations management in all years. This way 943 "extreme" observations (12.1% of the sample) are ignored.

Compared to the fixed effect logit regression, the random effect probit approach has the advantage that it does not discard any firms without time series variation in *DOWN*, but it imposes the restriction that the unit specific effects α_i be uncorrelated with the explanatory variables. The results are displayed in Table 5.7, Panel B. All the variables that were significant in the pooled logit regression remain significant with the same signs as in the random effects probit regression. Again with the exception of *RSG*, the coefficients of all compensation and ownership variables support our hypotheses relating expectations management to executive compensation. *SALARY*, *BONUS*, *SHARE*, and *INMONEX* are highly significant (with *p*-values <0.000) and LTIP is significant at the conventional level.

In a related robustness test, we check whether there is a bias in the standard errors obtained from the pooled logit regressions due to correlated regression residuals across years. We run separate yearly cross-sectional regressions for equation (10) and compute the time-series average coefficients and *t*-statistics in the style of Fama and McBeth (1973).

Table 5.8: Fama-MacBeth yearly regressions

Variable	Predicted sign	Average Coefficient	p-value	Sign
SALARY	-	-0.413	0.068	[7/8]
BONUS	+	0.676	0.000	[8/8]
LTIP	+	0.225	0.032	[6/8]
RSG	+	-0.094	0.319	[4/8]
SHARE	+	0.405	0.033	[7/8]
INMONEX	+	0.776	0.000	[8/8]
OPTSENS	+	0.173	0.101	[3/8]
LOSS	+/-	1.728	0.128	[6/8]
INCEPS	+/-	-2.127	0.071	[7/8]
MEET	+/-	3.786	0.007	[7/8]
IFE	-	-9.664	0.000	[8/8]
EARNRET	-	0.574	0.584	[4/8]
MB	+/-	-8.585	0.000	[8/8]
RCOV	+	-0.416	0.690	[5/8]
ICLAIM	+	0.875	0.411	[6/8]
LIT	+	-0.789	0.456	[5/8]
N	7'787			

Average coefficients of yearly logit regressions for equation (10). In the third column, *p*-values corresponding to the reported *t*-statistics are displayed. *t*-statistics are computed as the mean coefficient divided by its standard deviation multiplied by the square-root of the number of cross sections. In column 4, the number of yearly regressions is reported, for which the sign of the coefficient is as expected. For the variables for which no sign prediction can be made, column 4 reports the number of years, in which the sign of the coefficient corresponds to the sign obtained for the average coefficient value. All exogenous variables are defined in Table 5.2 and Table 5.3. SALARY, BONUS, LTIP, RSG, SHARE, INMONEX, OPTSENS, IFE, and MB are expressed in terms of the values assigned by their cumulative distribution functions.

Table 5.8 shows that our main results are robust to this estimation methodology as well. The significance levels of *SALARY* and *SHARE* are reduced, but *INMONEX* and *BONUS* remain highly significant, pinpointing the importance of CEO compensation components for causing analyst guidance. However, *OPTSENS* is no more significant at conventional levels, confirming that the sensitivity of recently granted (and not necessarily exercisable) options has less impact on expectations management practices. The most important differences with respect to the pooled regression results concern the control variables: *ICLAIM* which was previously highly significant is no more significant, *LOSS* is no more significant, and *INCEPS* is only weakly significant. *MB* and *IFE* remain highly significant.

To summarize, we find that pooling observations, estimating panel models, and performing Fama-MacBeth regressions altogether lend strong support to our hypotheses. Our major conclusions are not sensitive to the method applied.

We take the pooled logit specification to a final sensitivity analysis conditioning on the behavioral thresholds rather than including them directly in the regressions. This appears appropriate if the incentives produced by executive compensation components to manage analysts depend on reaching the earnings thresholds positive profits (LOSS = 0), positive change in earnings (*INCEPS* = 1), and reaching the consensus forecast (*MEET* = 1). The results of conditioning the logit regression on reaching these thresholds are displayed in Table 5.9 and those of the logit regression on missing these thresholds are displayed in Table 5.10.

The evidence is consistent with the view that reaching earnings thresholds is important for the influence of *certain* incentive variables on expectations management, although not for all variables. *SALARY*, *BONUS*, and *SHARE* are highly significant with the predicted signs in all regressions, conditional on reaching the respective thresholds (Panel A). When the thresholds have not been reached (Panel B), these variables are typically not significant anymore, except *SALARY* conditional on *INCEPS* = 0. However, *INMONEX* is always positive and highly significant, independent of reaching any of the thresholds. The same applies to *IFE*, which is always negative and highly significant. Similarly, *MB* is negative and significant throughout.

Again we interpret these results as strong support for our hypotheses, with the compensation in stock options providing a particularly strong incentive to manage analysts in all the scenarios under test. The result that *SALARY*, *BONUS*, and *SHARE* while being (strongly) significant in the unconditional regressions, are not significant when earnings thresholds have not been reached, can be reconciled with the fact that thresholds have been reached by far more often than missed in our sample.

Table 5.9: Conditioning on *reaching* behavioral thresholds.

Variable	Pred. sign	profit reporting firms Coeff.	p-value	Marginal Effect	meet = 1 firms Coeff.	p-value	Marginal Effect	firms with positive increase in EPS Coeff.	p-value	Marginal Effect
SALARY	-	-0.488	0.000	-0.109	-0.603	0.000	-0.128	-0.566	0.000	-0.120
BONUS	+	0.683	0.000	0.152	0.797	0.000	0.169	0.869	0.000	0.184
LTIP	+	0.241	0.009	0.054	0.112	0.321	0.024	0.217	0.046	0.046
RSG	+	-0.080	0.385	-0.018	-0.109	0.330	-0.023	-0.071	0.511	-0.015
SHARE	+	0.399	0.000	0.089	0.422	0.000	0.090	0.605	0.000	0.128
INMONEX	+	0.753	0.000	0.168	0.785	0.000	0.167	0.898	0.000	0.191
OPTSENS	+	0.185	0.089	0.041	0.067	0.599	0.014	0.137	0.269	0.029
IFE	-	-1.433	0.000	-0.320	-1.313	0.000	-0.279	-1.348	0.000	-0.286
EARNRET	-	0.000	0.982	0.000	-0.005	0.706	-0.001	0.000	0.990	0.000
MB	+/-	-0.596	0.000	-0.133	-0.633	0.000	-0.134	-0.493	0.000	-0.105
RCOV	+	0.022	0.721	0.005	0.104	0.164	0.022	0.033	0.652	0.007
ICLAIM	+	0.075	0.020	0.017	0.053	0.133	0.011	0.060	0.098	0.013
LIT	+	-0.082	0.169	-0.018	0.052	0.469	0.011	0.031	0.658	0.007
Wald chi2(20)		661.871	N	7100	456.891	N	5086	485.005	N	5392
Prob > chi2		0.000	Pseudo R2	0.085	0.000	Pseudo R2	0.086	0.000	Pseudo R2	0.087

Pooled logit estimates of *DOWN* on all explanatory variables except for the three threshold variables on which the regressions are conditioned; year effects are included but not reported. All exogenous variables are defined in Table 5.2 and Table 5.3. SALARY, BONUS, LTIP, RSG, SHARE, INMONEX, OPTSENS, IFE, and MB are expressed in terms of the values assigned by their cumulative distribution functions. All reported items are defined as in Table 5.5.

Table 5.10: Conditioning on *missing* behavioral thresholds

		loss reporting firms			**meet = 0 firms**			**firms without pos. increase in EPS**		
Variable	Pred. sign	Coeff.	p-value	Marginal Effect	Coeff.	p-value	Marginal Effect	Coeff.	p-value	Marginal Effect
SALARY	-	-0.060	0.868	-0.015	-0.172	0.318	-0.042	-0.392	0.027	-0.096
BONUS	+	-0.003	0.995	-0.001	0.135	0.481	-0.042	0.278	0.162	0.068
LTIP	+	-0.125	0.695	-0.031	0.383	0.009	0.093	0.149	0.340	0.037
RSG	+	-0.221	0.445	-0.055	-0.080	0.581	-0.020	-0.171	0.257	-0.042
SHARE	+	0.149	0.615	0.037	0.219	0.154	0.053	-0.079	0.629	-0.019
INMONEX	+	1.691	0.000	0.418	0.860	0.000	0.209	0.752	0.000	0.185
OPTSENS	+	0.932	0.014	0.230	0.527	0.004	0.128	0.384	0.051	0.094
IFE	-	-1.278	0.030	-0.316	-1.324	0.000	-0.322	-2.051	0.000	-0.504
EARNRET	-	0.022	0.516	0.005	0.007	0.656	0.002	-0.001	0.943	0.000
MB	+/-	-0.967	0.002	-0.239	-0.660	0.000	-0.161	-0.852	0.000	-0.004
RCOV	+	-0.152	0.395	-0.038	-0.222	0.017	-0.054	-0.016	0.871	-0.004
ICLAIM	+	0.182	0.010	0.045	0.196	0.000	0.048	0.204	0.000	0.050
LIT	+	-0.232	0.242	-0.057	-0.367	0.000	-0.090	-0.334	0.001	-0.082
Wald chi2(20)		104.831	N	687	302.203	N	2701	251.491	N	2395
Prob > chi2		0.000	Pseudo R2	0.146	0.000	Pseudo R2	0.094	0.000	Pseudo R2	0.089

Pooled logit estimates of *DOWN* on all explanatory variables except for the three threshold variables on which the regressions are conditioned; year effects are included but not reported. All exogenous variables are defined in Table 5.2 and Table 5.3. SALARY, BONUS, LTIP, RSG, SHARE, INMONEX, OPTSENS, IFE, and MB are expressed in terms of the values assigned by their cumulative distribution functions. All reported items are defined as in Table 5.5.

5.5.3 CEO compensation and earnings surprises

With the results in the previous subsections we have demonstrated the strong role of CEO remuneration in explaining analysts (downward) guidance. A related question is whether the same compensation and ownership variables also predict the sign of realized earnings surprises, measured by *MEET*. We expect the same signs for the coefficients of the compensation and ownership variables as in explaining downward guidance.

Table 5.11: Meeting or beating market estimates and CEO compensation components

Variable	Predicted sign	Coefficient	p-value	Marginal Effect
SALARY	-	-0.266	0.014	-0.061
BONUS	+	0.575	0.000	0.131
LTIP	+	0.045	0.616	0.010
RSG	+	0.019	0.830	0.005
SHARE	+	0.146	0.113	0.035
INMONEX	+	0.381	0.000	0.087
OPTSENS	+	0.116	0.270	0.031
LOSS	+/-	-0.607	0.000	-0.146
INCEPS	+/-	0.788	0.000	0.182
IFE	-	-0.562	0.000	-0.117
EARNRET	-	0.010	0.286	0.002
MB	+/-	-0.089	0.365	-0.018
RCOV	+	0.290	0.000	0.063
ICLAIM	+	0.092	0.001	0.020
LIT	+	0.183	0.002	0.041
Wald chi2(22)	793.824		N	7787
Prob > chi2	0.000		Pseudo R2	0.092

Pooled logit regression results of *MEET* on all explanatory variables; year effects are included but not reported. All exogenous variables are defined in Table 5.2 and Table 5.3. SALARY, BONUS, LTIP, RSG, SHARE, INMONEX, OPTSENS, IFE, and MB are expressed in terms of the values assigned by their cumulative distribution functions. All reported items are defined as in Table 5.5.

Table 5.11 shows that most of all *BONUS* and *INMONEX* positively predict the sign of earnings surprises at high levels of significance (with *p*-values <0.000), while *SALARY* has the expected negative coefficient and is significant at the conventional level. *LTIP*, *RSG*, and *SHARE* have the expected signs but are not significant. Moreover, earnings threshold variables *LOSS* and *INCEPS* are highly significant as well as *RCOV*, *ICLAIM*, and *LIT*, with the expected positive sign.

We infer that bonus, in-the-money exercisable options, and *SALARY* have an equally important role in explaining the sign of earnings surprises as they have in downward guidance of analyst forecasts.

5.5.4 Does the market discount discernible expectations management?

We conduct an event study to investigate whether the market discounts any discernible expectations management strategies. This requires the calculation of the cumulative abnormal returns around the earnings announcement date. We estimate the following equation:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \lambda_i D_{it} + \varepsilon_{it} \tag{13}$$

$$t \in [A_i - 248; A_i + 2]$$

$$D_{it} = \begin{cases} 1/5 & \text{if } t \in [A_i - 2; A_i + 2] \\ 0 & \text{otherwise} \end{cases}$$

where

A_i = earnings announcement date for firm *i*

R_{it} = log return of stock *i* on day *t* adjusted for capital changes and dividends

R_{mt} = log return of the market index on day *t*

λ_i = Cumulative abnormal return for stock *i* between $A_i - 2$ and $A_i + 2$.[63]

The earnings announcement date is taken from I/B/E/S, individual stock returns are obtained from CRSP, and the market index is the CRSP value-weighted stock index. Equation (13) is estimated with a weighted least square regression as in Heinkel and Kraus (1988)[64] to correct for missing returns. Announcement date returns are missing for 24 observations. As a result, we estimate the model for 7’763 firm-year observations.

---

[63] As a first step we conduct an analysis of abnormal returns around the earnings announcement date. We observe most significant abnormal returns during the five days chosen as the event window.

[64] The weights are the square roots of the number of days over which the return is computed.

Table 5.12 summarizes the cumulative abnormal returns earned by firms at the announcement dates. Consistent with previous research, firms that meet or beat analyst expectations (zero or positive earnings surprise) earn a significant positive abnormal return of 1.30% during the period surrounding the announcement date. On the other hand, firms that fail to meet analyst expectations display a cumulative abnormal return of –1.20% during that period. The return differential between firms that meet or beat expectations and those that fail to do so equals 2.40% and is highly significant.

Table 5.12: Cumulative abnormal returns at the announcement date

	Earnings surprise		
	Zero or Positive	Negative	Difference
CAR	0.013	-0.012	0.024
(p-value)	*<0.01*	*<0.01*	*<0.01*
N	5’073	2’690	2’383

Cumulative abnormal returns (CAR) for 7’763 firm-year observations around the earnings announcement dates between 1993 and 2000. CARs are estimated with a market model type regression over 250 days ending two days after the event date, using a WLS regression as in Heinkel and Krauss (1998). The event window ranges from two days preceding the earnings announcement date to two days after this date. Companies’ cumulative abnormal returns are classified into two distinct categories according to the sign of their earnings surprise. The earnings surprise is computed as the difference between the released earnings per share and the last consensus issued by analysts for a particular firm in a given year.

In Table 5.13, we present cumulative abnormal returns conditional on whether a particular company meets or beats analyst expectations and conditional on whether expectations management is suspected.

The cumulative abnormal returns earned by firms that meet or beat analyst forecasts by managing analyst expectations downward are 1.10% lower than the cumulative abnormal returns of firms reporting a zero or positive surprise without managing expectations downward. On average, managers who engage in analyst manipulation still earn a positive abnormal return, but this abnormal return amounts to only 0.90% over the period surrounding the announcement date. This suggests that the market has some ability to anticipate the expectations management strategies implemented by managers. For firms that do not meet analyst expectations, no significant difference is observed in cumulative abnormal returns conditional on whether expectations management is suspected.

Table 5.13: Market reaction when expectations management is suspected

Earnings surprise	Expectations management	N	CAR *(p-value)*	Difference *(p-value)*
Zero or Positive	Suspected (*DOWN=1*)	3'423	0.009	
			(<0.01)	
	Not suspected *(DOWN=0)*	1'650	0.020	-0.011
			(<0.01)	*(<0.01)*
Negative	Suspected *(DOWN=1)*	1'530	-0.012	
			(<0.01)	
	Not suspected *(DOWN=0)*	1'160	-0.011	-0.002
			(<0.01)	*(0.643)*

Cumulative abnormal returns (CAR) for 7'763 firm-year observations around the earnings announcement dates between 1993 and 2000. CARs are estimated with a market model type regression over 250 days ending two days after the event date with a WLS regression as in Heinkel and Krauss (1998). The event window ranges from two days preceding the earnings announcement date to two days after this date. Companies' cumulative abnormal returns are classified into four distinct categories according to the sign of their earnings surprise and the sign of their unexpected forecast error (UEF). Earnings surprise is computed as the difference between the released earnings per share and the last consensus issued by analysts for a particular firm in a given year. A given company is suspected of managing expectations in a given year if $UEF < 0$. UEF is computed as described in section 4.

The objective of the following analysis is to investigate whether the lower abnormal return reported for firms suspected of managing analyst expectations downward depends on CEO compensation components and on firm-specific variables which have been shown to impact analyst guidance. In other words, we aim to assess which variables are taken into account by investors to detect potential analyst manipulation strategies. In order to do so, we model the cumulative abnormal returns of firms that meet or beat analyst expectations as a function of a subset of our explanatory variables. This subset contains the explanatory variables that are either partially or fully known by the market at the earnings announcement dates. We estimate the following model.

$$\lambda_i = \delta_0 + \delta_1 SHR + \delta_2 INMONEX_i + \delta_3 MB_i + \delta_4 ICLAIM_i + \delta_5 LIT_i + \varepsilon_i , \qquad (14)$$

with all variables defined as before.[65] We expect the variables which were shown to be positively related to expectations management, to be negatively related with cumulative abnormal returns at the announcement dates. More precisely, the sign of the coefficients associated with *SHR*, *INMONEX*, *ICLAIM* and *LIT* are expected to be negative. If the abnormal returns of growth firms are entirely generated by their CEOs' stock and option positions, MB should not be significant, whereas, regarding our previous regression results, we could expect as well a positive coefficient.

Table 5.14: Explaining market reaction for firms suspected of managing earnings

	Predicted sign	Coefficient	*t*-stat.	(p-value)
Intercept		0.013	3.042	0.002
SHARE	-	0.008	1.827	0.068
INMONEX	-	-0.010	-2.093	0.036
MB	+	-0.002	-0.371	0.711
ICLAIM	-	-0.003	-0.725	0.469
LIT	-	0.008	2.893	0.004
N		5073		
Adj. R^2		0.40%		
F test		3.864		
(p-value)		*0.002*		

Regression results of the cumulative abnormal returns of firms that meet or beat analyst forecasts on CEO compensation components and firm-specific control variables, which are partially or entirely known by the market at the earnings announcement dates. CARs are estimated with a market model type regression over 250 days ending two days after the event date with a WLS regression as in Heinkel and Krauss (1998). The event window ranges from two days preceding the earnings announcement date to two days after this date. SHARE, INMONEX, and MB are expressed in terms of the values assigned by their cumulative distribution functions. *t*-statistics are based on White (1980).

Table 5.14 summarizes our estimation results for equation (14). Only the coefficients associated with *INMONEX* and *LIT* display statistical significance at the conventional level. As expected, *INMONEX* is significantly negatively related to the cumulative abnormal returns. This means that the abnormal returns at the announcement date are lower for firms whose CEOs hold an important amount of in-the-money exercisable options. Contrary to

[65] Note that it is probably difficult for investors to assess the exact value of *INMONEX* at announcement the date. However, due to the vesting period attached to the awarded stock options, *INMONEX* contains options that have generally been granted to CEOs during past fiscal years. Investors are therefore able to estimate the approximate value of *INMONEX* from companies' previous proxy statements. Concerning *SHR*, investors can also infer the shares owned by CEOs from the proxy statement. Moreover, companies have to report all insider trades on a regular basis.

expectation, the coefficient associated with firms with high litigation risk is positive and significant. However, as documented above, our regression results concerning this coefficient are difficult to reconcile as LIT does not seem to be positively associated with expectations management. Regarding the low adjusted R^2, there might be other variables that can explain the documented discount at the announcement date for firms that manage analyst expectations downward. We leave this issue for further research.

In summary, we show that the gains for CEOs from managing earnings expectations downward also comes at a cost for executives. The abnormal return for firms that manage to meet or beat analyst forecasts by manipulating expectations downward is significantly lower than the abnormal return for firms that fulfill market estimates without manipulating analyst expectations. Our results indicate that the discount attributed by the market to companies suspected of managing analysts is positively related to the value of in-the-money exercisable options owned by CEOs.

5.6 Conclusion

This paper investigates whether the increasing tendency of executives to manage analyst forecasts downward is, as informally suggested by past academic research and financial media, related to a change in the structure of executive compensation packages. Using CEO compensation components in conjunction with their share and option ownership, our results are consistent with this explanation. We show that CEOs who hold considerable share and option positions are more likely to manage analyst expectations downward. Moreover, other compensation components that are not directly related to share price movements are shown to have a significant impact on CEOs' analyst guidance motives. Expectations management is negatively related to salary, indicating that high fixed compensation decreases the incentives of managers to manipulate analyst forecasts. Furthermore, we document a positive relationship between the annual bonus paid to CEOs and expectations management. This suggests that board of directors' expectations are related to analyst expectations and that meeting analyst expectations may be an important criterion used by board of directors to measure CEO performance.

In a second set of investigations, we show that the cumulative abnormal return for firms that meet or beat analyst forecasts at the announcement date is significantly lower for firms that are likely to pursue expectations management strategies. We show that this lower return is significantly related to the amount of options held by CEOs. This suggests that the market has some ability to identify firms that manage analysts in order to meet or beat their forecasts more easily.

Using a large U.S. American sample, we document for the first time the importance and impact of CEO compensation components on expectations management. However, our results may not generalize to all market segments, since the substantial amount of data required to conduct this study biases our sample towards larger firms. Moreover, since executive compensation components are only available from the main provider on an annual basis, we conduct our study with annual earnings per share forecasts. As a result, our results may not be generalized to quarterly earnings forecasts. Naturally, the validity of our results depends on the quality of the proxy used in this paper to detect expectations management.

Promising directions for further research include extending the set of executives beyond the CEO to study compensation and ownership effects on expectations management, devising trading strategies based on executive compensation information and earnings "surprises", as well as modeling temporal trends more explicitly in order to examine whether the documented temporal patterns in analyst guidance and earnings surprises can be entirely explained by the strong growth in stock price sensitive components of executive compensation.

Appendix

Measuring the sensitivity of the CEO's stock option award to a 1% price change of the underlying company's stock price

The value of the options awarded yearly to CEOs can be calculated with the following formula:

$$Award\ value = N\left[Se^{-dT}\Phi(d1) - Xe^{-rT}\Phi(d1-\sigma\sqrt{T}) \right] \tag{15}$$

where

$$d1 = \frac{\ln\left(S/X\right) + \left(r - d + \sigma^2/2\right)T}{\sigma\sqrt{T}} \tag{16}$$

N = number of shares covered by the award,[66]

S = price of the underlying stock,

X = exercise price,

r = risk-free interest rate,

d = expected dividend rate over the life of the option,

σ = expected stock return volatility over the life of the option,

T = time to maturity,

Φ = cumulative probability for the normal distribution.

The incentive sensitivity from awarded options (*OPTSENS*) in a given year is estimated in the following way:

$$OPTSENS = N \cdot \Delta \cdot (S/100), \tag{17}$$

where $\Delta = e^{-dT}\Phi(d1)$.

[66] We include all awarded options in our measure even those that are awarded to adjust existing options such as "reload" options. Our results are not sensitive to this inclusion.

We use the following assumptions to estimate the parameters of the Black-Scholes formula:

S = market price of the company's stock on the date of the option grant.

r = ln(1+riskless interest rate), where the risk-free interest rate is the approximate average yield that could have been earned in the year in which the option was granted by investing in a U.S. Treasury bond carrying a seven year term. This yield is obtained from Execucomp.

d = ln(1+dividend rate), with dividend rate defined as the company's average dividend rate over the past three-years. If, in a particular year, the dividend rate is above the 95th percentile of the distribution of yields for that year, it is reduced to the 95th percentile value. Dividend rate and 95th percentile values are obtained from Execucomp.

σ = annualized volatility, estimated from past 60 months' returns. If, in a particular year, a company's stock volatility is in the bottom or top 5% of the cross-sectional volatility distribution, its volatility is increased or decreased to the 5th or 95th percentile values. Annualized volatility and percentile values are taken from Execucomp.

Conclusion

In this final conclusion, I summarize my empirical findings' broad contributions to the existing literature and discuss some unresolved issues as well as guidelines for future research.

The empirical findings reported in the first essay of this dissertation show that results obtained by studies that investigate the determinants of relative analysts' accuracy in the U.S. can not be generalized to other countries where analysts face different institutional, professional, and economic environments. This is also probably true for many other findings, even early ones, documented on US analyst forecasts. For instance, an investigation of the superiority of financial analyst earnings forecasts relative to econometric model forecasts in non-US countries would certainly be relevant. More precisely, analysts' superiority relative to econometric models may vary with the corporate informational environment. Therefore, given the different institutional context across countries, different results can be expected internationally. In addition, I show that, in markets where stock returns fail to incorporate accounting returns, analysts have lower incentives to provide accurate forecasts. On those markets, the demand for accurate forecasts by investors may be low and the time needed by market prices to converge toward their intrinsic values may be relatively long. As a consequence, on these markets, analysts' career concerns may be strongly related to their stock-picking abilities and not to their forecast accuracy. The recent availability of sufficient individual analysts' recommendations for non-US markets will probably enable future research to test non-US analysts' stock-picking abilities as well as the influence of the accuracy of their recommendations on their career concerns. Finally, I confirm the difficulties encountered by analysts confronted with various economic environments to incorporate macroeconomic shocks into their forecasts. The relationship between the macroeconomic situation and the properties of analyst forecasts deserves further investigations. In particular, the influence of macroeconomic forecasts on financial analyst forecasts, such as those issued in the Livingston Survey, should be examined in more details. Indeed, it is of interest to know whether analysts incorporate macroeconomic forecasts in their own forecasts, the extent of the influence of macroeconomic forecasts on analyst forecast revisions or dispersion, and the time needed by analysts to incorporate these macroeconomic forecasts into their information set. Moreover, studies that examine financial analysts' efficiency can be refined by extending analysts' information sets with macroeconomic forecasts or variables that have been shown to predict business-cycle variations instead of past forecast errors. More generally, I think that there is a need to better understand the judgment and decision process behind analyst forecasts.

In my second essay, I provide clear confirmation on the superior ability of some specific groups of analysts. Foreign analysts and leader analysts display better performance than other analysts. The superiority of foreign analysts is consistent with Higgins (2002) who reports superior accuracy on the part of US analysts in Japan. However, this is not consistent with Malloy (2002) who finds that analysts' performance decreases with their geographical distance from the firms' headquarters. These contradictory results underline the need to further investigate the impact of geographic proximity on analysts' performance. Moreover, I confirm the relationship between analysts' reputation – foreign analysts who work for major international brokerage houses are probably more reputed than local ones – and performance first documented by Stickel (1992). I also provide evidence confirming the herding behaviour of some analysts. However, my results do not include a clear insight on the origin of this herding behaviour. Local analysts may herd to protect their reputation, which is lower than the reputation of foreign analysts, or foreigners may lead because they have an informational advantage over local analysts. Consequently, the herding behaviour of analysts needs to be investigated in more details in order to identify precisely the reasons that lead analysts to herd. An investigation of the characteristics of leader and follower analysts may provide some explanations on the origin of their herding behaviour. For instance, if leaders are assigned less complex portfolios and have more resources available than followers, herding may be attributed to informational advantages.

My third essay clearly confirms that managers have strong incentives to manage analysts' expectations downward in order to release earnings that meet or beat market estimates. Therefore, I contribute to the debate on the origin of the changing pattern of financial analyst forecast bias. My results favour the managerial behaviour hypothesis. In this area, a very surprising fact is that analysts seem to have been steadily and repetitively manipulated over the recent decade. Consequently, it would be relevant to investigate whether they have incentives to actively participate in this guidance game. In other words, they may also profit from managers' expectations management practices. An appropriate way to solve this issue would be to investigate the characteristics (e.g. seniority) of manipulated analysts as well as their job separation outcomes (e.g. potential Institutional Investor All-American ranking).

Finally, I would like to mention two further topics not directly related to my results but that would deserve interesting further investigation. The first topic is related to the influence of earnings or analysts' related news on contrarian strategies. De Bondt and Thaler (1985, 1987) attribute price reversals to investors' tendencies to overreact. Competing explanations for long-term reversals are based on microstructure biases that are prevalent for low-priced securities (see Ball et al., 1985) or time-varying expected returns (see Ball and Kothari, 1989 among others). However, nobody has tried yet to relate the profitability of contrarian strategies to either earnings-related news, as Chan et al. (1996), or to analyst related news. The main difference between momentum and contrarian strategies is the pre formation window used to rank stocks on the basis of their past returns and the holding horizon. Both are longer for contrarian strategies. Therefore, instead of forming portfolios by ranking stocks on the basis of the most recent earnings surprises, stocks could be ranked on the basis of an average measure of earnings surprise computed over a longer window (e.g. 2 to 5 years). Similarly, stocks could also be ranked on the basis of their average one-year-earnings forecast growth rate computed over an identical period. The future returns of these strategies should be compared with those of portfolios formed on the basis of long term past returns. If the strategies built on the basis of earnings were to subsume contrarian strategies, long-term price reversals could be attributed to analysts' overreaction.

Second, analysts' data may provide good proxies in order to test several recent asset pricing models. Standard asset pricing theories assume that economic agents possess perfect knowledge of the probability law that governs the realization of the state of the world. Even more constraining, agents are supposed to have homogenous beliefs sot that a representative agent can be used. This is true for one-period (see Sharpe, 1964) and multi-periods (see Merton, 1973; Breeden, 1979) asset pricing models asset pricing models. The empirical success of this type of model, however, is limited. In particular, these models can not explain the size of the mean aggregate equity premium (see Mehra and Prescott, 1985 among others) and the assumed existence of a representative agent implies that there is no role for asset trading. The difficulty of reconciling existing asset pricing theories with empirical evidence has led to several models that relax the assumption of perfect knowledge of the state of the economy on the part of investors. This uncertainty appears under several names in the literature, such as incomplete information, model uncertainty or parameter uncertainty. They differ mainly in the way of modelling the uncertainty. One category of models formalise uncertainty in the Bayesian framework; see Detemple and Murthy (1994), Kandel and Stambaugh (1996), and Lewellen and Shanken (2001) among others. They study the implications of uncertainty for asset prices in representative agent and heterogeneous agent economies. The other category follows the view of Knight (1921). For him, the decision maker's view of uncertainty cannot be represented by a probability prior; see Epstein and Wang (1994, 1995) and Kogan and Wang (2002) among others. Overall, these models all suggest a relationship between stock prices and uncertainty. However, the form of this relationship may not be the same across the two categories. These asset pricing models display high practical relevance and can be directly related to the research performed on financial analysts. Indeed, they formalise the practical evidence that investors' decisions rely mostly on information through noisy channels and capture the fact that investors have access to differing information sets. This is consistent with research on financial analysts that shows that their forecasts are biased (i.e. noisy) and may display important dispersion. As a consequence, the availability of analyst forecasts provides a good opportunity to test these models. Some recent research investigates the influence of financial analyst forecast dispersion, used as proxy for differences of opinion among investors, and stock returns (see Gyssel and Juergens, 2001; Diether et al, 2002). They find that forecast dispersion is related to stock returns. However, they offer a mixed evidence on the sign of the relationship. These mixed results and the low number of studies that have tried to assess the empirical influence of both uncertainty and heterogeneous beliefs on asset prices suggest that additional investigation may be needed in this area. In order to be consistent with existing theoretical models, further research should examine the relationship between stock prices and both uncertainty and heterogeneous beliefs. Past empirical studies do not distinguish between uncertainty and heterogeneous beliefs. Typically, analyst forecast dispersion is used as proxy for both factors. For instance, in situations where investors are highly uncertain about future states of the world but agree on this uncertainty, future asset prices will differ from situations where there is a high uncertainty with high differences of opinion among investors. Therefore, distinct proxies for these variables should be investigated. Furthermore, further research should consider liquidity. Theoretical evidence suggests a relationship between uncertainty and shares' liquidity; see Routledge and Zin (2001). Empirical studies find a positive relationship between analyst dispersion and liquidity; see Ajinkya et al. (1991) among others.

Past studies offer clear evidence on a positive relationship between liquidity and asset returns (see Pastor and Stambaugh, 2001; Gibson and Mougeot 2000 among others) as well. However, Diether et al. (2002) document a negative relationship between dispersion and stock returns. These seemingly contradictory results highlight the need to consider future returns, dispersion, and liquidity altogether in order to investigate the causality relations between them.

References

Abarbanell, J.S., 1991, Do analysts' earnings forecasts incorporate information in prior stock price changes?, *Journal of Accounting and Economics* 14, 147-165.

Abarbanell, J.S. and R. Lehavy, 2003, Biased forecasts or biased earnings? The role of reported earnings in explaining the apparent bias and over/underreaction in analysts' earnings forecasts, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=232453.

Aboody, D. and R. Kaznik, 2000, CEO stock option awards and the timing of corporate voluntary disclosures, *Journal of Accounting Economics* 29, 73-100.

Ajinkya, B.B. and M.J. Gift, 1985, Dispersion of financial analysts' earnings forecasts and the (option model) implied standard deviations of stock returns, *Journal of Finance* 40, 1353-1365.

Ajinkya, B.B., Atiase, R.K. and M.J. Gift, 1991, Volume of trading and the dispersion in financial analysts' earnings, *Accounting Review* 66, 389-401.

Alford, A., Jones, J., Leftwich, R. and M. Zmijewski, 1993, The relative informativeness of accounting disclosure in different countries, *Journal of Accounting Research* 31, 183-223.

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

Ali, A. and S. Kallapur, 2001, Securities price consequences of the Private Securities Litigation Reform Act of 1995 and related events, *Accounting Review* 76, 431-461.

Baca, S.P., Garbe, B.L. and R.A. Weiss, 2000, The rise of sector effects in major equity markets, *Financial Analysts Journal* March/April, 31-39.

Ball, R. and S.P. Kothari, 1989, Nonstationary expected returns: Implications for tests of market efficiency and serial correlations in returns, *Journal of Financial Economics* 25, 51-74.

Ball, R., Kothari, S.P. and A. Robin, 2000, The effect of international institutional factors on properties of accounting earning, *Journal of Accounting Economics* 29, 1-51.

Ball, R., Kothari, S.P. and J. Shanken, 1995, Problems in measuring portfolio performance: An application to contrarian investment strategies, *Journal of Financial Economics* 38, 79-107.

Baltagi, B.H., 2002, Econometric analysis of panel data, John Wiley & Sons, second edition.

Barber, B.M., Lehavy, R., McNichols, M.F. and B. Trueman, 2001, Prophet and losses: Reassessing the returns to analysts' stock recommendations, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=269119.

Bartov, E., Givoly, D. and C. Hayn, 2002, The rewards to meeting or beating earnings expectations, *Journal of Accounting Economics* 33, 173-204.

Basu, S., Hwang, L. and C.L. Han, 1998, International variation in accounting measurement rules and analysts' earnings forecast errors, *Journal of Business Finance and Accounting* 25, 1207-1247.

Bildersee, J., Radhakrishnan, S. and J. Ronen, 1996, Dispersion of analysts' forecasts, precision of earnings, and trading volume reaction, *International Review of Financial Analysis* 5, 99-111.

Black, F. and M. Scholes, 1973, The pricing of options and corporate liabilities, *Journal of Political Economy* 81, 637-654.

Boni, L. and K. L. Womack, 2001, Wall Street Credibility: What do investors want and need?, Working Paper, University of New Mexico and Dartmouth College.

Boni, L. and K. L. Womack, 2002, Wall Street's credibility problem: Misaligned incentives and dubious fixes?, Working paper, The Wharton School, University of Pennsylvania.

Bowen, R.M., DuCharme, L. and D. Shores, 1995, Stakeholders' implicit claims and accounting method choice, *Journal of Accounting and Economics* 20, 255-295.

Brav, A. and R. Lehavy, 2003, Expected return and asset pricing, *Journal of Finance*, Forthcoming.

Breeden, D., 1979, An intertemporal asset pricing model with stochastic consumption and investment opportunities, *Journal of Financial Economics* 7, 265-296.

Brennan, M.J. and A. Subrahmanyam, 1995, Investment analysis and price formation in securities markets, *Journal of Financial Economics* 38, 361-381.

Brennan, M.J. and H.H. Cao, 1997, International portfolio investment flows, *Journal of Finance* 52, 1851-1880.

Brown, L.D., 1997, Analyst forecasting errors: Additional evidence, *Financial Analysts Journal* November/December, 81-88.

Brown, L.D., 2001a, A temporal analysis of earnings surprises: Profit vs. losses, *Journal of Accounting Research* 39, 221-241.

Brown, L.D., 2001b, Small negative surprises: Frequency and consequence, Working paper, Georgia State University, http://www-cba.gsu.edu/~wwwacc/lbrown/WorkingPaper.html.

Brown, L.D., 2001c, How important is past analyst forecast accuracy? *Financial Analysts Journal* November/December, 25-40.

Brown, L.D. and H.N. Higgins, 2002, Managers' guidance of analysts: International evidence, Working paper, Georgia State University and Worcester Polytechnic Institute, http://www-cba.gsu.edu/~wwwacc/lbrown/WorkingPaper.html.

Brown, L.D., Richardson, G.D. and S.J. Schwager, 1987, An information interpretation of financial analyst superiority in forecasting earnings, *Journal of Accounting Research* 25, 49-67.

Brown, L. and M. Rozeff, 1978, The superiority of analyst forecasts as measures of expectations: Evidence from earnings, *Journal of Finance* 33, 1-16.

Burgstahler, D. and I. Dichev, 1997, Earnings management to avoid earnings decreases and losses, *Journal of Accounting Economics* 24, 99-126.

Burgstahler, D. and M. Eames, 2001, Management of earnings and analysts' forecasts, Working paper, University of Washington and Santa Clara University.

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

Chan, L.K., Jegadeesh, N. and J. Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681-1713.

Chang, J.J., Khanna, T. and K.G. Palepu, 2000, Analyst activity around the world, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=204570.

Choe, H., Kho, B.C. and R.M. Stulz, 2000, Do domestic investors have more valuable information about individual stocks than foreign investors?, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=254574.

Chopra, V.K., 1998, Why so much error in analysts' earnings forecasts?, *Financial Analysts Journal* 54, 30-37.

Clement, M., 1999, Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter?, *Journal of Accounting Economics* 27, 285-303.

Clement, M., Rees, L. and E.P. Swanson, 2000, The influence of corporate governance, culture, and income predictability on the characteristics that distinguish superior analysts, Working Paper, The University of Texas at Austin and Texas A&M University.

Cooper, R.A., Day, T.E. and C.M. Lewis, 2001, Following the leader: A study of individual analysts' earnings forecasts, *Journal of Financial Economics* 61, 383-416.

Core J.E. and W.R. Guay, 2001, Stock option plans for non-executive employees, Journal *of Financial Economics* 61, 253-287.

Cornell, B., 2001, Is the response of analysts to information consistent with fundamental valuation? The cas of Intel, *Financial Management* Spring, 113-136.

Coval, J.D. and T.J. Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811-841.

Crichfield, T., Dyckman, T.R and J. Lakonishok, 1978, An evaluation of security analysts' forecasts, *Accounting Review* 73, 277-294.

Crockett, A., Harris, T., Mishkin, F. and E. White, 2003, Conflicts of interest in the financial services industry: What should we do about them?, Draft report prepared for the fifth Geneva Conference on the World Economy.

De Bondt, W.F.M. and R.H. Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793-805.

De Bondt, W.F.M. and R.H. Thaler, 1987, Further evidence on investor overreaction and stock market seasonality, *Journal of Finance* 42, 557-581.

De Bondt, W.F.M. and R.H. Thaler, 1990, Do security analysts overreact?, *American Economic Review* 80, 52-57.

Dechow, P., Sloan, R.G. and A.P. Sweeney, 1995, Detecting earnings management, *Accounting Review* 70, 193-225.

Dechow, P., Hutton P. and R.G. Sloan, 2000, The relation between analysts' long-term earnings forecasts and stock price performance following equity offerings, *Contemporary Accounting Research* 17, 1-32.

Degeorge, F., Patel, J. and R. Zeckhauser, 1999, Earnings management to exceed thresholds, *Journal of Business* 72, 1-33.

Desai, H., Liang, B. and K. Singh, 2000, Do all-stars shine? Evaluation of analyst recommendations, *Financial Analyst Journal* May/June, 20-29.

Detemple, J. and S. Murthy, 1994, Intertemporal asset pricing with heterogeneous information, *Journal of Economic Theory* 62, 294-320.

Diether, K., Malloy, C. and A. Scherbina, 2002, Differences of opinion and the cross-section of stock returns, *Journal of finance* 57, 2113-2141.

Dini, J., 2001, The All-American research team, *Institutional Investor* October, 119-123.

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

Eaterwood, J.C. and S.R. Nutt, 1999, Inefficiency in analysts' earnings forecasts: systematic misrecation or systematic optimism?, *Journal of Finance* 54, 1777-1797.

Epstein, L. and T. Wang, 1994, Intertemporal asset pricing under Knightian uncertainty, *Econometrica* 62, 283-322.

Epstein, L. and T. Wang, 1995, Uncertainty, risk-neutral measures and security price booms and crashes, *Journal of Economic Theory* 67, 40-80.

Fama, E.F., McBeth, J., 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 51, 55-87.

Fama, E.F. and M. Miller, 1972, The theory of finance, Dryden Press, Hinsdale, IL.

Foerster, S.R. and G.A. Karolyi, 1999, The effect of market segmentation and investor recognition on asset prices: Evidence from foreign stocks listing in the United State, *Journal of Finance* 54, 981-1013.

Francis, J. and K. Shipper, 1993, Shareholder litigation and corporate disclosures, *Journal of Accounting Research* 32, 137-164.

Frankel, R. and C.M.C. Lee, 1998, Accounting valuation , market expectation, and cross-sectional stock returns, *Journal of Accounting and Economics* 25, 283-319.

Fried, D. and D. Givoly, 1982, Financial analysts' forecasts of earnings: A better surrogate for market expectations, *Journal of Accounting and Economics* 4, 85-107.

Fuller, J. and M.C. Jensen, 2002, Just say no to Wall-Street, *Journal of Applied Corporate Finance* 14, 41-46.

Gao, P. and R.E. Shrieves, 2002, Earnings management and executive compensation: A case of overdose of option and underdose of salary?, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=302843.

Ghysels, E. and J.L. Juergens, 2001, Stock market fundamentals and heterogeneity of beliefs: Tests based on a decomposition of returns and volatility, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=301836.

Gibson, R. and N. Mougeot, 2000, The pricing of systematic liquidity risk: Empirical evidence from the US stock market, Working paper, University of Zürich.

Golliau, C., 2000. Analystes financiers: Les stars de la finance. *LePoint* 08.09.2000, http://www.lepoint.fr.

Grinblatt, M. and M. Keloharju, 2000, The investment behaviour and performance of various investor types: A study of Finland's unique data set, *Journal of Financial Economics* 55, 43-67.

Gu, Z. and J.S. Wu, 2003, Earnings skewness and analyst forecast bias, *Journal of Accounting and Economics* 35, 5-29.

Guay, W.R., Haushalter, D. and B.A. Minton, 2003, The influence of corporate risk exposures on the accuracy of earnings forecasts, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=375740.

Hamon, J. and B. Jacquillat, 1999, Is there value-added information in liquidity and risk premiums?, *European Financial Management* 5, 369-393.

Heinkel, R. and A. Kraus, 1988, Measuring event impacts on thinly traded stocks, *Journal of Financial and Quantitative Analysis* 23, 71-88.

Higgins, H.N., 1998, Analyst forecasting performance in seven countries, *Financial Analysts Journal* May/June, 58-62.

Higgins, H.N., 2002, Analysts' forecasts of Japanese firms' earnings: Additional evidence, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=306019.

Hensley, D.C. and J.W. Strouse, 2002, New rules regarding research analysts' perceived conflicts of interest: An ever-evolving landscape, *Journal of Investment Compliance* 3, 13-21.

Holmström, B., 1999, Managerial incentives problems: A dynamic perspective, *Review of Economic Studies* 66, 169-182.

Hong, H., Lim, T. and J.C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265-295.

Hong, H., Kubik, J.D. and A. Solomon, 2000, Security analysts' career concerns and herding of earnings forecasts, *Rand Journal of Economics* 31, 121-144.

Hong, H. and J.D. Kubik, 2003, Analyzing the analysts: Career concerns and biased earnings forecasts, *Journal of Finance* 58, 313-351.

Hope O., 2003, Accounting policy disclosures and analysts' forecasts, *Contemporary Accounting Research*, Forthcoming.

Imhoff, E.A and G.J. Lobo, 1984, Information content of analysts' composite forecast revisions, *Journal of Accounting Research* 22, 541-554.

Irvine, P.J.A., 2001, Do analysts generate trade for their firms? Evidence from the Toronto stock exchange, *Journal of Accounting and Economics* 30, 209-226.

Isakov, D. and F. Sonney, 2003, Are practitioners right? On the relative importance of industrial factors in international stock returns, FAME Research Paper Series, http://www.fame.ch/index.cfm?page=/fame/faculty_research/research_paper_series/complete_list/paper_72.

Jacob, J., Lys, T.Z. and M. Neale, 1999, Expertise in forecasting performance of security analysts, *Journal of Accounting Economics* 28, 51-82.

Jacquillat, B. and P. Grandin, 1994, Performance measurement of analysts' forecasts, *Journal of Portfolio Management* 21, 94-102.

Jones, J., 1991, Earnings management during import relief investigations, *Journal of Accounting Research* 29, 193-229.

Kandel, S. and R. Stambaugh, 1996, On the predictability of stock returns: An asset allocation perspective, *Journal of Finance* 51, 385-424.

Kang, S., O'Brien, J. and K. Sivaramakrishnan, 1994, Analysts' interim earnings forecasts: Evidence on the forecasting process, *Journal of Accounting Research* 32, 103-112.

Kang, J. and R.M. Stulz, 1997, Why is there a home bias? An analysis of foreign portfolio equity ownership in Japan, *Journal of Financial Economics* 46, 2-28.

Keane, M.P. and D.E. Runkle, 1998, Are financial analysts' forecasts of corporate profits rational?, *Journal of Political Economy* 106, 768-805.

Kennedy, P., 2000, A guide to econometrics, Blackwell publisher, 4th edition.

Knight, F., 1921, Risk, uncertainty and profit, Houghton, Mifflin, Boston.

Kogan, L. and T. Wang, 2002, A simple theory of asset pricing under model uncertainty, Working Paper, Massachussets Institute of Technology and University of British Columbia, http://finance.commerce.ubc.ca/~wang/ - wk.

Kothari, S.P., 2001, Capital market research in accounting, *Journal of Accounting and Economics* 31, 105-231.

Kothari, S.P., Sabino, J.S. and T. Zach, 2001, Implications of data restrictions on performance measurement and tests of rational pricing, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=195509.

Krische, S.D. and C.M.C. Lee, 2000, The information content of analyst stock recommendations, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=254547.

Lang, M.H. and R.J. Lundholm, 1993, Cross-sectional determinants of analyst rating of corporate disclosures, *Journal of Accounting Research* 31, 246-270.

Lang, M.H. and R.J. Lundholm, 1996, Corporate disclosure policy and analyst behavior, *Accounting Review* 71, 467-492.

Lang, M.H., Lins, K.V. and D. Miller, 2002, Do analysts matter most when investors are protected least? International evidence, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=323440.

Lang, M.H., Lins, K.V. and D. Miller, 2003, ADRs, analysts, and accuracy: Does cross listing in the U.S. improve a firm's information environment and increase market value?, *Journal of Accounting Research*, Forthcoming.

La Porta, R., Lopez-de-Silanes, F., Schleifer, A. and R. Vishny, 2000, Investor protection and corporate governance, *Journal of Financial Economics* 58, 3-27.

Lee, C.M.C., Myers, J. and B. Swaminathan, 1999, What is the Intrinsic Value of the Dow?, *Journal of Finance* 54, 1693-1741.

Leuz, C., Nanda, D. and P.D. Wysocki, 2003, Earnings management and investor protection: An international comparison, *Journal of Financial Economics*, Forthcoming.

Lewellen, J. and J. Shanken, 2002, Learning, asset-pricing tests, and market efficiency, *Journal of Finance* 57, 1113-1145.

Lin, H. and M.F. McNichols, 1998, Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics* 25, 101-127.

Lim, T., 2001, Rationality and analysts' forecast bias, *Journal of Finance* 56, 369-385.

Liu, J., and J. Thomas, 2000. Stock returns and accounting earnings, *Journal of Accounting Research* 38, 71-101.

Lopez, T.J. and L. Rees, 2000, The effect of meeting analyst forecasts and systematic positive forecast errors on the information content of unexpected earnings, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=181929.

Lys, T. and S. Sohn, 1990, The association between revisions of financial analysts' earnings forecasts and security price changes, *Journal of Accounting Economics* 13, 341-363.

Malloy, C.J., 2002, The geography of equity analysis, Working Paper, University of Chicago, http://home.uchicago.edu/~cmalloy/.

Matsumoto, D.A., 2002, Management's incentives to avoid negative earnings surprises, The *Accounting Review* 77, 483-514.

Merton, R.C., 1973, An intertemporal capital asset pricing model, *Econometrica* 41, 867-887.

Merton, R.C., 1973, Theory of rational option pricing, *Bell Journal of Economics and Management Science* 4, 141-183.

Michaely, R. and K.L. Womack, 1999, Conflict of interest and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653-686.

Mikhail, M., Walther, B. and R. Willis, 1997, Do security analysts improve their performance with experience?, *Journal of Accounting Research* 35, 131-166.

Mikhail, M., Walther, B. and R. Willis, 1999, Does forecast accuracy matter to security analysts?, *Accounting Review* 74, 185-200.

Miller, G.S., 1999, Earnings performance and discretionary disclosures, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=198973.

Miller, G.S. and J. Piotroski, 2000, The role of disclosure for high book-to-market firms, Working Paper, Harvard University.

Morgan Stanley Dean Witter, 1998, Apples to apples: A series of reports on accounting for value in world markets, Lead author: Harris, T. S., Morgan Stanley Dean Witter, New York.

Murphy, K.J., 1999, Executive compensation, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=163914.

Muth, J.F., 1961, Rational expectations and the theory of price movements, Econometrica 29, 315-335.

Nobes, C. and R. Parker, 1998, Comparative International Accounting, Sixth edition, Prentice Hall.

O'Brien, P.C., 1988, Analysts' forecasts as earnings expectations, *Journal of Accounting Economics* 10, 53-83.

O'Brien, P.C., 1998, Discussion of international variation in accounting measurement rules and analysts' forecast errors, *Journal of Business Finance and Accounting* 25, 1249-1254.

Ohlson, J.A., 1995, Earnings, book values, and dividends in equity valuation, *Contemporary Accounting Research* 11, 661-687.

Pastor, L. and R.F. Stambaugh, 2001, Liquidity risk and expected stock returns, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=331840.

Perotti, E.C. and E.L. Von Thadden, 2003, Strategic transparency and informed trading: Will capital market integration force convergence of corporate governance, *Journal of Financial and Quantitative Analysis* 38, 61-85.

Philbrick, D.R. and W.E. Ricks, 1991, Using Value Line and IBES analysts forecasts in accounting research, *Journal of Accounting Research* 29, 397-417.

Phillips D.J. and E.W. Zuckermann, 2001, Middle-status conformity: Theoretical restatement and empirical demonstration in two markets, Working paper, Stanford Business School.

Puffer, S.M. and J.B. Weintrop, 1991, Corporate performance and CEO turnover: The role of performance expectations, *Administrative Science Quarterly* 36, 1-19.

Rao, H. and K. Sivakumar, 1999, Institutional sources of boundary-spanning structures: The establishment of investor relations departments in the fortune 500 industrials, *Organization Science* 10, 27-42.

Richardson, S.A., Teoh, S.H. and P.D. Wysocki, 1999, Tracking analysts' forecasts over the annual earnings horizon: Are analysts' forecasts optimistic or pessimistic?, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=168191.

Richardson, S.A., Teoh, S.H. and P.D. Wysocki, 2001, The walkdown to beatable analyst forecasts: The roles of equity issuance and insider trading incentives, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=281196.

Rielle, C., 2001, La grande migration, *Bilan* January, 34-36.

Routledge, B. and S.E. Zin, 2001, Model uncertainty and liquidity, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=294732.

Securities Industry Association (SIA), 2001, Costs and benefits of regulation fair disclosures, http://www.sia.com/publications/html/online_publications.html.

Scharfstein, D. and J.C. Stein, 1990, Herd behavior and investment, *American Economic Review* 80, 465-479.

Seasholes, M., 2000, Smart foreign traders in emerging markets, Working paper, Harvard Business School, Cambridge, M.A.

Sharpe, W., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 422-442.

Shiller, R.J., 1981, Do stock prices move too much to be justified by subsequent changes in dividends?, *American Economic Review* 71, 421-436.

Sinha, P., Brown, L.D. and S. Das, 1997, A re-examination of financial analysts' differential earnings forecast accuracy, *Contemporary Accounting Research* 14, 1-42.

Skinner, D., 1994, Why firms voluntarily disclose bad news?, *Journal of Accounting Research* 32, 38-61.

Spiegel Online, 2000, Analysten noch schlimmer als Wetterfrösche. http://www.spiegel.de./witschaft/0,1518,109690,00.

Soffer, L., Thiagarajan, R. and B. Walther, 2002, Earnings preannouncement strategies, *Review of Accounting Studies* 5, 5-26.

Skinner, D.J. and R.G. Sloan, 2001, Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=172060.

Stickel, S., 1992, Reputation and performance among security analysts, *Journal of Finance* 47, 1811-1836.

Stickel, S., 1995, The anatomy of the performance of buy and sell recommendations, *Financial Analysts Journal* September/October, 25-39.

Teoh, S.H. and T.J. Wong, 1997, Analysts' credulity about reported earnings and overoptimism in new equity issues, SSRN Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=8529.

Trueman, B., 1994, Analyst forecasts and herding behavior, *Review of Financial Studies* 7, 97-124.

Yermack, D., 1997, Good timing: CEO stock option awards and company news announcements, *Journal of Finance* 52, 449-476.

Vial, T., 2002, Les analystes méritent-ils leur salaire?, *Bilan* January, 39-40.

Womack, K.L., 1996, Do brokerage analysts' recommendations have investment value ?, *Journal of Finance* 51, 137-167.

Welch, I., 2000, Herding among security analysts, *Journal of Financial Economics* 58, 369-396.

White, H., 1980, A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity, *Econometrica* 48, 817-838.

Zimmermann, J. and I. Gontcharov, Do accounting standards influence the level of earnings management?, SSRN Working paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=386521.