Does the firm-analyst relationship matter in explaining analysts' earnings forecast errors?

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Abstract

We study whether financial analysts' concern for preserving good relationships with firms' managers motivates them to issue pessimistic or optimistic forecasts. Based on a dataset of one-year-ahead EPS forecasts issued by 4 648 analysts concerning 241 French firms (1997-2007), we regress the analysts' forecast accuracy on its unintentional determinants. We then decompose the fixed effect of the regression and we use the firm-analyst pair effect as a measure of the intensity of the firm-analyst relationship. We find that a low (high) firm-analyst pair effect is associated with a low (high) forecast error. This observation suggests that pessimism and optimism result from the analysts' concern for cultivating their relationship with the firm's management.

Keyword : financial analysts, earnings forecasts, soft information, panel regression.

JEL classification: C58, D84, G17, G24

Introduction

Financial analysts' role as information producers is crucial for financial markets. By issuing forecasts regarding the value of firms' shares or earnings per share (EPS), they reduce information asymmetries between firms and investors or fund managers. Generally issued on behalf of brokers, forecasts and selling or buying recommendations are widely used by fund managers for taking portfolio allocation decisions. However, many studies have demonstrated that analysts' earnings forecasts can be inaccurate (Brown, 1997), thus increasing corporate agency costs, and reducing the informational efficiency of financial markets.

A large literature has developed, suggesting that close relationships between firms and analysts strongly matter for earnings forecasts or recommendations. As underlined by Michaely and Womack (1999), proximity between a firm and an analyst should improve the quality of information and the accuracy of forecasts or recommendations produced by analysts. Measuring the relationship intensity by the geographical distance between firms' headquarters and analysts, Malloy (2005) reports that closer analysts issue more accurate forecasts. Cohen, Frazzini and Malloy (2010) focus on the role played by social network in the dissemination of information. They show that analysts are more likely to outperform on their buying recommendations when they had an educational link with the firm's management, i.e. when they attended the same institution as a senior officer or a board member of the firm.

In these contributions, the existence of a close tie between firms and analysts appears as an unintentional determinant of forecast accuracy. However, another strand of literature indicates that analysts may be encouraged to intentionally biase their forecasts or recommendations in order to please the firm' manager and to cultivate their relationship with him. According to this view, the firm-analyst relationship decreases, rather than increases, the accuracy of the analyst's forecast.

A first set of paper is dedicated to conflicts of interest that can arise when the analyst is linked to an investment banking that provides underwritting, Initial Private Offerings (IPO) or merger services . Biasing forecasts or recommendations allows the analyst to please his employer by allowing him to win or to preserve potentially lucrative customer relationship with the firm. On the one hand, issuing pessimistic forecasts is a means for the analyst to secure the underwritting or the IPO conducted by his employer by making newly issued shares particularly attractive for investors. On the other hand, because pessimistic forecasts avoid managers to create a negative earnings surprise when they annouce the actual EPS, analysts may also be encouraged to win the favor of the firm's manager by biasing forecasts dowward. In this approach, the firm-analyst relationship's intensity is mainly measured through institutional indicators, such as being (or not) affiliated to an investment banking that underwrites securities (Dugar and Nathan, 1995; Lin and MacNichols, 1998) or completes IPO and mergers (Hayward Hayward and Boeker, 1998; Dechow, Hutton and Sloan (2000); Michaely and Womack, 1999; Lin, Mac Nichols and O'Brien, 2005).

Because they account for closeness between investment banks (themselves tied to firms through investment services) and analysts rather than between firms and analysts, such measures are only indirect. Moreover, they do not allow to capture another crucial dimension of the firm-analyst relationship. As analysts also provide to their clients, mainly fund managers, non-financial and 'raw' information, they are concerned about participating to phone calls, one-on-one meetings and conference calls organized by the firm (Barber, Lehavy and Trueman 2007; Fogarty and Rogers, 2005; Breton and Taffler, 2001). For this reason, analysts are encouraged to please the firm's manager and to cultivate a close relationship in order to maintain their access to information selectively disclosed by the firm's manager. Biasing their forecasts is as a means to reach this goal. Its consists either to issue optimistic forecasts, to create a positive reaction from stock markets, or to produce pessimistic forecasts, to allow the firm manager to avoid negative earnings surprises at the announcement of actual earnings (Libby, Hunton, Tan and Seybert, 2008). To check for this argument, the empirical literature mainly resort to indirect tests. For example, Lim01 provides evidence that highly experienced analysts, who are less concerned with preserving their relationships with firm managers, are generally less optimistic than low-experience ones. Similarly, Das et al. (1998) and Francis and Philbrick (1993) show that optimistic forecasts or recommendations are all the more optimistic when firms received unfavorable ratings from the well-known American financial publication Value Line. Their interpretation of this result is that the need to preserve their relationships with firm managers is stronger for badly-rated firms. Finally, although these findings suggest that analysts are prompt to biase their forecasts to keep the favor of the firms' management, they do not provide any explicit measure of the firm-analyst relationship and of its contribution to the forecast process.

This is precisely the aim of this paper to propose a direct, explicit and comprehensive measure of the firm-analyst relationship's intensity and to check whether a close tie between a firm and an analyst, as measured by our innovative indicator, is associated with intentional biased (optimistic or optimistic) EPS forecats. To do so, we use an IBES data set provided by ThomsonReuters, which contains forecasts issued by 4 648 analysts regarding the earnings of 241 French firms between 1997 and 2007. We regress the analysts' forecast accuracy on its unintentional determinants. We then capture the disturbance term of the regression and we compute a measure of the relationship intensity based on the firm-analyst specific effect. We then study the link between this indicator and analysts' forecasts to determine whether high (negative or positive) forecast errors are associated with a high firm-analyst pair effect. We provide interesting evidence that the need to preserve their relationships with firm managers prompts analysts to issue biased (pessimistic or optimistic) forecasts about firms' EPS.

The paper is organized as follows. Section 2 presents the background of our research. Section 3 presents our empirical investigation while our results are reported in Section 4. Section 5 considers some robustness checks. Section 6 concludes.

2 Literature

In this section, we review the literature dedicated to forecast accuracy and its determinants. We first focus on unintentional drivers of forecast accuracy (firms', analysts' and pairs' characteristics). Then, we point out the intentional determinant of biased forecasts, based on the analyst' concern for creating or preserving a friendly relationship with firms' management.

2.1 Unintentional Determinants of Forecast Accuracy

Analysts' forecasts can be unintentionally inaccurate for three reasons. First, firm characteristics can make its EPS difficult to predict. Second, the characteristics of the analyst might reduce its ability to forecast. Finally, the characteristics of both the firm and the analyst can decrease the analyst's ability to predict the firm's EPS.

2.1.1 Firms' Characteristics

Concerning the firm characteristics, the empirical literature documents that forecast errors are negatively correlated with information availability and earnings predictability. Using a data set of firms from the Value Line Survey between 1989 and 1993, DasLevine98 report that the forecast error (the difference between forecasted and realized earnings) increases in firms' profit volatility. This result is confirmed by Lim01 using a set of forecasts provided by I/B/E/S (Institutional Brokers Estimate System) for the period 1984-1996. Further corroboration is provided by Jackson05 who employs a data set of brokers on the Australian security market over the period 1992-2002. Moreover, as greater public information is available for large firms and those followed by a large number of analysts, optimism is shown to decrease in firm size (Das et al., 1998; Lim, 2001; Jackson, 2005) and analyst coverage (Lim, 2001). Regarding interactions between the determinants of forecast accuracy, DasLevine98 establish that analyst coverage mitigates the increasing effect of earnings volatility on forecast optimism. Finally, past optimistic consensus about a firm deters analysts from contradicting the consensus forecast when it is inaccurate and thus increase their forecast error (Lim, 2001).

2.1.2 Analysts' Characteristics

Analyst characteristics also affect earnings forecasts. Using a set of I/B/E/S forecasts over the period 1983-1994, Clement99 finds that general experience, measured by the number of years in which an analyst supplied at least one forecast, is associated with accuracy. When general experience increases, two effects are at play. First, the skill of the analyst increases, due to a learning-by-doing process. Second, the analyst is identified as highly capable because low-skilled analysts do not last in the profession. Forecast error also increases in the complexity of the analyst's portfolio (Clement, 1999). When an analyst follows a large number of firms, he devotes less resources to each one. When he follows a large number of industrial sectors, he benefits from sector specialization to a lesser extent. Another important characteristic is the size of the broker employing the analyst. This feature affects forecast accuracy and optimism bias. As a large broker can devote more resources to analyzing firms, analysts issue more accurate forecasts (Clement, 1999). This result is confirmed by Clement and Tse (2005) using an I/B/E/S dataset from 1989 to 1998.

2.1.3 Firm-analysts' Characteristics

Finally, firm-analyst characteristics are important determinants of forecast accuracy. For the same reasons as above (learning-by-doing and analyst survival effects), specific experience, measured by the number of years in which an analyst supplied at least one forecast on a given firm, should increase forecast accuracy. Clement's (1999) results are in accordance with this assumption. He reveals a negative relationship between specific experience and the absolute value of the forecast error. Using a set of I/B/E/S forecasts between 1988 and 2000, Clarke06 confirm the role of specific experience. The forecast frequency is a signal of forecast accuracy, in the sense that analysts react more to new information about a given firm when the frequency is high. This result appears in Jacob, Lys and Neale (1999), using a Zacks Investment Research database from 1981 to 1992. It is also the case in Clement (1999), Clement and Tse (2005). In the same vein, those studies reveal that the time elapsed between two forecasts indicates how outdated the forecast is: the longer a forecast goes unrevised, the less accurate it is. They also provide evidence that the greater the forecast horizon, the less accurate it is. Finally, Brown (2001), using an I/B/E/S database over 1986-1998 as well as Clement and Tse (2005), and Clarke and Subramanian (2006), explore the role played by past accuracy. They find that low past accuracy is associated with a low current absolute value of the difference between forecasted and actual earnings. This result suggests that forecast errors are persistent.

2.2 The Concern to Establish or to Maintain a Good Relationship with the Firm’s Management

Sell-side analysts can also be encouraged to intentionnally biase their EPS forecasts in order to establish or to maintain a friendly relationship with the firm’s management. This behaviour has at least two sources.

2.2.1 Conflicts of Interest

First, the desire not to compromise its relationship with a firm’s manager can emerge when the analyst is linked to (employed by) a financial institution that provides investment banking services to the firm.

On the one hand, issuing optimistic forecasts or recommendations on a firm allows the analyst to please his employer by helping him to win or to preserve potentially lucrative customer relationship with the firm . This theoretical intuition is confirmed by Dugar and Nathan (1995). Using a sample of 400 firms traded on the NYSE/AMEX between 1983 and 1988, they document that analysts in investment banking produce more optimistic forecasts and recommendations than others. Among various investment banking services that can give birth to conflicts of interest, underwritting has received particular attention in the literature. When an investment bank has been hired as a lead- or co-underwritter, optimist forecasts allow the analyst to secure the underwriting activity of the investment bank by enticing investors to buy newly issued securities. Relying on an I/B/E/S data set over the period 1989-1994, Lin and MacNichols (1998) find that affiliated analysts, i.e. analysts employed by an investment bank that intervenes as a lead- or co-underwriter for a firm issue more optimistic forecasts about this firm than non-affiliated analysts. This result also holds in the case of analysts' recommendations, as shown by Michaely and Womack (1999), using a data set of 391 IPO on the NYSE/AMEX/NASDAQ in 1990 and 1991, and by McKnight, Tavakoli and Weir (2010), relying on a large I/B/E/S data set covering 13 countries (Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland and United Kingdom). fINALLY, investment banking services that consists to complete IPO or mergers also create conflicts of interest (Michaely and Womack, 1999). Here again, analysts have strong incentive to issue optimistic forecasts about a firm when the investment bank they are linked to takes this firm to the market. Using a sample of I/B/E/S forecasts between 1981 and 1990, Dechow, Hutton & Sloan (2000) show that analysts who are employed by an investment bank that manages a public offering issue more optimistic forecasts than others. Michaely & Womack (1999) and Lin, Mac Nichols and O'Brien (2005) observe the same bias for analysts' recommendations.

On the other hand, issuing pessimistic forecast is also a means for an analyst to please a firm's manager. The desire to win or to keep a customer for investment banking business can encourage analysts to make a pessimistic forecast in order to avoid the firm's manager to create a negative earnings surprise when he reports actual EPS. As shown by the literature on the 'earnings management strategy' (Payne and Robb, 2000; Matsumoto, 2002; Burgstahler and Eames, 2006), this strategy consists of the manipulation of earnings forecasts such that the actual EPS ultimately appears to be higher than the forecast. In this case, investors in financial markets may have a favorable reaction, thus increasing the price of firm's shares. Chan, Karceski and Lakonishok (2003) report that this behaviour has been particularly strong during the bull market of the 90ies (during which investment banking business was booming) and for growth stocks (which are the most likely to need investment banking services in the future).

Altogether, these arguments suggest that the desire to preserve or to create a priviligied investment banking relationship with a firm can encourage analysts to issue biased (either optimistic or pessimistic) forecasts or recommendations about this firm.

2.2.2 The Access to Information Selectively Disclosed by Firm's Management

Second, it is noteworthy that analysts do not only provide EPS forecasts but also 'raw' information about firms to their customers. This information, which is highly valued by fund managers (Barker, 1998), refers to firm strategy, management methods, inside organization or relationships between the firm and customers or its suppliers... It is selectively disclosed by firms' managers through phone calls, one-on-one meetings and conference calls (Barber, Lehavy and Trueman 2007; Fogarty and Rogers, 2005; Breton and Taffler, 2001) . As it is important for analysts to preserve their access to this information, they are prone to adopt forecasting behavior that satisfies firms' managers, notably by issuing inacurate forecasts. Consequently, the forecast can be biased in two ways.

On the one hand, the analyst can issue optimistic forecasts, with the aim of presenting the firm under a favourable light and creating a positive reaction from stock markets (Easterwood and Nutt, 1999; Lim, 2001). Pratt93, Gibson95, Womack96 and BoniWomack02 provide several examples of situations in which analysts lost access to a firm's manager due to an unfavorable recommendation or earnings forecast about the firm. Moreover, Das et al. (1998) reveal that the need to preserve their relationships with managers entices analysts to issue particularly optimistic forecasts about firms that received unfavorable ratings from the well-known American financial publication Value Line. The same result is obtained by Francis and Philbrick (1993) using a set of Value Line recommendations for 1987, 1988 and 1989. Finally, highly experienced analysts, who are less concerned with preserving their relationships with firm managers, are shown to be less optimistic than others (Lim, 2001).

On the other hand, as explained in the previous section, the analyst can issue pessimistic forecasts to please the firm's manager by allowing him to 'beat the forecast' at the earnings announcement and prompt a positive earnings surprise on the market or, at least, avoid a negative surprise.

The view that the concern for maintaining their access to selectively disclosed information encourages analysts to issue either optimistic or pessimistic forecasts is globally corroborated by Libby, Hunton, Tan and Seybert (2008). Conducting an experiment on a set of 81 brokerage analysts, the authors report that forecasts are all the more biased (optimistic or pessimistic) when the analyst has a friendly relationship with the firm's management. Analysts recognize that this strategy is intentional and mainly due to the concern for keeping the favor of the firms' management and to preserve their access to selective information disclosure.

Taken together, these contributions suggest that (positive or negative) forecast errors also depend on the analyst's concern to please firm managers in order not to compromise his access to the firm's management.

3 Empirical Investigation

Turning to our empirical investigation, we present our general methodology, as well as our data and econometric model.

3.1 General Methodology

Taken together, the arguments provided in the previous section lead us to state the following testable assumption:

H1: High (negative or positive) forecast errors are associated with a close relationship between a firm and an analyst.

Hence, the goal of our econometric study is to assess the strength of the relationship between a firm and an analyst in earnings forecasts. The main contribution of our empirical approach is to propose an explicit and comprehensive measure of the firm-analyst relationship's intensity. Regressing the analysts' forecast accuracy on observable and unintentional determinants described in section 2.1, we decompose the fixed-effect of the estimate into firm-specific, analyst-specific, and firm-analyst specific effects. This allows us to compute a measure of the relationship intensity based on the firm-analyst specific effect. We then study the link between this indicator and analysts' forecasts to determine whether the relationship intensity contributes to biased (pessimistic or optimistic) EPS forecasts.

3.2 Data

We use data provided by ThomsonReuters. These data include I/B/E/S earnings forecasts and additional data from Worldscope. Our sample contains 241 French firms from the largest Paris' stock index SBF 250, diversified according to the firms' size and sector. We study one-year ahead EPS forecasts by 4 648 analysts from 1997 to 2007 on a monthly basis. This raw database consists of 265 238 firm-analyst-time observations. Several steps were required to clean the data. First, once issued, a forecast is frequently repeated for several months in the database. We obtained the number of monthly occurrences of each forecast by storing it in a variable called . Then, for each forecast, we dropped repeated occurrences of the same forecast, to avoid artificially counting it several times. Second, the date of realized EPS, i.e., the final day of the fiscal year's, was carefully checked. While some firms do not close their fiscal years prior to the 31st of December, the database systematically reports the realized EPS each month from January to December. Thus, some EPS artificially appear in January in the database although they are issued in march, for example. When a difference was detected, forecast errors were computed using fiscal years and not calendar years. Third, we dropped aberrant observations (for example when there are several different forecasts from the same analyst, on the same day, regarding the same firm, etc). As the reported forecasts are supposed to be one-year ahead earnings forecasts, we created a variable denoted , measuring the number of days between the earnings announcement date and the forecast release date. We then dropped forecasts with a negative 'horizon' value, or with a 'horizon' value exceeding 365 days (366 for leap years). Finally we obtain 102 876 firm-analyst-time forecast' observations.

3.3 Econometric model

Assessing the importance of a priviligied relationship between a firm and an analyst in analysts' forecasts requires two steps, which are presented in the two following subsections.

3.3.1 First Step: Estimation

The first step of our investigation consists of estimating the following model:

(1)

The dependent variable, denoted , is the absolute forecast error for the firm 's EPS, forecasted by analyst at date .

Our empirical model contains three sets of explanatory variables. The variable denotes firm characteristics which are invariant across analysts in . Symmetrically, denotes analyst characteristics which are invariant across firms in . Finally, contains a set of variables which are specific both to firm and analyst in . The dummy variables indicate a specific analyst or a firm . The disturbance effect is decomposed into three effects: the firm-specific effect , the analyst-specific effect , and the pair-specific effect . Finally, denotes the time-specific effect. We assume that these effects are fixed (non stochastic). However, it is well known that the use of a within approach (OLS on demeaned variables) in the presence of invariant and/or rarely changing variables may lead to inefficiency and incorrect inferences. In model (1), this issue could arise not only in the firm's dimension but also in the analyst's dimension Indeed, many of our explanatory variables and/or exhibit very small variation in one of these dimensions. Therefore we propose the use the Fixed Effect Vector Decomposition (FEVD) methodology proposed by Plümper and Troeger (2007). This approach consists of a three-stage procedure (similar to that proposed by Mundlak (1978), for the random effects model). The first stage of the estimator runs a fixed-effects model to obtain the unit effects. The second stage decomposes the unit effects into a component explained by the time-invariant and/or rarely changing variables and an error term. The third stage reestimates the first stage by pooled OLS including the time-invariant variables and the error term from stage 2, which then accounts for the unexplained component of the unit effects.

In line with determinants presented in section 2.1, when estimating model (1), we consider three categories of explanatory variables. Variables denoted refer to firms' characteristics.As shown by Jackson05, the absolute forecast error is expected to increase in earnings predictability (denoted), decrease in firm size (denoted) and decrease in analysts coverage (denoted). Following DasLevine98, we also consider two interactive terms. The term . accounts for interactions between EPS predictability and firm size. As firm size should mitigate impact of EPS variability, its coefficient should be negative. The term . stands for interactions between EPS predictability and coverage. For the same reason as above, its coefficient should be negative. Finally, as in Lim01, we include past optimistic consensus about a firm, denoted . The expected sign of this variable is positive.

The second category of explanatory variables refer to analysts' characteristics, denoted . As underlined by Clement99, absolute forecast errors are expected to: decrease in , which stands for the general experience of analyst , increase with and , the number of firms and the number of sectors followed by the analyst respectively, and decrease in , the size of the brokerage house.

The third category of variables relates to determinants specific both to firm and analyst in , . First, as in Clarke06 and Clement99, the error should decrease with , the specific experience of analyst with firm . Following Clement05, absolute forecast errors should: be greater if the forecast is far from the end of the fiscal year (variable denoted), decrease if the analyst frequently revises his forecasts (variable denoted), and hence increase in the forecast's lifetime in the database (variable denoted) and increase in past errors (variable denoted).

Table 1, in the Appendix, reports the list of regression variables mentioned above and how they are computed while Tables 2 and 3, also in the Appendix, provide summary statistics and correlation coefficients, respectively. The coefficients reported in Table 3 are generally consistent with the expected correlations. The forecast error of analyst for firm is positively correlated with the degree of firm EPS predictability, the past median forecast error regarding firm , the number of firms and sectors covered by analyst , the number of days to the fiscal year end and the latest forecast for the firm-analyst pair. It is negatively correlated with the size of firm , the general and the specific experience of analyst , the size of the broker and the forecast's lifetime in the database. Some other correlations are also noteworthy. First, specific and general experience are positively correlated. Moreover, both variables are positively linked to the size of the broker and the frequency of forecasts. Finally, there is also a negative correlation between the size of the firm and its degree of EPS variability, which lends some support to the notion that mitigates the positive impact of on the forecast error.

3.3.2 Second Step: Analyzing the Pair-Specific Effect

In a second step, we focus on the pair-specific effect of our estimate to measure the intensity of the relationship between the firm and the analyst that is not captured in the unintentional determinants defined in the previous section.

Our methodology decomposes the fixed effect of the panel regression into three components: the firm effect ( ), the analyst effect ( ), and the firm-analyst' pair effect ( ).

Having estimated our model, we are able to compute , the 'contribution of the pair-specific effect', defined as follows:

, where is the unconditional constant of the regression. The pair-specific effect, computed by the STATA procedure of PlumperTroeger07, is centered on a mean calculated over all observations.

Adding the unconditional constant in both the denominator and the numerator of makes it possible to correct for this bias and construct a consistent indicator.

, defined as the pair-specific effect in absolute value relative to the absolute value of the total fixed effect, measures the importance of the pair-specific effect as a determinant of , relative to firm-specific and analyst-specific effects. For a given forecast, the greater the contribution of the pair-specific effect, the closer the relationship between a particular firm and a particular analyst. When is low, the unexplained component of the forecast error is primarily due to either the firm alone or to the analyst alone. When is high, the unexplained component of the forecast error is primarily due to the specific firm -analyst pair. Finally, we rank observations by 'twentiles' of the relative median forecast error , defined as the median, over the full sample period, of the difference between the EPS forecasts and the EPS realization of each firm by each analyst for a forecast issued in . We obtain 20 groups from the 5% most pessimistic to the 5% most optimistic . For each observation of , we are able to match the value that concerns the analyst and the firm involved in this observation. We then compute the mean value of for each 'twentile' (from the 5% most pessimistic to the 5% most optimistic). We plot the median forecast error 'twentiles' against the pair effect contribution. Such a graph should allow us to verify our testable assumption H1. If we observe that is greater for the most extreme (negative or positive) forecast error 'twentiles', this means that the pair effect accounts for most of the residuals when the forecast error is high. In other words, controlling for all observed variables (including analyst and firm dummies), the unintentional factors specifically related to the firm -analyst pair play a greater role than analyst- or firm-specific intentional factors, when the forecast error is high. We interpret this result as the demonstration of the role played by the firm-analyst relationship. It captures the fact that the need to maintain access to the firm's management provide analysts with an incentive to issue pessimistic or optimistic forecasts. Conversely, we should observe that is weaker for central 'twentiles' (i.e. forecast error around zero). If this prediction is true, H1 is validated.

To make sure the contribution of the pair effect differs according to the size of the forecast error, we also test for the relationship between and . We first conduct a median test that allows us to investigate whether the median of in a given 'twentile' equals the median of the full sample. We then conduct the Bartlett test that checks for the equality of variance of across 'twentiles'. Finally, we use the Krusal-Wallis equality-of-population rank test, which determines whether the rank sum of each observation ranked by differs across 'twentiles'.

4 Results

We now present our findings. We first present our results concerning the estimation of model [1]. Second, we comment on our findingsconcerning the relationship between the pair effect contribution and the forecast error.

4.1 Results of Panel Regressions with Vector Decomposition

The results of panel regressions with vector decomposition for model [1] are reported in Table 4, in the Appendix. Although the aim of our study is check for the role of the relationship intensity in analysts' forecasts errors, we briefly comment on the results we obtained concerning observable and unintentional determinants. First, we focus on variables , that capture firm-specific characteristics. We observe that has a positive impact on the dependent variable, suggesting that the more difficult it is to predict the firm's EPS, the larger the analyst's forecast error (Das et al., 1998; Lim, 2001; Jackson, 2005). has a negative impact on the dependent variable. As public information availability is enhanced for firms followed by a large number of analysts, a higher analyst coverage decreases forecast error (Lim, 2001). The coefficient for the interaction term also has the expected negative sign. This finding indicates that analyst coverage mitigates the impact of EPS variability (Das et al., 1998). Finally, following Lim (2001), the coefficient for has the expected positive sign. The greater the past optimistic consensus, the larger the analysts' forecast error. Table 4 also indicates that, in contrast to the prior empirical literature, a firm's size has no effect on the dependent variable. Finally, the coefficient for the interaction term is positive, indicating that firm size amplifies the impact of EPS variability.

We now turn to variables , that represent analysts' characteristics. General experience ( ) reduces forecast error. In line with Clement99 and Lim01, the greater the general experience of the analyst, the lower the analysts' forecast error. has a significant and positive sign. when an analyst follows a large number of firms, he dedicates fewer resources to each of them such that the forecast error is higher (Clement, 1999). Table 4 also reveals that the number of sectors followed by the analyst ( ) has no impact on the dependent variable. Finally, as expected, the coefficient for has a significant and negative sign. This result, which is in line with Lim01 and Clement99, suggests that being employed by a large broker allows an analyst to dedicate more resources to prediction and produce more accurate forecasts.

Finally, we comment on our results concerning variables , that are specific both to firm and analyst . First, the coefficient for exhibits a negative sign: as expected, the absolute forecast error decreases in the specific experience of analysts. In line with theory, the coefficient for is significant and positive: the further from the end of the fiscal year, the less accurate the analyst's forecast. However, while the coefficient for is not significant, the coefficient for is positive, which is not the expected impact on the dependent variable. Finally, has the expected positive sign, which indicates inertia in forecast dynamics.

4.2 Results Concerning the Pair-specific Effect

Let us now concentrate on the graph of pair effect contribution by 'twentiles' of median forecast error .Graph 1 provides interesting representations of by 'twentiles' of . The first 'twentile' represents the most pessimistic forecasts (FE approximately -2), the 10th 'twentile' represents the most accurate forecasts (approximately 0) and the 20th ‘twentile’ represents the most optimistic forecast (FE approximately +9). We observe that there is a non-linear relationship between and . This is represented by a convex curve. is at its lowest level when lies in the tenth ‘twentile’. When the forecast error is weak, the pair effect only accounts for approximately 30% of the total fixed effect. When the forecast error is high, the pair effect account for over 40% of the fixed effect. This result is interesting for at least two reasons. First, it suggests that the relationship between and can be represented by a non-linear curve. Second, this finding indicates that the contribution of the pair-specific effect reaches its minimum for intermediate values of while is at its maximum for both the most optimistic and the most pessimistic forecast ‘twentile’. This observation means that the contribution of the pair-specific effect is more important when the forecast error is high.

Our results thus validate our testable assumption H1 and provide evidence that the firm-analyst relationship matters for earnings forecasts. They suggest that some analysts attempt to create or to maintain friendly relationships with some firms’ managers in order to generate investment banking business or to maintain their access to selectively disclosed information and that this leads them to intentionally biasing their EPS forecasts. It is noteworthy that this effect appears after capturing observable and unintentional determinants of the forecast accuracy. A forecast error can be observed because the firm is particularly difficult to predict, because the analyst as low inability to predict or because both firm’s and analyst’s characteristics decrease the analyst’s ability to predict the firm’s EPS. But as all these elements have been accounted for, the remaining forecast error reflects the intentional impact of the firm-analyst relationship in the forecasting process.

Finally, the results of the median test, the Bartlett test and the Krusal-Wallis test are reported in Table 5, in the Appendix. They confirm that for each test, testable assumption H1 is validated: the contribution of the pair effect differs according to the size of the forecast error.

5 Robustness Checks

In this section, we propose two robustness checks for our findings. We first estimate several variants of our model, inspired by the literature. We then discuss the FEVD estimator.

5.1 Variants of the Model

First, we estimate several variants of model [1]. The goal of this subsection is to 'reproduce', using ou own sample, the estimates conducted in some papers in the empirical literature and to examine whether they result in the same representations of by 'twentiles' of as model [1].

In variant [2], we refer to the estimate by Jackson05, which only considers earnings predictability ( ), firm size ( ) and analysts coverage ( ). Specification [3] relates to the study by DasLevine98, which considers the three variables mentioned above and the two interactive terms, and . In variant [4], we follow Lim (2001) by including all variables contained in specification [3] and past optimistic consensus ( ). Variant [5] refers to the study by Clement99, which considers the general experience of analyst ( ), the number of firms ( ) and sectors ( ), brokerage house size ( ) as well as the specific experience of analyst with firm ( ). Finally, specification [6] is inspired by Clement and Tse (2005), who add four additional variables to those included in variant [5]: how far the forecast is from the end of the fiscal year ( ), analyst revision frequency ( ), the forecast's lifetime in the database ( ) and past errors ( ). Results of panel regression are presented in Table 6, in Appendix. Except some rare cases, they are globally consistent with the literature and with findings obtained in the previous section.

Graphs 2 to 6, in Appendix, provide interesting representations of by 'twentiles' of for specifications [2] to [6] respectively. Graphs 2, 3, 4 and 6 exhibit a non-linear relationship between and . In all specifications except variant [5], it is represented by a convex curve. These findings suggest that the results obtained in Section 4.2 are quite robust. Whatever the variant and the number of characteristics included in the estimation, the contribution of the pair-specific effect is at its minimum for intermediate values of and at its maximum for both the most optimistic and for the most pessimistic forecast ‘twentile’ . Overall, these findings reinforce the notion that the desire to create or to maintain good relationships with firm managers incentivizes some analysts to issue pessimistic or optimistic forecasts.

The results of the median test, the Bartlett test and the Krusal-Wallis equality-of-population rank test for variants 2 to 6 are reported in Table 7, in the Appendix. They indicate that for each test, the contribution of the pair effect differs according to the size of the forecast error. This result seems particularly robust since its holds for each of our five variants.

5.2 Discussion on the FEVD Estimator

In this section, we discuss the FEVD estimator used to estimate model [1] and variants [2]-[6]. It is worth noting that the FEVD estimator is equivalent to a standard instrumental variables approach, for a specific set of instruments as recently shown by Breusch et al. (2011). Greene (2011) argues that the FEVD approach does not provide an estimator for the coefficients for time invariant variables in a fixed effects model: that component of the parameter vector remains unidentified. However in the presence of slowly changing variables as in our context, this estimator remains consistent, even if the efficiency gains (compared to Hausman and Taylor’s, 1981, approach) are controversial. One advantage of the FEVD is that, as the Fixed Effects (Within) estimator, and unlike that of Hausman and Taylor, it does not require specifying the exogeneity status of the explanatory variables. For Greene (2011), the FEVD estimator simply reproduces (identically) the linear fixed effects (dummy variable) estimator, and then substitutes an inappropriate covariance matrix for the correct one. This is why we propose an additional estimate of the covariance matrix here.

The results reported in Section 4 are based on the covariance matrix defined in the context of the three stages estimation procedure by Plümper and Troeger (2007). In Table 8 (in Appendix), we compute the value of the standard errors obtained using the covariance matrix proposed by Greene

(2011), which corresponds to the matrix estimated in the first stage of the Plümper and Troeger (2007) procedure, for model [1] and for variants [2] to [6]. Our goal is to compare both standard errors to show that Greene's (2011) argument has limited relevance for our purposes, which is to investigate the relationship between pair effects and forecast errors. Our results indicate that in most cases, standard errors using the covariance matrix from the first stage of the estimation procedure of Plümper and Troeger (2007), as is proposed by Greene (2011), are higher than those obtained through the third stage. Although this observation modifies the significance of the coefficients reported in Section 4, the coefficients and residuals remain unchanged. Therefore our use of the decomposition of the fixed effect is appropriate for our data and purposes.

6 Conclusion

The goal of this paper was to determine whether the analysts' concern for winning or preserving the favor of firm's management provides them with incentives to intentionally issue biased (optimistic or pessimistic) forecasts. We employed a Thomson Reuters data set that contains the forecasts issued by 4 648 analysts concerning the earnings of 243 French firms over the period 1997-2007.

One important innovation of our approach is to propose a comprehensive and explicit measure of the relationship that exists between a firm and an analyst. Having regressed analysts forecast error on unintentional firm-specific, analyst-specific and pair-specific determinants, we decompose the disturbance effect to extract a pair-specific effect. This effect provides a measure of the firm-analyst relationship, allowing us to determine whether closeness between firms and analysts contributes to analysts' pessimism or optimism. Finally, we provide interesting evidence that the need to create or to preserve relationships with firms' managers encourages some analysts to issue pessimistic forecasts while prompting some others to issue optimistic forecasts about firms' EPS.

Our results undoubtedly call for further research. Of course, our work could be extended to the case of other countries, to determine whether the effect of the telationship between firms and analysts has a national dimension. More ambitiously, it would be interesting to examine the consequences of analysts’ forecast on portfolio investment strategies. For example, this investigation could be performed by studying what type of forecasting profile (accurate, pessimistic or optimistic) leads to the most profitable investment recommendations for asset managers.

References

Barber, Lehavy & Trueman2007Barber07 Barber, B., Lehavy, R. and Trueman, B., 2007. Comparing the stock recommendation performance of investment banks and independent research firms. Journal of Financial Economics. 85, 490-517.

Barker1998Barker98 Barker, R.G., 1998. The market for information: evidence from finance directors, analysts and fund managers. Accounting and Business Research. 29, 3-20.

Boni and Womack2002BoniWomack02 Boni, L. and Womack, K.L., 2002. Wall Street credibility problem: misaligned incentives and dubious fixes. Brookings Wharton Papers on Financial Services, 93-130.

Breton and Taffler2001BretonTaffler01 Breton, G. and Taffler, R., 2001. Accounting information and analyst stock recommendation decisions: a content analysis approach. Accounting and Business Research. 31, 91-101.

Breusch & Ward & Nguyen & Kompas2011Breusch2011 Breusch, T., Ward, M., Nguyen, H. and Kompas T., 2011. On the fixed-effects vector decomposition. Political Analysis. 19, 129-134

Brown1997Brown1997 Brown, L., 1997. Analyst forecasting error: additional evidence. Financial Analysts Journal. 53, 81-88.

Brown2001Brown2001 Brown, L., 2001. How important is past analyst forecast accuracy. Financial Analysts Journal. 57, 46-49.

Burgstahler2006Burgstahler06 Burgstahler, D. and Eames, M., 2006. Management of earnings and analysts' forecasts to achieve zero and small positive earnings surprises. Journal of Business Finance and Accounting. 33, 633-652.

Cen & Hilary & Wei2013Cen13 Cen, L., Hilary, G. and Wei, K., 2013. The role of anchoring bias in the equity market: evidence from analysts' earnings forecasts and stock returns. Journal of Financial and Quantitative Analysis, 48, 47-76.

Chan & Karceski & Lakonishok2007Chan07 Chan, L.K.C., Karceski, J. and Lakonishok, J., 2007. Analysts' conflicts of interest and biases in earnings forecasts. Journal of Financial and Quantitative Analysis. 42, 893-914.

Clarke and Subramanian2006Clarke06 Clarke, J., Subramanian, A., 2006. Dynamic forecasting behavior by analysts: theory and evidence. Journal of Financial Economics. 80, 81-113.

Clement1999Clement99 Clement, M., 1999. Analyst forecast accuracy: do ability, resources, and portfolio complexity matter? Journal of Accounting and Economics. 27, 285-303.

Clement and Tse2005Clement05 Clement, M., Tse S., 2005. Financial analyst characteristics and herding behavior in forecasting Journal of Finance. 60, 307-341.

Cohen, Malloy and Frazzini2010Cohen10 Cohen, L., Malloy, C. and Frazzini, A., 2010. "Sell-side school ties." Journal of Finance. 65, é 1409-1437.

[Das et al.]Das, Levine and Sivaramakrishnan1998DasLevine98 Das, S., Levine, C. and Sivaramakrishnan C., 1998. Earnings predictibility and bias in analysts' earnings forecasts. Accounting Review. 73, 277-294.

Dechow, Hutton and Sloan 2000 DechowHuttonSloan00 Dechow, P, Hutton, A. and Sloan, R., 2000. The relation between an alysts' forecasts of long-term earnings growth and stock price performance following equity offerings. Contemporary Accounting Research. 17, 1-32.

Dugar & Nathan1995DugarNathan95 Dugar, A. and Nathan, S., 1995. The effect of investment banking relationships on financial analyst's earnings forecasts and investment recommendations. Contemporary Accounting Research. 12, 131-160.

Easterwood & Nutt1999EasterwoodNutt99 Easterwood, J. and Nutt, S., 1999. Inefficiency in analysts' earnings forecasts: systematic misreaction or systematic optimism. Journal of Finance. 54, 1777-1797.

Fogarty and Rogers2005FogartyRogers05 Fogarty, T. and Rogers, K., 2005. Financial analysts' reports: an extended institutional theory evaluation. Accounting, Organization and Society. 30, 331-356.

Francis and Philbrick1993FrancisPhilbrick93 Francis, J. and Philbrick, D., 1993. Analysts' decisions as product of multi-task environment. Journal of Accounting Research. 31, 216-230.

Gibson1995Gibson95 Gibson, R., 1995. Analysts take heat for 'sell' rating on Archer-Daniels. Wall Street Journal. august 31.

Greene2011Greene2011 Greene, W., 2011. Fixed effects vector decomposition: a magical solution to the problem of time invariant variables in fixed effects models? Political Analysis. 19, 135-146.

Hausman and Taylor1981Hausman81 Hausman, J., Taylor, W., 1981. Panal data and unobservable individual effects. Econometrica. 49, 1377-1398.

Hayes1998Hayes98 Hayes, R., 1998. The impact of trading commission incentives on analysts' stock coverage decisions and earnings forecasts. Journal of Accounting Research. 36, 299-320.

Hayward & Boecker1998HaywardBoecker98 Hayward, M. and Boecker, W., 1998. Power and conflicts of interest in professional firms: evidence from investment banking. Administrative Science Quarterly. 43, 1-22.

Hong and Kubik2003HongKubik Hong, H. and Kubik, J., 2003. Analyzing the analysts: career concerns and biased earnings forecasts Journal of Finance. 58, 313-351.

Jackson2005Jackson05 Jackson, A., 2005. Trade generation, reputation and sell-side analysis. Journal of Finance. 60, 673-717.

Jacob & Lys & Neale1999JacobLysNeale99 Jacob, J., Lys, T.Z. and Neale, M.A., 1999. Expertise in forecasting performance of security analysts. Journal of Accountings and Economics. 28, 51-82.

Libby & Hanton & Tan & Seybert2008 Libby08 Libby, R., Hunton, J. and Seybert, N., 2008. Relationship incentives and the optimistic/pessimistic pattern in analysts' forecasts. Journal of Accountings Research. 46, 173-198.

Lim2001Lim01 Lim, T., 2001. Rationality and analysts' forecast bias. ournal of Finance. 56, 369-385.

Lin and McNichols1998 Lin98 Lin, H. and McNichols, M., 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. Journal of Accounting and Economics. 253, 101-127.

Lin, McNichols & O'Brien2005Hsiou05 Lin, H.W., McNichols, M. and O'Brien, P., 2005. Analyst impartiality and investment banking relationships. Journal of Accounting Research. 43, 623-650.

McKnight, Tavakoli, & Weir 2010 McKnightTavakoliWeir10 McKnight, P., Tavakoli, M. and Weir, C., (2010). Underwriting relationships and analyst independence in Europe financial markets. Institutions and Instruments. 19, 189-213.

Malloy2005Malloy05 Malloy, C., 2005. "The geography of equity analysis". Journal of Finance. 60, 719–755.

Matsumoto2002Matsumoto02 Matsumoto, D., 2002. Management's incentives to avoid negative earnings surprises. Accounting Review. 77, 483-514.

Mehran and Stulz2007 Mehran07 Mehran, H. and Stulz, R., 2007. The economics of conflicts of interest in financial institutions. Journal of Financial Economics. 85, 267-296.

Michaely and Womack1999 Womack99 Michaely, R. and Womack, K.L., 1999. Conflicts of interest and the credibility of underwriter analyst recommandations. Review of Financial Studies. 12, 653-686.

Mundlak1978Mundlak78 Mundlak, Y., 1978. On the pooling of times series and cross section data. Econometrica, 46, 69-85.

Payne and Robb2000Payne00 Payne, J. and Robb, S., 2000. Earnings management: the effect of ex-ante earnings expectations. Journal of Accounting, Auditing and Finance. 15, 371-92.

Plümper and Troeger2007PlumperTroeger07 Plümper, T. and Troeger, V., 2007. Efficient estimation of time-invariant and rarely changing variables in finite sample panel analyses with unit fixed effects. Political Analysis, 15, 124-139.

Pratt1993Pratt93Pratt, T., 1993. Wall Street four letter word. Investment Dealers' Digest, march 29.

Womack1996Womack96 Womack, K.L., 1996. Do brokerage analysts' recommendations have investment value? Journal of Finance. 51, 137-167.vol.21,n°1,pp.57-73.

Table 1.**List of regression variables**

Variables described in Table 1 are defined on a set of one-year-ahead EPS forecasts issued by 4 648 analysts concerning 241 French firms (1997-2007).

DEPENDENT VARIABLE	
AFE	**Absolute forecast error (absolute difference between the EPS forecast and the EPS realization of each firm i**
	by each analyst j at date t of forecast issue)
INDEPENDENT VARIABLES AND EXPECTED SIGNS	
Firm's characteristics $\mathbf{X}_{i,t}$	
$EPSPREV$ **(+)**	**Predictibility of EPS (volatility of firm i's EPS over the last 3 years)**
$SIZE$ **(-)**	**Size of the firm (log of the market capitalization of firm i in t)**
$COVER$ **(-)**	**Coverage of the firm in t (number of analysts who follow firm i in t)**
$PASTMedFE$ **(+)**	**Consensus surprise (for each firm i, the median of the difference between the consensus and the realized EPS**
	in the previous year)
Analysts' characteristics $\mathbf{Y}_{j,t}$	
$GENEXP$ **(-)**	**General experience of analyst j (in t, number of days since the analyst's first forecast)**
$NBFIRM$ **(+)**	**Number of firms followed by analyst j in t**
$NBSECT$ **(+)**	**Number of sectors followed by analyst j in t**
$BROKER$ **(-)**	**Size of the broker (number of analysts working for analyst j's broker in t)**
Firm-analysts' characteristics $\mathbf{Z}_{i,j,t}$	
$SPECEXP$ **(-)**	**Specific experience of the analyst (in t, number of days since the first forecast by analyst j about firm i)**
$TERM$ **(+)**	**Number of days from t to fiscal year end for a forecast issued by analyst j on firm i**
$FREQ$ **(-)**	**Frequency of forecasts (number of forecasts per year by analyst j on a firm i in t)**
$PASTAFE$ **(+)**	**forecast error of analyst j on firm i in the previous year**
$DURATION$ **(+)**	**forecast lifetime in the database in months (by analyst j on a firm j in t)**

Table 2.**Statistical summary for regression variables (1997-2007)**

Table 2 presents descriptive statistics for variables. The sample period is from 1997 to 2007. The statistics are both cross-sectional and cross-period. AFE is the absolute difference between the EPS forecast and the EPS realization of each firm i by each analyst j at date t of forecast issue. $EPSPREV$ is the volatility of firm i's EPS over the last 3 years. $SIZE$ is the log of the market capitalization of firm i in t. $COVER$ is the number of analysts who follow firm i in t. $PASTMedFE$ is, for each firm i, the median of the difference between the consensus and the realized EPS in the previous year. $GENEXP$ is, in t, the number of days since the analyst's first forecast. $NBFIRM$ is the number of firms followed by analyst j in t. $NBSECT$ is the number of sectors followed by analyst j in t. $BROKER$ is the number of analysts working for analyst j's broker in t. $SPECEXP$ is, in t, number of days since the first forecast by analyst j about firm i. $TERM$ is tumber of days from t to fiscal year end for a forecast issued by analyst j on firm i. $FREQ$ is the number of forecasts per year by analyst j on a firm i in t. $PASTAFE$ is the forecast error of analyst j on firm i in the previous year. $DURATION$ is the forecast lifetime in the database in months by analyst j on a firm j in t.

Variables	Mean	Standard deviation	Max	Min	Nonmissing observations
AFE	2.46	6.12	162.57	0	102 876
$EPSPREV$	1.79	4.72	85.17	1.15	94 231
$SIZE$	21.93	1.77	25.95	15.30	102 627
$COVER$	19.49	9.60	47	1	102 876
$PASTMedFE$	2	6.54	75.97	-39.90	94 595
$GENEXP$	1 344.29	1 141.75	6 434	0	102 875
$NBFIRM$	4.61	3.49	24	1	102 876
$NBSECT$	2.22	1.39	9	1	102 876
$BROKER$	17.93	10.15	62	1.	102 876
$SPECEXP$	849.65	912.73	6 253	0	102 875
$TERM$	187.88	102.26	365	0	102 875
$FREQ$	4.01	1.98	13	1	102 876
$PASTAFE$	2.48	6.16	127.27	0	69336
$DURATION$	2.82	2.14	18	1	102 876

Table 3.**Correlation coefficients of regression variables**

Table 3 presents correlation coefficients of variables. The sample period is from 1997 to 2007. Coefficients are cross-sectional and cross-period. For each pair of variables, the correlation coefficient is calculated as the ratio between the covariance of both variables and the product of each variable's standard errors.

	AFE	*EPSPREV*	*SIZE*	*COVER*	*PASTMedFE*	*GENEXP*
AFE	**1**					
EPSPREV	**0.187**	**1**				
SIZE	**-0.024**	**-0.040**	**1**			
COVER	**0.063**	**0.016**	**0.741**	**1**		
PASTMedFE	**0.391**	**0.007**	**-0.046**	**0.127**	**1**	
GENEXP	**-0.054**	**0.004**	**-0.028**	**-0.073**	**-0.078**	**1**
NBFIRM	**-0.004**	**-0.015**	**-0.379**	**-0.272**	**0.017**	**0.249**
NBSECT	**-0.03**	**-0.010**	**-0.360**	**-0.305**	**0.013**	**0.190**
BROKER	**-0.065**	**0.008**	**-0.141**	**-0.217**	**-0.088**	**0.124**
SPECEXP	**-0.041**	**0.005**	**0.126**	**0.094**	**-0.061**	**0.728**
TERM	**0.012**	**-0.005**	**0.016**	**-0.257**	**0.001**	**-0.016**
FREQ	**-0.002**	**-0.014**	**-0.113**	**0.140**	**0.018**	**-0.024**
PASTAFE	**0.462**	**0.039**	**-0.037**	**0.096**	**-0.772**	**0-.068**
DURATION	**-0.008**	**-0.016**	**-0.119**	**-0.138**	**0.019**	**-0.035**
	SPECEXP	*TERM*	*FREQ*	*PASTAFE*	*DURATION*	
SPECEXP	**1**					
TERM	**-0.007**	**1**				
FREQ	**-0.037**	**0.055**	**1**			
PASTAFE	**-0.054**	**-0.005**	**-0.002**	**1**		
DURATION	**-0.044**	**0.129**	**-0.451**	**0.010**	**1**	

Table 4.**Results of panel regression with vector decomposition for model [1]**

Table 4 presents the results of panel regression for the following model: $AFE_{i,j,t} = \alpha + \beta X_{i,t} + \gamma Y_{j,t} + \delta Z_{i,j,t} + \lambda_i D_i + \mu_j D_j + \eta_{i,j} + \upsilon_t + \varepsilon_{i,j,t}$. The variable $X_{i,t}$ denotes firm characteristics which are invariant across analysts in t. The variable $Y_{j,t}$ denotes analyst characteristics which are invariant across firms in t. The variable $Z_{i,j,t}$ contains a set of variables which are specific both to firm i and analyst j in t. The dummy variables D indicate a specific analyst j or a firm i. We use the Fixed Effect Vector Decomposition (FEVD) methodology proposed by Plümper and Troeger (2007). * and ** denote significance at the 5% and 1% levels, respectively.

Variables (expected sign)	
Firms' characteristics $\mathbf{X}_{i,t}$	
$EPSPREV$ (+)	2.359**
	(0.081)
$SIZE$ (-)	0.016
	(0.041)
$COVER$ (-)	-0.021**
	(0.004)
$EPSPREV.COVER$ (-)	-0.112**
	(0.004)
$EPSPREV.SIZE$ (-)	0.012**
	(0.000)
$PASTMedFE$ (+)	0.088**
	(0.004)
Analysts' characteristics $\mathbf{Y}_{j,t}$	
$GENEXP$ (-)	-0.000**
	(0.000)
$NBFIRM$ (+)	0.077**
	(0.009)
$NBSECT$ (+)	0.000

	(0.336)
BROKER (-)	-0.009 **
	(0.002)
Firm-analysts' characteristics $\mathbf{Z}_{i,j,t}$	
SPECEXP (-)	-0.000 **
	(0.000)
TERM (+)	0.001 **
	(0.000)
DURATION (+)	-0.003
	(0.008)
FREQ (-)	0.145 **
	(0.011)
PASTAFE (+)	0.091 **
	(0.004)
Sector dummies	yes
Analyst dummies	yes
Firm dummies	yes
Nb. obs.	65 586

Graph 1: median $C_{i,j}$ by 'twentiles' of $MedFE_{i,j}$

$C_{i,j}$, the 'contribution of the pair-specific effect', is defined as follows:

$C_{i,j} = \frac{|\eta_{i,j} + \alpha|}{|\lambda_i| + |\mu_j| + |\eta_{i,j} + \alpha|}$, where α is the unconditional constant of the regression reported in Table 4, λ_i the firm effect, μ_j the analyst effect, and $\eta_{i,j}$ the firm-analyst' pair effect. $MedFE_{i,j}$ is the median, over the full sample period, of the difference between the EPS forecasts and the EPS realization of each firm i by each analyst j for a forecast issued in t. Ranking observations by 'twentiles' of the (relative) median forecast error, we obtain 20 groups from the 5% most pessimistic AFE to the 5% most optimistic AFE. For each observation of $MedFE_{i,j}$, we match the $C_{i,j}$ value that concerns the analyst and the firm involved in this observation. The median value of $C_{i,j}$ is then computed for each 'twentile' (from the 5% most pessimistic to the 5% most optimistic).

Table 5.**Tests for the relationship between $C_{i,j}$ and $MedFE_{i,j}$ for model [1]**

The median-test investigates whether the median of $C_{i,j}$ in a given 'twentile' equals the median of the full sample. The Bartlett-test tests for the equality of variance of $C_{i,j}$ across 'twentiles'. The Krusal-Wallis is an equality-of-population rank test, which determines whether the rank sum of each observation ranked by $C_{i,j}$ differs across 'twentiles'. * and ** denote significance at the 5% and 1% levels, respectively.

Median test (Chi ^{2} stat)
(1)
**

The null is the equality of the median of $C_{i,j}$ in each 'twentile' to the median of the whole sample.

Bartlett test (Chi ^{2} stat)
(1)
**

The null is the equality of variances of $C_{i,j}$ across 'twentiles'.

Krusal-Wallis test (Chi ^{2} stat)
(1)
**

The null is the equality of the rank-sum of each observation ranked by $C_{i,j}$ across 'twentiles'.

Table 6.**Results of panel regression with vector decomposition for variants [2] to [6]**

Table 6 presents the results obtained when we 'reproduce', using our own sample, the estimates conducted in some papers in the empirical literature. Variants [2], [3], [4], [5] and [6] refer to the estimates by Jackson05, DasLevine98, Lim (2001), Clement99 and Clement and Tse (2005), respectively. * and ** denote significance at the 5% and 1% levels, respectively.

Variables (expected sign)	Specifications				
	(2)	(3)	(4)	(5)	(6)
Firms' characteristics $\mathbf{X}_{i,t}$					
$EPSPREV$ (+)	0.208**	1.677**	3.521**		
	(0.003)	(0.070)	(0.088)		
$SIZE$ (-)	-1.066	-1.084**	-0.224**		
	(0.033)	(0.032)	(0.037)		
$COVER$ (-)	0.023**	-0.002	-0.016**		
	(0.002)	(0.003)	(0.003)		
$EPSPREV.CO$ (-)		0.012**	-0.163**		
		(0.006)	(0.004)		
$EPSPREV.SIZ$ (-)		-0.081**	0.008**		
		(0.003)	(0.000)		
$PASTMedFE$ (+)			0.130**		
			(0.003)		
Analysts' characteristics $\mathbf{Y}_{j,t}$					
$GENEXP$ (-)				-0.003**	-0.000**
				(0.000)	(0.000)
$NBFIRM$ (+)				0.070**	0.053**
				(0.008)	(0.010)

NBSECT (+)				0.162	-0.010**
				(0.002)	(0.002)
BROKER (-)				-0.016**	-0.010**
				(0.002)	(0.002)
Firm-analysts' characteristics $\mathbf{Z}_{i,j,t}$					
SPECEXP (-)				0.002**	0.000
				(0.000)	(0.000)
TERM (+)					0.001**
					(0.000)
DURATION (+)					-0.005
					(0.008)
FREQ (-)					0.165**
					(0.003)
PASTAFE (+)					0.134**
					(0.003)
Sector dummies	yes	yes	yes	yes	yes
Analyst dummies	yes	yes	yes	yes	yes
Firm dummies	yes	yes	yes	yes	yes
Nb. obs.	85 398	94 026	79 778	102 875	69 336

Graph 2: Median $C_{i,j}$ by 'twentiles' of $MedFE_{i,j}$ for specification [2]

$C_{i,j}$, the 'contribution of the pair-specific effect', is calculated as: $C_{i,j} = \frac{|\eta_{i,j} + \alpha|}{|\lambda_i| + |\mu_j| + |\eta_{i,j} + \alpha|}$,

where α is the unconditional constant of specification [2], λ_i the firm effect, μ_j the analyst effect, and $\eta_{i,j}$ the firm-analyst' pair effect.

Graph 3: Median $C_{i,j}$ by 'twentiles' of $MedFE_{i,j}$ for specification [3]

$C_{i,j}$, the 'contribution of the pair-specific effect', is calculated as: $C_{i,j} = \frac{|\eta_{i,j} + \alpha|}{|\lambda_i| + |\mu_j| + |\eta_{i,j} + \alpha|}$,

where α is the unconditional constant of specification [3] reported in Table 5, λ_i the firm effect, μ_j the analyst effect, and $\eta_{i,j}$ the firm-analyst' pair effect.

Graph 4: Median $C_{i,j}$ by 'twentiles' of $MedFE_{i,j}$ for specification [4]

$C_{i,j}$, the 'contribution of the pair-specific effect', is calculated as: $C_{i,j} = \dfrac{|\eta_{i,j} + \alpha|}{|\lambda_i| + |\mu_j| + |\eta_{i,j} + \alpha|}$,

where α is the unconditional constant of specification [4] reported in Table 5, λ_i the firm effect, μ_j the analyst effect, and $\eta_{i,j}$ the firm-analyst' pair effect.

Graph 5: Median $C_{i,j}$ by 'twentiles' of $MedFE_{i,j}$ for specification [5]

$C_{i,j}$, the 'contribution of the pair-specific effect', is calculated as: $C_{i,j} = \frac{|\eta_{i,j} + \alpha|}{|\lambda_i| + |\mu_j| + |\eta_{i,j} + \alpha|}$, where α is the unconditional constant of specification [5] reported in Table 5, λ_i the firm effect, μ_j the analyst effect, and $\eta_{i,j}$ the firm-analyst' pair effect.

Graph 6: Median $C_{i,j}$ by 'twentiles' of $MedFE_{i,j}$ for specification [6]

$C_{i,j}$, the 'contribution of the pair-specific effect', is calculated as: $C_{i,j} = \frac{|\eta_{i,j} + \alpha|}{|\lambda_i| + |\mu_j| + |\eta_{i,j} + \alpha|}$, where α is the unconditional constant of specification [6] reported in Table 5, λ_i the firm effect, μ_j the analyst effect, and $\eta_{i,j}$ the firm-analyst' pair effect.

Table 7.**Tests for the relationship between $C_{i,j}$ and $MedFE_{i,j}$ for variants [2] to [6]**

The median-test investigates whether the median of $C_{i,j}$ in a given 'twentile' equals the median of the full sample. The Bartlett-test tests for the equality of variance of $C_{i,j}$ across 'twentiles'. The Krusal-Wallis is an equality-of-population rank test, which determines whether the rank sum of each observation ranked by $C_{i,j}$ differs across 'twentiles'. * and ** denote significance at the 5% and 1% levels, respectively.

Median test (Chi ^{2} stat)				
(2)	(3)	(4)	(5)	(6)
1 100**	244**	369**	495**	81**

The null is the equality of the median of $C_{i,j}$ in each 'twentile' to the median of the whole sample.

Bartlett test (Chi ^{2} stat)				
(2)	(3)	(4)	(5)	(6)
600**	334**	377**	114**	82**

The null is the equality of variances of $C_{i,j}$ across 'twentiles'.

Krusal-Wallis test (Chi ^{2} stat)				
(2)	(3)	(4)	(5)	(6)
**	314**	524**	524**	99**

The null is the equality of the rank-sum of each observation ranked by $C_{i,j}$ across 'twentiles'.

Table 8.**Standard deviations using the FEVD procedure and using the covariance matrix proposed by Greene (2011) for model [1] and variants [2] to [6]**

Table 8 reports the value of the standard errors obtained using the covariance matrix proposed by Greene (2011), which corresponds to the matrix estimated in the first stage of the Plümper and Troeger (2007) procedure. In parentheses: standard error using the FEVD procedure. In italics: the standard errors using the covariance matrix proposed by Greene (2011).

	Specifications					
	[1]	[2]	[3]	[4]	[5]	[6]
Firms' characteristics $\mathbf{X}_{i,t}$						
EPSPREV	(0.081)	(0.003)	(0.070)	(0.088)		
	0.093	*0.003*	*0.079*	*0.078*		
SIZE	(0.041)	(0.033)	(0.032)	(0.037)		
	0.052	*0.040*	*0.041*	*0.044*		
COVER	(0.004)	(0.002)	(0.003)	(0.003)		
	0.004	*0.003*	*0.003*	*0.003*		
EPSPREV.CO	(0.004)		(0.006)	(0.004)		
	0.004		*0.004*	*0.004*		
EPSPREV.SIZ	(0.000)		(0.003)	(0.000)		
	0.000		*0.000*	*0.000*		
PASTMedFE	(0.004)			(0.003)		
	0.005			*0.003*		
Analysts' characteristics $\mathbf{Y}_{j,t}$						
GENEXP	(0.000)				(0.000)	(0.000)
	n.a.				*0.002*	*0.000*
NBFIRM	(0.009)				(0.008)	(0.010)

	0.012				*0.010*	*0.012*
NBSECT	(0.336)				(0.002)	(0.002)
	0.039				*0.031*	*0.038*
BROKER	(0.002)				(0.002)	(0.002)
	0.002				*0.002*	*0.002*
Firm-analysts' characteristics $\mathbf{Z}_{i,j,t}$						
SPECEXP	(0.000)				(0.000)	(0.000)
	0.000				*0.000*	*n.a.*
TERM	(0.000)					(0.000)
	0.000					*0.000*
DURATION	(0.008)					(0.008)
	0.009					*0.009*
FREQ	(0.011)					(0.003)
	0.013					*0.004*
PASTAFE	(0.004)					(0.003)
	0.006					*0.004*
Sector dummies	yes	yes	yes	yes	yes	yes
Analyst dummies	yes	yes	yes	yes	yes	yes
Firm dummies	yes	yes	yes	yes	yes	yes
Nb. obs.	65 586	85 398	94 026	79 778	102 875	69 336

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