Document de travail

N°1

Institut de Recherche en Management et en Pratiques d'Entreprise

The Groupe ESC PAU Institute for Research in Management and Best Practices

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Septembre 2015

Institut de Recherche
IRMAPE
en Management et en Pratiques d'Entreprise
GROUPE ESC PAU

Rising and Senior Stars in European Financial Analyst Rankings: The Talented and the Famous[1]

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Abstract

Using *Institutional Investors* (I/I) and Extel rankings and I/B/E/S data for European analysts over 15 years, we show that European analyst rankings are determined more by popularity than by intrinsic skills, the first determinant of recognition being employer size. Becoming an I/I star is like joining a club: talent for issuing high-quality recommendations is required to be initially ranked but is irrelevant to being re-elected or reaching the top level. Our findings also underline the importance of analyst rankings' design features. These features could probably be improved by reducing the impact of recognition in the election process.

JEL Classification: G17

Keywords: Analyst forecasts, analys rankings, reputation, analyst recommendations

[1] We are grateful to Martjin Cremers, Alain François-Heude, Jean-François Gajewski, Roland Gillet, Pascal Grandin, Hubert de La Bruslerie, Gaëlle Le Fol, Ronald Matsulis, Sanjay Sehgal, and Kent Womack, as well as participants at the 2009 FMA European Conference in Turin and the 2010 AFFI Spring Conference in Saint-Malo for helpful comments.

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1. INTRODUCTION

Financial analysts' forecasts and recommendations play a major role in security valuation and asset managers' investment decisions. The quality of fundamental research is therefore instrumental in achieving an efficient allocation of resources on stock markets. By enhancing the quantity of public information available on stocks, analysts contribute to decreasing information asymmetry and improving market liquidity (Irvine 2003). Further, the quality of sell-side fundamental research is known to influence the choice of brokers by investors. For these reasons, any information that helps identify the best analysts is crucial for the financial community.

Analyst rankings, such as those of *Institutional Investors* (I/I), *The Wall Street Journal* (WSJ), and Extel, are an attempt to provide such identification. Whether they actually reflect superior skills or result only from fame or visibility is a matter of debate in the literature on US analysts. While some authors find that these rankings are based on actual performance (Fang and Yasuda 2007 2009, Hunton and McEwen 2000, Stickel 1992 1995), others show that they are mainly the result of popularity contests (Emery and Li 2009, Li 2002). The issue remains unresolved not only in the US environment; it has not even been studied elsewhere. Our paper therefore aims to complement this literature by exploiting European analyst data from 1996 to 2009 and by examining two European analyst rankings, that published by I/I and the Extel survey managed by the Thomson Financial group. Our first objective is to determine whether nomination for a ranking results from the ability to issue earlier and more accurate earnings forecasts as well as more informative investment decisions or whether it is determined by factors other than expertise. We then go deeper in the analysis by distinguishing between first elections in a ranking from re-elections and between top-level nominations from nominations at lower levels.

As Emery and Li (2009) for the United States, we conclude that European analyst rankings are determined more by popularity than by superior skills, but our main contribution lies in certain differences with their study. Our results suggest that the design of the rankings matter for their effectiveness, since we obtain different findings for Extel and I/I. While the Extel ranking is fully determined by visibility factors, issuing more profitable recommendations matters for I/I ranking nominations, specifically when entering the I/I ranking for the first time. Continuing to be an I/I star or becoming a senior star (at the top level vs. lower levels) is, however, not impacted by recommendation profitability or other objective skills. This tends to demonstrate that I/I nominations are a clubbish process in which talent is required to join the circle but being famous suffices for remaining a member. This conclusion completely differs from the findings of Emery and Li (2009) for the WSJ ranking, where it takes more skill to remain in the WSJ ranking than to enter it. This result confirms the importance of rankings' design features for their relevance and usefulness for investors. For instance, expanding survey populations to non-expert investors or favoring ranking turnover can harm the relevance of analyst rankings for security valuation and stewardship.

The remaining of the paper is organized as follows: Section 2 reviews the literature and derives our testable hypotheses; Section 3 describes the data and the sample; Section 4 presents the scores used to measure analysts' skills; Section 5 tests whether ranked analysts are more talented than others; Section 6 analyzes whether talent makes the difference between rising stars and senior stars in the rankings; and Section 7 concludes the paper.

2. LITERATURE REVIEW AND TESTABLE HYPOTHESES

Several studies focused on the US stock market document systematic differences in the accuracy of financial analysts' forecasts (Clement 1999, Sinha et al. 1997, Stickel 1992) and report specific features characterizing analysts with superior forecasting skills. Analysts making more accurate forecasts are generally more experienced, are employed by bigger brokerage houses, follow a small number of firms (Mikhail et al. 1997, Clement 1999, Jacob et al. 1999), and are more likely to be men than women (Green et al. 2009). When an analyst issues more accurate forecasts on a particular stock, the analyst also does so for the other stocks of the same industry (Brown and Mohammad 2010). Furthermore, superior forecasting abilities are persistent. Analysts who made more accurate forecasts in the past generally continue to do so (Malloy 2005). In Europe, analysts making the best forecasts do not exhibit the same characteristics as their US counterparts: They do not necessarily belong to the largest brokers and are not the most experienced (Bollinger 2004).

Efforts have also been spent on identifying analysts who make more informative investment recommendations. Analysts who produce more profitable recommendations issue recommendations more frequently and are employed by larger firms (Li 2002). Further, Li (2005) finds that an analyst's ability to make more profitable recommendations is persistent. Analysts who make superior recommendations are also found to be included in the I/I ranking (Fang and Yasuda 2007, Stickel 1995).

Analyst rankings are based on surveys of fund managers and express their views on analysts' performance. Nomination to an analyst ranking, more than a reputational factor, is an important determinant of analyst compensation (Groysberg et al. 2011, Michaeli and Womack 1999). However, the relevance of these rankings and their actual benefits for investors are widely debated. For some, rankings proxy for the expertise of analysts and reveal high-profile analysts, and thus, they fairly contribute to their reputation (Fang and Yasuda 2007 2009, Hunton and McEwen 2000, Stickel 1992 1995). For others, rankings do not reflect any intrinsic quality but are only popularity contests that increase the fame of winners (Li 2002, Emery and Li 2009). Reputation and fame are different attributes. As described by Pfarrer et al. (2010), reputation is based on a collective recognition of the ability to create value while fame is due to an emotional resonance.

Our research objective is twofold. First, we seek to determine whether European analyst rankings have to be considered as a reputation token rewarding talent or whether they only reflect popularity. We therefore examine whether an analyst's nomination to a ranking is explained by superior performances, namely, earlier earnings forecasts, smaller earnings forecast errors, and recommendations providing higher returns. We do so by testing the following hypotheses.

H1a. Issuing earnings forecasts earlier than peers inside a given industry over the two years preceding a best analyst ranking positively impacts the probability of being elected in the ranking.
H2a. Issuing more accurate earnings forecasts inside a given industry over the two years preceding a best analyst ranking positively impacts the probability of being elected in the ranking.
H3a. Stock recommendations providing greater abnormal returns in the year preceding a best analyst ranking positively impact the probability of being elected in the ranking.

Second, in comparison with the literature, our analysis digs deeper by investigating whether talent and fame play different roles at different stages of the ranking process. We therefore distinguish between the initial entry in a ranking and a re-election and between a ranking at the top level from rankings at lower levels. If talent is more important than fame at any stage, the following hypotheses would be supported.

H1b. Issuing earnings forecasts earlier than peers inside a given industry over the two years preceding a best analyst ranking positively impacts the probability of entering the ranking for the first time.
H1c. Issuing earnings forecasts earlier than peers inside a given industry over the two years preceding a best analyst ranking positively impacts the probability of being re-elected in the ranking.
H1d. Issuing earnings forecasts earlier than peers inside a given industry over the two years preceding a best analyst ranking positively impacts the probability of being ranked at the top level rather than at lower levels.

H2b. Issuing more accurate earnings forecasts inside a given industry over the two years preceding a best analyst ranking positively impacts the probability of entering the ranking for the first time.
H2c. Issuing more accurate earnings forecasts inside a given industry over the two years preceding a best analyst ranking positively impacts the probability of being re-elected in the ranking.
H2d. Issuing more accurate earnings forecasts inside a given industry over the two years preceding a best analyst ranking positively impacts the probability of being ranked at the top level rather than at lower levels.

H3b. Stock recommendations providing greater abnormal returns in the year preceding a best analyst ranking positively impact the probability of entering the ranking for the first time.

H3c. Stock recommendations providing greater abnormal returns in the year preceding a best analyst ranking positively impact the probability of being re-elected in the ranking.

H3d. Stock recommendations providing greater abnormal returns in the year preceding a best analyst ranking positively impact the probability of being ranked at the top level rather than at lower levels.

Not rejecting H1a to H3d would lead us to consider analyst rankings as informative about the quality of the information produced by analysts and would support the notion of reputation in the sense of Pfarrer et al. (2010).

3. DATA AND SAMPLE

We exploit the analyst rankings of I/I from 1998 to 2009 and those of Extel from 2004 to 2009 for stocks listed on Western European exchanges.

The I/I ranking is the ranking of the “Best European Analyst of the Year” published each year in the February issue of the *Institutional Investor* journal. Fund managers from the 100 most important fund management firms in continental Europe are polled each year. Additional fund managers proposed by brokerage firms are also part of the survey. The aggregate of all voters represents about five trillion euros under management. Each fund manager votes for individual sell-side financial analysts and their teams, based on four criteria: ideas on stocks, earnings forecasts, written reports, and global investment services. The vote results in a four-level ranking. The process is described by I/I as follows:

> ‘A numerical score is produced by weighting each vote based on the respondent's European equity assets under management -- or convertible securities, if the voter participates in that category -- and on the place it awards to the brokerage firm (first, second, third, fourth). Rankings are determined using those scores. Teams are designated runners-up when their scores came within 35 percent of the third teamers' scores.’

Analysts can be elected from the first to the fourth place. The fourth place, or *runner up,* can be attributed to several analysts from different brokerage firms, while the first three places are attributed only to analysts of one brokerage firm.

The Extel ranking is based on surveys managed by the Thomson Financial Group. This ranking was created in 1974 and initially only concerned the UK market. It developed to other markets in the late 1990s but is available to us only from 2004 on. In comparison with I/I’s four ranking levels, Extel has three, with only one analyst elected per rank, and polls a wider range of market actors: fund managers, brokerage firms, and the representatives of listed companies.

Analysts’ characteristics, earnings forecasts, and investment recommendations are extracted from I/B/E/S. The I/B/E/S database identifies analysts with a unique code over their entire professional life, even if they change affiliations. We nevertheless identified a substantial number of analysts—up to 15% of the total population—with several codes in the database, which is likely to bias our analysis. Two analysts with distinct codes were therefore considered the same analyst and the older code in the database was reassigned to both of them if they met the following criteria: (1) they had the same last name and first name’s initial, (2) they followed the same industry and the same stocks, (3) they issued earnings forecasts on the same dates, and (4) they belonged to the same brokerage firm.[4]

[4] After this procedure, analysts with the same last name and distinct codes represented only 4% of the population. They were, however, likely to be different persons.

Our research requires us to examine earnings forecasts over two years before each ranking and recommendations over one year before each ranking. Therefore, earnings forecasts were obtained from January 1, 1996, to December 31, 2008, while recommendations were obtained from January 1, 1997, on.

From there, we excluded data relative to companies that ended their fiscal year on a different date than December 31. We consider earnings forecasts issued until 120 days prior to the year-end date.[5]

The forecasts and recommendations remaining in the samples are those issued on stocks belonging to sectors covered by the I/I and Extel rankings. A forecast and a recommendation, denoted $F_{i,j,s,t}$ and $R_{i,j,s,t}$, respectively, are characterized by the stock *i* to which they relate, the issuing analyst *j*, the sector *s* to which stock *i* pertains, and the year of issue *t*. Forecasts and recommendations from analysts who issued only one recommendation during the observation period, this recommendation being "hold,"[6] were excluded. Forecast accuracy is measured as by Clement (1999), by comparing the analyst's forecast errors with the average forecast errors made by all analysts covering the stock in question. To make sense, this average should be calculated with at least three observations (Clement and Tse 2005). This leads us to drop from the sample forecasts and recommendations relative to stocks covered by fewer than three analysts. For consistency, we require that an analyst cover at least three companies. Finally, since forecast accuracy is measured over two successive years, we select only the earnings forecasts of analysts who made forecasts over the two years preceding the year of the ranking. These screening criteria reduced the number of observed forecasts by between 75% and 80%, an observation being a forecast issued by a given analyst over a given company in a given year.

The analysts appearing in the I/I and Extel rankings for a given industrial sector in a given year do not necessarily meet the sampling criteria described above. For each year of the observation period, sectors for which we cannot sample both ranked and non-ranked analysts are excluded from the analysis. Table 1 presents the sizes of the samples by year and by ranking. The I/I ranking sample comprises 14,387 recommendations and 17,873 earnings forecasts issued by 1,851 analysts, of which 10.6% are nominated in the rankings. The sample for the Extel ranking is smaller due to the later availability of this ranking: 910 analysts, 6,793 recommendations, and 6,864 forecasts in total. Further, the proportion of Extel-ranked analysts is lower than that of I/I-ranked analysts: First, the Extel rankings count three levels of rankings instead of the I/I's four; second, Extel nominates one analyst per level, while I/I may nominate several.

[Insert Table 1 about here]

4. MEASURING ANALYST SKILLS

All hypotheses are tested with a logistic regression approach in which the dependent variables represent the ranking or the absence of ranking, the level of ranking, and, alternatively, the move to a higher level in a given analyst's ranking in a given sector in a given year, and in which the independent variables of interest are measures of the quality of the earnings forecasts and recommendations. We use measures of forecast accuracy inspired by Clement (1999) and we measure the performance of recommendations by building recommended stock portfolios (Barber et al. 2007). An original aspect of our method is that we standardized all analyst performance measures by calculating scores ranging from zero to 100 according to Hong and Kubik (2003).

[5] As a robustness check, all tests are also conducted with samples of earnings forecasts issued until 60 days and 30 days before the year-end.

[6] The rationale is that a single "hold" recommendation can be interpreted as neither a buy signal nor a sell signal.

4.1. MEASURES OF FORECAST QUALITY

We evaluate the quality of forecasts according to two criteria: earliness and accuracy.

The earlier the forecasts are issued, the earlier portfolio managers can base investment selection decisions on them and the longer the horizon over which they can be exploited. The earliness of analyst *j*'s forecasts over year *t* - 1 is measured as the average number of days between the analyst's forecast date and the year-end date. This average, denoted $Earl_{j,s,t-1}$, is established across all stocks followed by analyst *j* in sector *s* over year *t* – 1. We also consider the value of this variable over the year *t* – 2.

More important than earliness, forecast accuracy is the main criterion of forecast quality. We measure it by the variable $ForAccScore_{j,s,t-1}$, which is the score of analyst *j* regarding his/her average earnings forecast accuracy on the stocks of sector *s* over the year preceding the ranking. The average forecast error is measured relative to the average error of other analysts in the same sector (Clement 1999). Then, the average relative forecast errors are ranked in ascending order and a score *à la* Hong and Hubik (2003) is calculated. The higher the score, the more accurate the analyst's forecast in comparison with the forecasts of others. The score is computed for the years *t* – 1 and *t* – 2.

As an alternative to $ForAccScore_{j,s,t-1}$ and $Earl_{j,s,t-1}$, we use a combined score, denoted $AccEarlScore_{j,s,t-1}$, in which analyst *j*'s forecast errors are divided by their earliness, that is, the number of days between the forecast issue date and the year-end date. Earnings forecasts are typically more accurate when issued later in the year. $AccEarlScore_{j,s,t-1}$ is designed to measure the analyst's ability to issue accurate forecast long before the year-end. The score obtained for this variable is higher for analysts who issued more accurate forecasts earlier than others did.

We also consider a dummy indicating whether the analyst was able to improve his/her forecast between $t-2$ and $t-1$. This dummy, denoted $ForAccInc_{j,s,t-1}$, equals one if the forecast error score of analyst *j* increased between *t* – 2 and *t* – 1 and zero otherwise.

Finally, $VarFor_{j,s,t-1}$ is a dummy that measures the ability of analyst *j* to predict earnings changes between *t* – 2 and *t* – 1 in sector *s.* For each company, we compare the change in earnings forecasted by the analyst with the actual earnings change published by the company. The dummy is set to one when the analyst has correctly forecasted the change in earnings and to zero otherwise. We then average those dummies over sector *s* to obtain a variable that takes values between zero and one. We rank analysts in descending order and a score according to Hong and Hubik (2003) is calculated. The higher the score, the more accurate the analyst's forecasts on earnings changes.

4.2. RECOMMENDATION PERFORMANCE

The variable $RecScore_{j,s,t-1}$ measures the added value of an analyst's recommendations in a given industry over the year preceding the ranking. This score is based on the average daily abnormal return of a portfolio invested in the stocks recommended by analyst *j* relative to that of portfolios recommended by the analyst's peers in the same sector over year *t* – 1.

Each analyst portfolio is built on a calendar year basis, using stocks on which the analyst issued recommendations. A stock is purchased any time the analyst issues a *Buy* or *Add* recommendation and a stock is shorted any time the analyst issues a *Sell, Reduce,* or *Hold* recommendation. The treatment of *Hold* recommendations is motivated by the literature on analysts' recommendations, which shows that *Hold* recommendations should be considered negative signals: Boni and Womack (2002) report that 79% of fund managers consider a downgrade to *Hold* as a sell recommendation and Brown et al. (2009) show that stocks downgraded from *Buy* to *Hold* experience negative abnormal returns. Stocks are entered into or taken out from the portfolio two business days before the recommendation issue date to catch the entire market reaction to the recommendation (Li 2002, Menedez-Requejo 2005, Green 2006). The duration of recommendations is set to 60 business days: If the analyst does not issue any further recommendation within the 60 trading days following the considered recommendation date, the stock is removed from the portfolio.

The abnormal return of the portfolio is estimated by the alpha coefficient of the international capital asset pricing model of Solnik (1974) and Sercu (1980):

$$r_{j,s,d} - r_{f,d} = \alpha_{j,s} + \beta_{j,s}\left(r_{msci,d} - r_{f,d}\right) + \sum_{k=1}^{K} \lambda_{j,s,k}\left(s_k + r_{f,d}^{k} - r_{f,d}\right) + \varepsilon_j \quad (1)$$

where $r_{j,s,d}$ is the return on day d of the stock portfolio recommended by analyst j for sector s.

Since portfolios are built with stocks from several European countries, they are exposed to foreign exchange rate risk. This risk in priced in Equation (1) by $\sum_{k=1}^{K} \lambda_{j,s,k}\left(s_{k,d} + r_{f,d}^{k} - r_{f,d}\right)$, where $s_{k,d}$ represents the daily change in the foreign exchange rate of currency k against the home currency, $r_{f,d}^{k}$ is the risk-free rate in country k on date d, and $r_{f,d}$ is the risk-free rate in the home country. We choose the Deutsche Mark as the home, or reference, currency before the introduction of the euro on January 1, 1999, and the euro afterward.[7] Exchange rates were extracted from either Datastream, the European Central Bank, or other national central banks.[8] The risk-free rates, listed in Table 2, were gathered from the European Central Bank and national central banks' data rooms. The variable $r_{f,d}$ is the one-month Frankfurt Interbank Offered Rate (FIBOR) before January 1, 1999, and the one-month Euribor afterward.

[Insert Table 2 about here]

The return $r_{j,s,d}$ is calculated by using the methodology of Barber et al. (2007), as follows:

$$r_{j,s,d} = \frac{\sum_{i=1}^{N_{j,s,d}} x_{i,j,s,d-1} \times r_{i,d}}{\sum_{i=1}^{N_{j,s,d}} x_{i,j,s,d-1}} \quad (2)$$

where $N_{j,s,d}$ is the number of stocks included in analyst j's portfolio on day d, $r_{i,d}$ is the logarithmic return of stock i on day d, $x_{i,j,s,d-1}$ is the return of stock i cumulated from its date of entry in the portfolio recommended by analyst j for sector s until date d - 1, and $\sum_{i=1}^{N_{j,s,d}} x_{i,j,s,d-1}$ represents the cumulated return of the portfolio on day d. The term $r_{msci,d}$ is the daily return of the MSCI World index[9] on day d.

Equation (1) is the ordinary least squares regression estimated for each analyst and each sector that analyst follows. Average abnormal returns measured by the coefficients $\alpha_{j,s}$ are then ranked in

[7] After January 1, 1999, the non-euro countries in our sample are Denmark, Norway, Sweden, Switzerland, and the United Kingdom.

[8] These banks include Deutsche Bundesbank, Oesterreichische Nationalbank, Banque Nationale de Belgique, Banco de Portugal, De Nederlandsche Bank, Finlands Bank, and Banque de France.

[9] The MSCI World index is a stock market index of 1,612 world stocks. It is maintained by MSCI Inc., formerly Morgan Stanley Capital International. The index includes a collection of stocks of all the developed markets in the world, as defined by MSCI, (23 countries) but excludes stocks from emerging and frontier economies.

descending order, so that the highest abnormal return is ranked first. Following Hong and Hubik (2003), $RecScore_{j,s,t-1}$ is determined by dividing the rank of the α coefficient of analyst *j* for sector *s* by the total number of portfolios. $RecScore_{j,s,t-1}$ is the score of a portfolio built upon the recommendations of analyst *j* during year *t* – 1. Testing the link between $RecScore_{j,s,t-1}$ and the position of analyst *j* in the rankings of year *t* allows us to test H3a through H3c, that is, whether investors and other market actors tend to vote for analysts whose recommendations add value to investments.

5. RANKED VERSUS NON-RANKED ANALYSTS: DOES TALENT MAKE A DIFFERENCE?

This section is dedicated to testing H1a, H2a, and H3a, that is, determining whether superior skills, namely, forecast accuracy and recommendation quality, motivate analysts' rankings. We first present the logistic regression models. We then compare ranked and non-ranked analysts. Finally, we comment on the results of the regressions.

5.1. REGRESSION DESIGN

We model the probability of an analyst being ranked as a linear function of (1) control variables known in the literature to influence either the popularity of analysts or the quality of their production, such as employer size, experience, boldness, and optimism, and (2) the measures of analysts' skills. The corresponding binary logistic regression is as follows:

$$\begin{aligned} &Logit\left(Ranked_{j,s,t}=1\right)\\ &=\alpha_0+\alpha_1^c SizeScore_{j,s,t-1}+\alpha_2^c ExpScore_{j,s,t}\\ &\quad+\alpha_3^c Bold_{j,s,t-1}+\alpha_4^c Optim_{j,s,t-1}+\alpha_5^c Ranked_{j,s,t-1}\\ &\quad+\alpha_1 Earl_{j,s,t-1}+\alpha_2 Earl_{j,s,t-2}+\alpha_3 ForAccScore_{j,s,t-1}+\alpha_4 ForAccScore_{j,s,t-2}\\ &\quad+\alpha_5 ForAccInc_{j,s,t-1}+\alpha_6 VarFor_{j,s,t-1}+\alpha_7\, RecScore_{j,s,t-1}+\varepsilon_{j,s,t}^{Rank} \end{aligned} \tag{3a}$$

where $Ranked_{j,s,t}$ is a dichotomous variable that equals one if analyst *j* is nominated in the ranking of year *t* for sector *s* and zero otherwise and $SizeScore_{j,s,t-1}$ is a score related to the size of the broker employing analyst *j*. The size of a broker is measured by the number of analysts it employs according to the I/B/E/S database during the year preceding the ranking.[10] The brokers are then ordered by decreasing size to obtain the score assigned to analyst *j*. Analyst experience is measured by the number of years during which the analyst followed the stocks of sector *s* between 1985 and the year preceding the ranking. These numbers are ranked by descending order to calculate experience scores, denoted $ExpScore_{j,s,t-1}$.

The regression also controls for boldness and optimism, two characteristics that may capture the attention of voters in the ranking surveys. Boldness, denoted $Bold_{j,s,t-1}$, assesses the analyst's capacity to issue forecasts deviating from the consensus (Hong et al. 2000). This variable corresponds to the average forecast boldness of analyst *j* over the firms he or she follows in sector *s* in year *t* - 1, with analyst *j*'s forecast boldness on a given firm being the absolute difference between analyst *j*'s last forecast on that firm and the average forecast issued by all other analysts. A weak optimism bias has been found to characterize ranked analysts (Leon and Wu 2002). Forecast optimism has also been

[10] Broker size is determined by using the total number of European analysts registered in the I/B/E/S database before applying the screening procedure described in Section 3.

shown to have an impact on analysts' careers by helping them move to larger brokerage firms (Hong and Hubik 2003). Forecast optimism is thus controlled for by the score $Optim_{j,s,t-1}$. This score is based on dummies that equal one if analyst *j*'s earnings forecast for firm *i* exceed the average forecast of other analysts for that firm and zero otherwise. These dummies are averaged for analyst *j* over sector *s* and then ranked in descending order to compute the optimism score of analyst *j* for sector *s* in year *t* - 1. Finally, we add the $Ranked_{j,s,t-1}$ dummy to control for ranking persistence. This dummy takes the value of one if the analyst appeared in the ranking survey in year *t* - 1 and zero otherwise.

The remaining independent variables are our variables of interest, that is, measures of analyst performance as established in Section 4. The variables $Earl_{j,s,t-1}$ and $Earl_{j,s,t-2}$ measure the earliness of an analyst's forecasts in the one and two years, respectively, preceding the ranking. The variables $ForAccScore_{j,s,t-2}$, $ForAccScore_{j,s,t-1}$, $ForAccInc_{j,s,t-1}$, and $VarFor_{j,s,t-1}$ are measures of forecast accuracy in the two years preceding the ranking and $RecScore_{j,s,t-1}$ measures the performance of the analyst's recommendations in the year preceding the ranking.

A similar model is used to explain the probability of being ranked at a given level. The dependent variable is represented by the polytomous variable $RankLev_{j,s,t}$, which is the ranking level of analyst *j* in a given ranking for sector *s* in year *t*. It can take values one through four in the I/I ranking and one through three in the Extel ranking, one being the highest level. If the analyst is not ranked, $RankLev_{j,s,t}$ is set to zero. The analysis is completed with a multinomial logistic regression designed as follows:

$$\begin{aligned} Logit\left(RankLev_{j,s,t} = m\right) &= \beta_0 + \beta_c.ControlRank_{j,s,t} + \beta_1 Earl_{j,s,t-1} + \beta_2 Earl_{j,s,t-2} \\ &\quad + \beta_3 ForAccScore_{j,s,t-1} + \beta_4 ForAccScore_{j,s,t-2} + \beta_5 ForAccInc_{j,s,t-1} \\ &\quad + \beta_6 VarFor_{j,s,t-1} + \beta_7 RecScore_{j,s,t-1} + \varepsilon_{j,s,t}^{Lev} \end{aligned} \tag{4a}$$

where *m* = 0, 1, 2, 3, 4 for the I/I ranking and *m* = 0, 1, 2, 3 for the Extel ranking and $ControlRank_{j,s,t}$ is a vector composed of the same control variables as in model (3a), that is, broker size ($SizeScore_{j,s,t-1}$), experience ($ExpScore_{j,s,t-1}$), boldness ($Bold_{j,s,t-1}$), optimism ($Optim_{j,s,t-1}$), and ranking persistence ($Ranked_{j,s,t-1}$).

Finding significantly positive values for α_1, α_2, β_1, and β_2 would support H1a. Finding significantly positive values for α_3, α_4, α_5, and α_6 in Model (3a) and for β_3, β_4, β_5 and β_6 in Model (4a) would support H2a. Finding significantly positive values for α_7 and β_7 would support H3a.

Models (3a) and (4a) are then modified by replacing $Earl_{j,s,t-2}$ and $ForAccScore_{j,s,t-2}$, and $Earl_{j,s,t-1}$ and $ForAccScore_{j,s,t-1}$, by the combined variables $AccEarlScore_{j,s,t-2}$ and $AccEarlScore_{j,s,t-1}$, respectively:

$$\begin{aligned} Logit\left(Ranked_{j,s,t} = 1\right) &= \gamma_0 + \gamma_c.ControlRank_{j,s,t} + \gamma_1 AccEarlScore_{j,s,t-1} + \gamma_2 AccEarlScore_{j,s,t-2} \\ &\quad + \gamma_3 ForAccInc_{j,s,t-1} + \gamma_4 VarFor_{j,s,t-1} + \gamma_5 RecScore_{j,s,t-1} + \eta_{j,s,t}^{Rank} \end{aligned} \tag{3b}$$

$$\begin{aligned} Logit\left(RankLev_{j,s,t} = m\right) &= \delta_0 + \delta_c.ControlRank_{j,s,t} + \delta_1 AccEarlScore_{j,s,t-1} + \delta_2 AccEarlScore_{j,s,t-2} \\ &\quad + \delta_3 ForAccInc_{j,s,t-1} + \delta_4 VarFor_{j,s,t-1} + \delta_5 RecScore_{j,s,t-1} + \eta_{j,s,t}^{Lev} \end{aligned} \tag{4b}$$

Hypothesis H2a would be supported by positive values of γ_1, γ_2, γ_3, γ_4 and δ_1, δ_2, δ_3, and δ_4 and H3a would be supported by positive values of γ_5 and δ_5.

As recommended by Wooldridge (2012), in all regressions, standard errors are calculated by using the quasi-maximum likelihood proposed by Huber (1967) and White (1980) to account for heteroskedasticity.

5.2. DIFFERENCES BETWEEN RANKED AND NON-RANKED ANALYSTS

Table 3 reports the mean values and standard deviations of the independent variables used in regressions (3a), (4a), (3b), and (4b) for ranked and non-ranked analysts. The table also reports the differences in means between the two groups, as well as their levels of statistical significance. These descriptive statistics are estimated from 1998 to 2009 for the I/I ranking and from 2004 to 2009 for the Extel ranking.

[Insert Table 3 about here]

The comparison shows that ranked analysts work for larger brokerage firms, are more experienced in the sector for which they are ranked, and have a greater probability of being past nominees than non-ranked analysts. The score measuring employer size is higher than 90, on average, for ranked analysts, while it is close to 80 for other analysts.[11] The differences in the mean size scores, mean experience scores, and mean values of the previous year's ranked dummies are statistically significant for both the I/I and Extel rankings at the 1% level. Further, I/I-ranked analysts issue their forecasts slightly later than non-ranked peers, the difference being statistically significant at the 1% level. In addition, I/I-ranked analysts issue bolder forecasts in the year preceding the ranking, but the difference is only significant at the 10% level. No significant difference is found in forecast optimism between ranked and non-ranked analysts. While findings relative to broker size and experience converge with those of Emery and Li (2009) for the United States, our findings on boldness and optimism are slightly different.

Regarding forecast accuracy, the result of our comparison differs from findings on US analysts. Unlike Stickel (1992), we do not find that the earnings forecasts of ranked analysts are more accurate than those of others. For our samples of European analysts, the forecast errors' scores of ranked analysts are not statistically lower than those of non-ranked analysts, although their forecasts are issued later, on average. This finding holds for all the scores considered: $ForAccScore_{j,s,t-1}$, $ForAccScore_{j,s,t-2}$, $AccEarlScore_{j,s,t-1}$, and $AccEarlScore_{j,s,t-2}$. With respect to their ability to forecast variations in earnings from $t-2$ to $t-1$ ($VarFor_{j,s,t-1}$), ranked analysts do not perform better either. The mean differences of this variable are not statistically different from zero for any ranking and sample. The only score for which ranked analysts do better than their peers is $ForAccInc_{j,s,t-1}$, which measures their ability to improve their forecast from $t-2$ to $t-1$. This variable is greater, on average, for Extel-ranked and I/I-ranked analysts.

In terms of portfolio performance, the recommendations of I/I-ranked analysts are more valuable than those of others. This is in accord with previous studies in the US market by Stickel (1992, 1995) and Fang and Yasuda (2007). However, this is not true for Extel-ranked analysts, whose recommendations do not yield higher returns than those of non-ranked analysts.

[11] The reason why the average score exceeds the median for both ranked and non-ranked analysts is that sampled analysts have employer size scores above 80, on average. The average total number of analysts in the firms of our samples is greater than that of all brokerage firms in the I/B/E/S database by more than 40%.

In light of these preliminary univariate statistics, the ranking of European analysts seems to be determined more by analyst situation, such as employer size or experience, than by analysts' intrinsic skills in forecasting earnings and making profitable recommendations. This result contradicts the work of Stickel (1992, 1995) on US analysts.

5.3. RESULTS OF THE LOGISTIC REGRESSION ANALYSIS

The estimates of the binomial logit regressions (3a) and (3b), reported in Table 4, reveal that recognition factors such as broker size ($SizeScore_{j,s,t-1}$), experience ($ExpScore_{j,s,t-1}$), and previous election in the ranking ($Ranked_{j,s,t-1}$) are the main determinants of the probability of being designated in analyst rankings. This finding is in line with Emery and Li (2009) for the US market. Nonetheless, in contrast with their findings, boldness ($Bold_{j,s,t-1}$) and optimism ($Optim_{j,s,t-1}$) do not significantly influence the rankings of our sample.

[Insert Table 4 about here]

Forecast earliness does not increase the probability of being ranked. On the contrary, the earliness of forecasts issued in the year preceding the ranking negatively impacts the probability of being ranked by I/I. We thus reject H1a. The negative relation between $Earl_{j,s,t-1}$ and ranking probability suggests that portfolio managers prefer analysts who issue forecasts later. This preference may be related to the observation that later forecasts are more accurate (Brown et al., 2003). More importantly, the accuracy of forecasts issued before the rankings fail to convincingly explain nominations in rankings. The coefficients of $ForAccScore_{j,s,t-2}$ and $ForAccScore_{j,s,t-1}$ in regressions (3a) and the coefficients of $AccEarlScore_{j,s,t-2}$ and $AccEarlScore_{j,s,t-1}$ in regressions (3b) are not significantly different from zero, except for the coefficient of $ForAccScore_{j,s,t-2}$ for the Extel ranking, which is significantly positive at the 10% level. This result provides very little support for H2a. Further, on the one hand, the coefficient of $ForAccInc_{j,s,t-1}$ is significantly positive for the I/I and Extel rankings, with greater statistical significance for Extel, which means that the ability to improve forecast accuracy from $t-2$ to $t-1$ is rewarded in rankings. On the other hand, the ability to predict earnings changes in a given sector negatively affects ranking probabilities. In total, our evidence in favor of H2a is mitigated. Apart from the impact of the ability to improve forecast accuracy from $t-2$ to $t-1$, all other findings lead us to reject H2a. The only skill measure that significantly explains the event to be ranked is excess returns provided by recommendations over $t-1$ ($RecScore_{j,s,t-1}$) in the case of the I/I ranking, with 1% statistical significance, so that H3a is not rejected for the I/I ranking while it is rejected for the Extel ranking.

With regard to the results of the multinomial logit regressions which that are displayed in Tables 5 and 6, the dominance of employer size and experience as determinants of the rankings is confirmed at all ranking levels. Hypothesis H1a is rejected again, since none of the β_1 and β_2 coefficients significantly differ from zero. Hypothesis H2a is more strongly rejected than with the binomial logit regressions. The coefficients of forecast accuracy measures (β_3 and β_4 in Model 4a and δ_1 and δ_2 in Model 4b) do not significantly differ from zero for any level of any ranking. The coefficients β_5 and $\delta_{3,}$ which measure the impact of $ForAccInc_{j,s,t-1}$, are either insignificant or, in a few cases, significantly positive at the 10% level. The coefficients β_6 and δ_4 are never significantly positive. Finally, consistent with binomial logit regressions, we find some evidence in support of H3a. The ability to issue more profitable recommendations is found to influence the choice of I/I voters, but not that of Extel voters, and this influence only applies to analyst nominations at the lowest level (level 4) or nominations at the top level (level 1).

[Insert Table 5 about here]

[Insert Table 6 about here]

In summary, European analyst rankings are determined more by factors of recognition and popularity, such as the size of the brokerage firm or experience, than by intrinsic skills reflected by accurate forecasts or profitable recommendations. Among these, employer size is by far the factor with the largest economic impact when considering the elasticity of the regression coefficients. The elasticity of the size variable exceeds two in all regressions, while the elasticity coefficients of all the other variables are always below two in absolute terms (except that of $Earl_{j,s,t-2}$ in Table 5 for the Extel ranking).

5.4. Robustness check

Our measures of forecast accuracy are established using forecasts issued 120 days prior to the end of the fiscal year at the latest. Because the timing of earnings forecasts has been shown to impact their accuracy (Clement 1999), with late forecasts being more accurate than early ones (Brown and Mohd 2003), we ran the tests with two other samples: one built with earnings forecasts issued until 60 days before the year-end and the other built with earnings forecasts issued 30 days before the year-end at the latest. The conclusions are unchanged.

6. Are the factors making rising stars different from those making senior stars?

After showing that rankings are generally determined more by recognition than by intrinsic skills, we now investigate (1) whether analysts' skills are more instrumental in determining a first election (H1b, H2b, and H3b) or a re-election (H1c, H2c, and H3c) and (2) to what extent contribute to promoting star analysts from lower levels in the ranking to the highest (H1d, H2d, and H3d).

6.1. First-timers versus veterans

Testing H1b, H2b, and H3b while H1a and H2a are rejected and H3a is only partially validated is based on the assumption that a first-time ranking could result from better performances by the awarded analysts because their recognition is not yet established, whereas a re-election could take root in a momentum of recognition generated by previous elections. We test this differential effect with the following multinomial logistic regressions:

$$
\begin{aligned}
&Logit\left(RankHist_{j,s,t} = n\right) \\
&\quad = \mu_0 + \mu_c.ControlRank_{j,s,t} + \mu_1 Earl_{j,s,t-1} + \mu_2 Earl_{j,s,t-2} \\
&\qquad + \mu_3 ForAccScore_{j,s,t-1} + \mu_4 ForAccScore_{j,s,t-1} \\
&\qquad + \mu_5 ForAccInc_{j,s,t-1} + \mu_6 VarFor_{j,s,t-1} + \mu_7 \mathrm{Re}cScore_{j,s,t-1} + \varepsilon^{Hist}_{j,s,t}
\end{aligned} \tag{5a}
$$

$$
\begin{aligned}
&Logit\left(RankHist_{j,s,t} = n\right) \\
&\quad = \nu_0 + \nu_c.ControlRank_{j,s,t} + \nu_1 AccEarlScore_{j,s,t-1} + \nu_2 AccEarlScore_{j,s,t-2} \\
&\qquad + \nu_3 ForAccInc_{j,s,t-1} + \nu_4 VarFor_{j,s,t-1} + \nu_5 \mathrm{Re}cScore_{j,s,t-1} + \eta^{Hist}_{j,s,t}
\end{aligned} \tag{5b}
$$

with n = 0, 1, 2. The variable $RankHist_{j,s,t}$ represents the ranking history of analyst j for sector s in year t. It equals zero if the analyst is not ranked in year t, one if the analyst is ranked for the first time in year t, and two if the analyst is ranked in year t and was already ranked in any preceding year, from 1998 to t - 1 for the I/I survey and from 2004 to t - 1 for the Extel survey. Finding significantly positive μ_1 and μ_2 for n = 1 (n = 2) would support H1b (H1c). Finding significantly positive μ_3, μ_4, μ_5, and μ_6 in (5a) and significantly positive ν_1, ν_2, ν_3, and ν_4 in (5b) for n = 1 (n = 2) would support H2b (H2c). Finding significantly positive μ_7 and ν_5 for n = 1 (n = 2) would support H3b (H3c).

The estimates of regression (5b) are displayed in Table 7. Those of regression (5a) are not reported for the sake of brevity but are available on request. They show significant discrepancies between first-time elections and re-elections. Although employer size is confirmed to be the most prominent factor explaining rankings for either first-timers or veterans, experience has a significant positive influence only for re-elections. More importantly, the ability to issue more profitable recommendations than others, which was identified as a necessary skill to be ranked at levels 4 and 1 in the I/I survey, appears to influence I/I voters only for first-timers ($\mu_7 > 0$ and $\nu_5 > 0$ at the 10% level for *m* = 1) and not for veterans (μ_7 and ν_5 not significantly different from zero for *m* = 1). The only measure of intrinsic competence that impacts the probability of re-election is the ability to improve forecast accuracy from *t* – 2 to *t* – 1. Apart from these findings, no other measure of professional skills is found to explain ranking probabilities for either a first ranking or a re-election, so that, in sum, H1b, H1c, H2b, and H2c are rejected. Our differentiated findings with respect to the quality of investment recommendations result in the non-rejection of H3b and the rejection of H3c when considering the I/I ranking. In brief, rising as a new star in the I/I survey requires greater ability to issue profitable recommendations, while continuing to be an I/I star does not. This is in contrast with the Extel ranking, for which both H3b and H3c are rejected.

[Insert Table 7 about here]

6.2. BECOMING A SENIOR STAR

We then study to what extent issuing high-quality earnings forecasts and investment recommendations help ranked analysts reach top ranking levels. This is completed by testing whether an analyst's probability of being ranked at level 1, given that the analyst is elected in the considered ranking, is significantly impacted by our skill measures. The corresponding binary logistic regressions are as follows:

$$\begin{aligned} &Logit\left(TopRankLev_{j,s,t} = 1 \middle| Ranked_{j,s,t} = 1\right) \\ &\quad = \omega_0 + \omega_c.ControlRank_{j,s,t} + \omega_1 Earl_{j,s,t-1} + \omega_2 Earl_{j,s,t-2} \\ &\qquad + \omega_3 ForAccScore_{j,s,t-1} + \omega_4 ForAccScore_{j,s,t-1} \\ &\qquad + \omega_5 ForAccInc_{j,s,t-1} + \omega_6 VarFor_{j,s,t-1} + \omega_7 RecScore_{j,s,t-1} + \varepsilon^{Change}_{j,s,t} \end{aligned} \tag{6a}$$

$$\begin{aligned} &Logit\left(TopRankLev_{j,s,t} = 1 \middle| Ranked_{j,s,t} = 1\right) \\ &\quad = \delta_0 + \delta_c.ControlRank_{j,s,t} + \delta_1 AccEarlScore_{j,s,t-1} + \delta_2 AccEarlScore_{j,s,t-2} \\ &\qquad + \delta_3 ForAccInc_{j,s,t-1} + \delta_4 VarFor_{j,s,t-1} + \delta_5 RecScore_{j,s,t-1} + \eta^{Change}_{j,s,t} \end{aligned} \tag{6b}$$

Regressions (6a) and (6b) are run on the sub-population of ranked analysts, that is, analysts for whom $Ranked_{j,s,t} = 1$. The variable $TopRankLev_{j,s,t}$ equals one if analyst *j* is ranked at level 1 for sector *s* in year *t* and zero if ranked lower. Positive values of ω_1 and ω_2 in (6a) would lead to the non-rejection of H1d. Positive values of $\omega_3, \omega_4, \omega_5$, and ω_6 in (6a), and $\delta_1, \delta_2, \delta_3$, and δ_4 in (6b) would lead to the non-rejection of H2d. Finally, positive values of ω_7 in (6a) and δ_5 in (6b) would lead to the non-rejection of H3d.

According to the results obtained for regression (6a), not reported here for the sake of brevity, forecast earliness is never significant in any of the situations examined, so that H1d is rejected. According to the results obtained for regression (6b), reported in Table 8, neither the forecast accuracy measures nor the recommendation profitability scores are significant for any of the I/I or Extel rankings, so that H2d and H3d are rejected. Issuing accurate forecasts or high-quality recommendations does not turn out to be a determinant in achieving the top level in rankings or becoming a senior star analyst in comparison with being at lower levels.

[Insert Table 8 about here]

7. Conclusion

We use I/I and Extel rankings combined with I/B/E/S data to investigate whether European financial analyst rankings reflect superior skills or whether they are due to popularity contests (Emery and Li, 2009). Our findings for European analysts ranked by I/I and Extel are consistent with those of Emery and Li (2009) for US analysts ranked by I/I and the WSJ. Those authors show that European analyst rankings are determined more by factors of recognition and popularity, such as the size of the brokerage firm or experience, than by intrinsic skills reflected by accurate forecasts or profitable recommendations. Among these factors, employer size has by far the largest economic impact.

The ability to issue more profitable recommendations in the year preceding the ranking is, however, found to influence the election only at the lowest level (level 4) or at the top level (level 1) in the I/I survey. Going further in the analysis, it seems that becoming an I/I star is akin to joining a club, in the sense that special skills in issuing high-quality recommendations are required to obtain a first-time ranking but are completely irrelevant to being re-elected or reaching the first level. On the one hand, this result confirms the conclusions of Emery and Li (2009) for the I/I survey in the United States but, on the other hand, it completely contradicts their conclusions regarding WSJ rankings, for which they find that maintaining one's star ranking is more difficult and requires more talent than becoming a rising star in the first place. These differences probably arise from differences in the way eligibility requirements are designed for the two surveys. Another feature that seems to influence the informativeness of rankings about analysts' performances is the profile of the voters. While the I/I survey polls only portfolio managers, the population of voters in the Extel ranking is much more diverse. This may well explain why recommendation profitability prior to the ranking year is never a determinant of the Extel rankings while it significantly influences the I/I rankings.

Our findings underline the weaknesses of these analysts' rankings. First, they say little about analysts' intrinsic skills. Only first-timers can be seen as more talented when elected by a population of fund managers. In other cases, ranked analysts are essentially famous professionals for whom the rankings maintain their fame. Second, the design of these surveys could probably be improved by reducing the impact of recognition in the election process.

Appendix

Table 1

Analysts' forecasts and recommendations sample sizes

	1998	*1999*	*2000*	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*Total*
Panel A : I/I													
No. of analysts	46	138	157	116	106	170	267	226	170	135	144	176	1,851
% ranked	13.00%	8.70%	12.70%	12.90%	13.20%	11.80%	12.00%	8.00%	10.60%	11.10%	6.90%	9.10%	10.60%
No. of recommendations	329	1,197	1,304	894	920	1,617	2,225	1,573	1,089	915	970	1,354	14,387
No. of forecasts	478	1,373	1,671	1,062	953	1,743	2,579	2,252	1,636	1,205	1,331	1,590	17,873
Panel B : Extel													
No. of analysts							239	207	77	108	123	156	910
% ranked							6.30%	3.90%	7.80%	6.50%	5.70%	5.80%	5.74%
No. of recommendations							2,017	1,465	451	811	838	1,211	6,793
No. of forecasts							1,373	1,385	940	1,074	1,037	1,055	6,864

Note: This table displays the size of our sample as the number of analysts, forecasts, and recommendations per year and per ranking. For forecasts and recommendations, an observation is characterized by a stock, an analyst, an industry, and a year of issue. The percentage of analysts nominated in each ranking is also provided.

Table 2

List of national risk-free rates

Country	*Risk-free rate*	*Source*
France	Treasury Bills – 1 month	Banque de France
Spain	Interbank – 1 month middle rate	Bank of Spain
Italy	Treasury Bills – 3 month auction gross rate	Datastream
Switzerland	Interbank - 1 month bid rate	Datastream
Germany	FIBOR – 1 month	Datastream
Belgium	Treasury Bills – 1 month	Banque Nationale de Belgique
Netherlands	AIBOR - 1 month	De Nederlandsche Bank
Sweden	STIBOR - 1 month	Datastream
Denmark	CIBOR - 1 month	Datastream
Finland	HELIBOR - 1 month	Finlands Bank
Norway	NIBOR - 1 month	Datastream
Greece[a]	Treasury Bill - 1 year, middle rate	Datastream
Austria	Federal Government secondary market yields – 1 month	Oesterreichische Nationalbank
United Kingdom	LIBOR - 1 month	Datastream
Euro area	EURIBOR – 1 month	European Central Bank

[a] Monthly rate unavailable.

Table 3

Descriptive statistics

		Extel		I/I	
		Mean	Standard deviation	Mean	Standard deviation
$SizeScore_{j.s.t-1}$	0	3.58	0.93	3.56	0.95
	1	4.38	0.42	4.35	0.50
	Diff.	0.81^{***}		0.79^{***}	
$ExpScore_{j.s.t-1}$	0	49.09	29.73	48.16	29.94
	1	65.08	27.98	65.52	25.23
	Diff.	16.00^{***}		17.35^{***}	
$Bold_{j.s.t-1}$	0	49.63	18.24	49.61	18.27
	1	52.09	18.05	52.23	16.90
	Diff.	2.46		2.62^{*}	
$Optim_{j.s.t-1}$	0	49.91	29.88	49.85	30.23
	1	51.45	30.36	51.23	29.68
	Diff.	1.54		1.38	
$Ranked_{j.s.t-1}$	0	0.01	0.10	0.01	0.12
	1	0.48	0.50	0.65	0.48
	Diff.	0.47^{***}		0.64^{***}	
$Earl_{j.s.t-1}$	0	183.96	39.82	187.39	40.13
	1	186.26	41.60	180.22	34.25
	Diff.	2.31		-7.17^{***}	
$Earl_{j.s.t-2}$	0	175.56	33.67	178.99	34.28
	1	175.86	36.47	177.17	32.09
	Diff.	0.30		-1.82	
$ForAccScore_{j.s.t-1}$	0	49.64	30.18	50.17	30.46
	1	55.97	29.79	48.60	31.25
	Diff.	6.33		-1.57	
$ForAccScore_{j.s.t-2}$	0	50.16	30.14	49.73	30.34
	1	47.29	30.97	52.30	32.15
	Diff.	-2.88		2.57	
$ForAccInc_{j.s.t-1}$	0	0.53	0.50	0.54	0.50
	1	0.71	0.46	0.61	0.49
	Diff.	0.18^{***}		0.07^{*}	
$VarFor_{j.s.t-1}$	0	50.03	28.41	50.30	28.77
	1	49.43	30.26	47.47	27.82
	Diff.	-0.60		-2.83	
$AccEarlScore_{j.s.t-1}$	0	49.91	30.24	50.07	30.41
	1	51.44	29.32	49.43	31.65
	Diff.	1.53		-0.64	
$AccEarlScore_{j.s.t-2}$	0	50.21	30.14	50.11	30.42
	1	46.51	30.81	49.06	31.54
	Diff.	-3.71		-1.05	
$RecScore_{j.s.t-1}$	0	49.80	30.27	49.35	30.77
	1	53.29	28.61	55.50	27.96
	Diff.	3.49		6.15^{***}	

Note: This table compares the mean values of the characteristics' and skill measures' of analysts ranked in the I/I survey from 1998 to 2009 and the Extel survey from 2004 to 2009 with those of non-ranked analysts. The rankings are considered in year *t*. The variables $SizeScore_{j.s.t-1}$, $ExpScore_{j.s.t-1}$, , $Bold_{j.s.t-1}$, and $Optim_{j.s.t-1}$, respectively, measure employer size, experience, boldness, and optimism in year $t - 1$; $Ranked_{j.s.t-1}$ is an indicator of whether the analyst was ranked in the previous year; $Earl_{j.s.t-1}$ and $Earl_{j.s.t-2}$ are forecast earliness measures; $ForAccScore_{j.s.t-1}$, $ForAccScore_{j.s.t-2}$, $ForAccInc_{j.s.t-1}$, $VarFor_{j.s.t-1}$, $AccEarlScore_{j.s.t-1}$, and $AccEarlScore_{j.s.t-2}$ are forecast accuracy measures; and $RecScore_{j.s.t-1}$ is a score measuring recommendation profitability in year t - 1. Standard deviations are also reported. The second column indicates the ranking status of the analysts: one for ranked analysts, zero for non-ranked analysts. The 'diff.' column reports the mean differences. The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

.

Table 4

Factors explaining the probability of being elected to an analysts’ ranking

	I/I	Extel	I/I	Extel
Intercept	-8.252	-11.745	-8.607	-11.569
$Earl_{t-1}$	-0.007**	-0.005		
p-Value	0.043	0.365		
Elasticity	-1.194	-0.856		
$Earl_{t-2}$	0.005	0.004		
p-Value	0.121	0.556		
Elasticity	0.864	0.692		
$ForAccScore_{t-1}$	0.006	0.000		
p-Value	0.268	0.975		
Elasticity	0.280	-0.015		
$ForAccScore_{t-2}$	0.000	0.011		
p-Value	0.987	0.267		
Elasticity	0.004	0.542		
$AccEarlScore_{t-1}$			-0.003	-0.007
p-Value			0.518	0.326
Elasticity			-0.130	-0.337
$AccEarlScore_{t-2}$			0.008*	0.010
p-Value			0.066	0.235
Elasticity			0.388	0.492
$ForAccInc_{t-1}$	0.566	1.180*	0.752***	1.311**
p-Value	0.121	0.092	0.008	0.012
Elasticity	0.296	0.630	0.393	0.700
$VarFor_{t-1}$	-0.008*v	-0.010	-0.007*	-0.008
p-Value	0.043	0.189	0.070	0.276
Elasticity	-0.404	-0.490	-0.357	-0.375
$RecScore_{t-1}$	0.010***	0.001	0.010***	0.000
p-Value	0.008	0.929	0.008	0.970
Elasticity	0.492	0.027	0.482	0.011
$SizeScore_{t-1}$	0.991***	1.607***	0.994***	1.608***
p-Value	0.000	0.000	0.000	0.000
Elasticity	3.473	5.737	3.483	5.739
$ExpScore_{t-1}$	0.009***	0.017**	0.009***	0.016**
p-Value	0.007	0.028	0.007	0.024
Elasticity	0.448	0.826	0.444	0.807
$Bold_{t-1}$	0.002	0.008	0.001	0.006
p-Value	0.722	0.486	0.861	0.593
Elasticity	0.101	0.396	0.049	0.292
$Optim_{t-1}$	0.002	-0.005	0.002	-0.004
p-Value	0.520	0.469	0.636	0.461
Elasticity	0.111	-0.226	0.082	-0.220
$Ranked_{t-1}$	4.461**v	4.351**v	4.425***	4.237**v
p-Value	0.000	0.000	0.000	0.000
Elasticity	0.353	0.155	0.349	0.151
R^2	0.493	0.411	0.490	0.408
# obs.	1,851	910	1,851	910

Note: This table displays the estimates of binomial logistic regressions in which the dependent variable is the probability of analyst *j* being ranked in either the I/I or the Extel survey for sector *s* in year *t*. Independent variables include forecast earliness measures ($Earl_{j.s.t-1}$ and $Earl_{j.s.t-2}$), forecast accuracy measures ($ForAccScore_{j.s.t-1}$, $ForAccScore_{j.s.t-2}$, $ForAccInc_{j.s.t-1}$, $VarFor_{j.s.t-1}$, $AccEarlScore_{j.s.t-1}$, and $AccEarlScore_{j.s.t-2}$), and a score measuring recommendation profitability in year *t* - 1 ($RecScore_{j.s.t-1}$). Control variables comprise employer size ($SizeScore_{j.s.t-1}$), experience ($ExpScore_{j.s.t-1}$), forecast boldness

($Bold_{j.s.t-1}$), forecast optimism ($Optim_{j.s.t-1}$), and the event to be ranked in the previous year ($Ranked_{j,,s,t-1}$). The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 5

Factors explaining the probability of being elected in analyst rankings, by ranking level (Model 4a)

	I/I				Extel		
RankLevel$_t$	1	2	3	4	1	2	3
p-Value	0.338	0.065	0.300	0.108	0.407	0.277	0.955
Elasticity	-1.029	-1.029	-1.069	-1.109	-1.171	-1.814	-0.069
p-Value	0.725	0.011	0.254	0.143	0.140	0.776	0.960
Elasticity	0.429	0.429	-1.419	1.003	2.310	-0.571	0.071
p-Value	0.690	0.720	0.030	0.656	0.613	0.054	0.109
Elasticity	0.184	0.184	0.972	0.129	-0.372	-1.691	1.072
p-Value	0.471	0.897	0.390	0.481	0.861	0.362	0.191
Elasticity	-0.356	-0.356	-0.423	0.218	0.124	0.721	0.784
p-Value	0.500	0.441	0.066	0.378	0.145	0.308	0.318
Elasticity	0.259	0.259	0.684	0.210	0.943	0687	0.510
p-Value	0.234	0.072	0.009	0.486	0.907	0.240	0.134
Elasticity	-0.459	-0.459	-0.941	-0.167	0.069	-0.747	-0.743
p-Value	0.045	0.974	0.305	0.005	0.174	0.130	0.987
Elasticity	0.747	0.747	0.350	0.637	0.693	-0.901	-0.007
p-Value	0.064	0.015	0.020	0.000	0.022	0.013	0.012
Elasticity	2.639	2.639	2.998	4.104	6.745	8.963	4.431
p-Value	0.049	0.349	0.122	0.093	0.014	0.041	0.746
Elasticity	0.817	0.817	0.568	0.390	1.547	1.423	0.153
p-Value	0.621	0.778	0.325	0.528	0.498	0.815	0.161
Elasticity	0.304	0.304	-0.561	0.234	0.558	-1.023	1.093
p-Value	0.924	0.855	0.720	0.527	0.919	0.273	0.170
Elasticity	0.032	0.032	0.116	0.133	-0.050	-0.135	-0.603
p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Elasticity	0.439	0.439	0.389	0.307	0.388	0.391	0.328
# obs.		1,851				910	

Note: This table displays the estimates of multinomial logistic regressions in which the dependent variable is the probability of analyst *j* being ranked at a specific level in either the I/I or the Extel survey for sector *s* in year *t*. Ranking levels range from level 4 to level 1 in the I/I survey and from level 3 to level 1 in the Extel survey, level 1 being the highest rank. Independent variables include forecast earliness measures ($Earl_{j.s.t-1}$ and $Earl_{j.s.t-2}$), forecast accuracy measures ($ForAccScore_{j.s.t-1}$, $ForAccScore_{j.s.t-2}$, $ForAccInc_{j.s.t-1}$, and $VarFor_{j.s.t-1}$), and a score measuring recommendation profitability in year *t* - 1 ($RecScore_{j.s.t-1}$). Control variables comprise employer size ($SizeScore_{j.s.t-1}$), experience ($ExpScore_{j.s.t-1}$), forecast boldness ($Bold_{j.s.t-1}$), forecast optimism ($Optim_{j.s.t-1}$), and the event to be ranked in the previous year ($Ranked_{j,.s,t-1}$). The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6

Factors explaining the probability of being elected in analyst rankings, by ranking level (Model 4b)

	I/I				Extel		
$RankLevel_t$	1	2	3	4	1	2	3
Intercept	-10.216	-9.040	-9.103	-10.292	-17.717	-13.348	-11.257
$AccEarlScore_{t-1}$	-0.008	-0.007	-0.001	-0.001	-0.009	-0.023	0.002
p-Value	0.348	0.367	0.876	0.898	0.456	0.100	0.817
Elasticity	-0.374	-0.344	-0.059	-0.032	-0.444	-1.126	0.123
$AccEarlScore_{t-2}$	0.004	0.009	0.012	0.007	0.008	0.000	0.016
p-Value	0.584	0.249	0.108	0.165	0.516	0.999	0.135
Elasticity	0.221	0.429	0.596	0.351	0.404	0.001	0.808
$ForAccInc_{t-1}$	0.481	0.915*	0.760	0.754**	2.072**	0.129	1.569**
p-Value	0.398	0.087	0.153	0.035	0.035	0.893	0.048
Elasticity	0.261	0.495	0.411	0.409	1.120	0.070	0.843
$VarFor_{t-1}$	-0.008	-0.013*	-0.018**	-0.002	-0.001	-0.014	-0.009
p-Value	0.273	0.079	0.012	0.619	0.959	0.234	0.341
Elasticity	-0.419	-0.628	-0.903	-0.118	-0.028	-0.703	-0.439
$RecScore_{t-1}$	0.015**	-0.001	0.008	0.013***	0.013	-0.015	-0.001
p-Value	0.049	0.904	0.226	0.006	0.191	0.185	0.943
Elasticity	0.730	-0.041	0.413	0.627	0.646	-0.744	-0.030
$SizeScore_{t-1}$	0.724*	0.870**	0.840	1.155***	1.855**	2.451**	1.236**
p-Value	0.064	0.018	0.015	0.000	0.020	0.013	0.011
Elasticity	2.628	3.150	3.042	4.191	6.704	8.863	4.440
$ExpScore_{t-1}$	0.016*	0.007	0.011	0.008*	0.031**	0.024**	0.004
p-Value	0.057	0.369	0.133	0.080	0.011	0.063	0.667
Elasticity	0.788	0.327	0.552	0.411	1.532	1.193	0.202
$Bold_{t-1}$	0.007	0.002	-0.010	0.003	0.012	-0.020	0.016
p-Value	0.529	0.879	0.368	0.692	0.469	0.273	0.290
Elasticity	0.372	0.084	-0.488	0.146	0.592	-0.996	0.792
$Optim_{t-1}$	0.000	0.000	0.001	0.002	-0.004	0.002	-0.009
p-Value	0.993	0.941	0.821	0.600	0.703	0.872	0.281
Elasticity	-0.003	0.024	0.072	0.112	-0.182	0.091	-0.459
$Ranked_{t-1}$	5.343***	5.000***	4.789***	3.778***	4.601***	4.598***	3.893***
p-Value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Elasticity	0.437	0.408	0.391	0.309	0.166	0.166	0.140
R^2		0.480				0.432	
# obs.		1,851				910	

Note: This table displays the estimates of multinomial logistic regressions in which the dependent variable is the probability of analyst *j* being ranked at a specific level in either the I/I or the Extel survey for sector *s* in year *t*. Ranking levels range from level 4 to level 1 in the I/I survey and from level 3 to level 1 in the Extel survey, level 1 being the highest rank. Independent variables include forecast accuracy measures ($ForAccScore_{j.s.t-1}$, $ForAccScore_{j.s.t-2}$, $ForAccInc_{j.s.t-1}$, $VarFor_{j.s.t-1}$,

$AccEarlScore_{j.s.t-1}$, and $AccEarlScore_{j.s.t-2}$) and a score measuring recommendation profitability in year t - 1 ($RecScore_{j.s.t-1}$). Control variables comprise employer size ($SizeScore_{j.s.t-1}$), experience ($ExpScore_{j.s.t-1}$), forecast boldness ($Bold_{j.s.t-1}$), forecast optimism ($Optim_{j.s.t-1}$), and the event to be ranked in the previous year ($Ranked_{j,,s,t-1}$). The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 7

Factors explaining ranking probabilities for first-timers and veterans

	I/I		Extel	
RankHist$_t$	1	2	1	2
Intercept	-10.122	-11.799	-17.148	-15.180
AccEarlScore$_{t-1}$	0.002	-0.002	0.001	-0.006
p-Value	0.737	0.637	0.964	0.461
Elasticity	0.096	-0.084	0.030	-0.313
AccEarlScore$_{t-2}$	0.005	0.004	0.014	0.013
p-Value	0.401	0.273	0.307	0.152
Elasticity	0.243	0.199	0.675	0.635
ForAccInc$_{t-1}$	0.551	0.581**	1.958*	1.622**
p-Value	0.179	0.025	0.059	0.015
Elasticity	0.295	0.307	1.064	0.874
VarFor$_{t-1}$	-0.006	-0.006	-0.010	0.007
p-Value	0.247	0.100	0.399	0.402
Elasticity	-0.305	-0.276	-0.489	0.345
RecScore$_{t-1}$	0.009*	0.003	0.009	0.003
p-Value	0.090	0.298	0.397	0.683
Elasticity	0.424	0.160	0.451	0.142
SizeScore$_{t-1}$	1.232***	1.686***	2.408***	1.960***
p-Value	0.000	0.000	0.010	0.000
Elasticity	4.416	5.972	8.758	7.071
ExpScore$_{t-1}$	0.001	0.027***	0.015	0.017**
p-Value	0.881	0.000	0.206	0.037
Elasticity	0.038	1.327	0.767	0.823
Bold$_{t-1}$	0.009	0.010*	0.008	0.018
p-Value	0.268	0.067	0.667	0.163
Elasticity	0.463	0.479	0.409	0.877
Optim$_{t-1}$	0.006	-0.001	-0.004	0.005
p-Value	0.215	0.830	0.718	0.529
Elasticity	0.307	-0.032	-0.191	0.224
R^2	0.238		0.238	
# obs.	1,851		910	

Note: This table displays the estimates of multinomial logistic regressions in which the dependent variable is the probability of analyst *j* being ranked for the first time in year *t* (event 1) or ranked in year *t* after having already been ranked in the past (event 2). Independent variables include forecast accuracy measures (*ForAccScore*$_{j.s.t-1}$, *ForAccScore*$_{j.s.t-2}$, *ForAccInc*$_{j.s.t-1}$, *VarFor*$_{j.s.t-1}$, *AccEarlScore*$_{j.s.t-1}$, and *AccEarlScore*$_{j.s.t-2}$) and a score measuring recommendation profitability in year *t* - 1 (*RecScore*$_{j.s.t-1}$). Control variables comprise employer size (*SizeScore*$_{j.s.t-1}$), experience (*ExpScore*$_{j.s.t-1}$), forecast boldness (*Bold*$_{j.s.t-1}$), and forecast optimism (*Optim*$_{j.s.t-1}$). The superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8

Factors explaining the probabilities of reaching the top levels

	I/I	Extel
Intercept	-2.513	-2.723
$AccEarlScore_{t-1}$	-0.003	-0.004
p-Value	0.709	0.765
Elasticity	-0.127	-0.142
$AccEarlScore_{t-2}$	-0.004	-0.008
p-Value	0.534	0.592
Elasticity	-0.185	-0.249
$ForAccInc_{t-1}$	-0.375	0.739
p-Value	0.455	0.549
Elasticity	-0.192	0.350
$VarFor_{t-1}$	0.001	0.006
p-Value	0.849	0.599
Elasticity	0.051	0.206
$RecScore_{t-1}$	0.006	0.020
p-Value	0.341	0.109
Elasticity	0.293	0.704
$SizeScore_{t-1}$	-0.153	-0.294
p-Value	0.713	0.757
Elasticity	-0.562	-0.859
$ExpScore_{t-1}$	0.008	0.016
p-Value	0.347	0.172
Elasticity	0.437	0.858
$Bold_{t-1}$	0.010	0.012
p-Value	0.472	0.528
Elasticity	0.425	0.414
$Optim_{t-1}$	0.000	0.003
p-Value	0.958	0.806
Elasticity	-0.015	0.092
$Ranked_{t-1}$	1.060**	0.501
p-Value	0.034	0.418
Elasticity	0.583	0.160
R^2	0.060	0.134
# obs.	196	52

Note: This table displays the estimates of binomial logistic regressions in which the dependent variable is the probability of a ranked analyst being ranked at the top level in either the I/I or the Extel survey rather than being ranked lower. Independent variables include forecast accuracy measures ($ForAccScore_{j.s.t-1,}$ $ForAccScore_{j.s.t-2}$, $ForAccInc_{j.s.t-1}$, $VarFor_{j.s.t-1}$, $AccEarlScore_{j.s.t-1}$, and $AccEarlScore_{j.s.t-2}$) and a score measuring recommendation profitability in year *t* - 1 ($RecScore_{j.s.t-1}$). Control variables comprise employer size ($SizeScore_{j.s.t-1}$), experience ($ExpScore_{j.s.t-1}$), forecast boldness ($Bold_{j.s.t-1}$), forecast optimism ($Optim_{j.s.t-1}$), and the event to be ranked at any time before the considered ranking ($Ranked_{j,,s,t-1}$). The superscripts *, **, and *** denotes significance at the 10%, 5%, and 1% levels, respectively.

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