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The Determinants of Sell-side Analysts' Forecast Accuracy and Media Exposure

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Abstract

This study examines contributing factors to the differential forecasting abilities of sell-side analysts and the relation between the sentiments of these analysts and their media exposure. In particular, I investigate whether the level of optimism expressed in sell-side analysts' reports of fifteen constituents of primarily the S&P 500 Oil and Gas Industry1, enhance the media appearance of these analysts. Using a number of variables estimated from the I/B/E/S Detail history database, 15,455 analyst reports collected from Thompson Reuters Investext and analyst media appearances obtained from Dow Jones Factiva from 1999 to 2014, I run a multiple linear regression to determine the effect of independent variables on dependent variables. I find that an analyst's forecast accuracy (as measured by the errors inherent in his forecasts) is negatively associated with the analyst's level of media exposure, experience, brokerage size, the number of times he revises his forecasts in a year and the number of companies followed by the analyst, and positively associated with the analyst's level of optimism expressed in his reports, forecast horizon and the size of the company he follows.

Keywords: analyst's forecast, media exposure, experience, brokerage size, firm size

INTRODUCTION

Analysts' recognition as expert financial intermediaries through their essential role of receiving and processing financial information for various market participants including investors and accounting researchers has intensified over the years. Schipper (1991) and Brown (2001) reveal in their studies that sell-side analysts have higher audience since they assess large volumes of both private and public information to help make recommendations on the best investment decision to clients. As these analysts are considered to have high forecasting knowledge and expertise, their recommendations are of great value to their clients (Jegadeesh & Kim, 2009).

Exploring the determinants of forecast accuracy according to Clement (1999) is essential firstly because of the growing interest of accounting researchers to know whether variations exist in analysts' earnings forecasts accuracy and the contributing factors to those differences and secondly because capital market expectations are surrogated by analyst forecasts. If there are predictable variations in analysts' forecast accuracy, and if they are recognized by capital markets then the accuracy of earnings expectations' proxies can be improved by increasing the weights assigned to analysts who are more accurate.

One of the primary channels through which information (financial and non-financial) is disseminated to the general public is the media. News media contents according to Tetlock (2007) cause shifts in broad stock market activities' indicators. This implies that media outlets play an equally important role as they facilitate the dissemination of information such as analyst forecasts and recommendations to a broad audience, especially individual and institutional investors, managers and regulators (Fang & Peress, 2009). More so, "celebrity" sell-side analyst forecasts according to Bushee, et al., (2010) facilitate the efficient functioning of capital markets.

The question then is whether the media gives more audience to analysts who express a higher level of optimism in their lexical sentiments than to other analysts. To address the concern, this dissertation explores the factors that potentially influence sell-side analysts' forecasts accuracy and how accuracy is associated with the level of media popularity of the analysts receive. I specifically investigate how analysts' attributes including their experience, number of companies they follow, size of the brokerage house they work for (suggested by Clement, 1999), size of the firms they follow and forecast characteristics including the number of forecast revisions and forecast horizon influence forecast accuracy and how analysts' sentiments is associated with their media appearances for constituents of the S&P 500 oil and Gas constituents. Why Oil and gas?

Notwithstanding the recent fall in the prices of crude oil and petroleum products, which brought about huge losses to many oil companies, the Oil and Gas sector is among the world's largest sectors. Oil exports including crude oil and other refined products, which have for many years been the leading world trade commodity constituted 13 percent of total commodity trade by value in 2006 (Smith, 2009). In the last decade, world dependence on energy has grown steadily with oil consumption of countries such as China doubling between 1996 and 2006 (Ramos & Veiga, 2011). The Central Intelligence Agency (CIA) world Fact Book provides that as at 2013, world crude oil production and refined petroleum products consumption reached 85.86 million and 90.05 million barrels a day respectively. The industry's profitability over the years has attracted a number of investors with oil-related funds gaining more recognition in financial markets.

Prior research including Mikhail, et al., (1997) provide evidence that analysts' general experience to a great extent has a positive effect on their forecasting abilities, which is supported by Clement (1999) whose studies present a similar conclusion. Additionally, Jacob, et al. (1999) find that the amount of resources available to an analyst potentially affects his forecast accuracy. With regards to media exposure, it has been found that highly ranked analysts are capable of causing a 'sale', 'hold' or 'purchase' of a stock because of their ability to significantly influence the investing public (Dechow & Skinner, 2000).

More recent studies identify that factors such as boldness and timeliness of forecasts (Hong, Kubik, & Solomon, 2000) and analysts' incentives to optimism (Jackson, 2005) may negatively impact their forecasts. Specifcally, Hong, et al. (2000) show that less experienced analysts in comparison to their experienced counterparts have a lower probability of issuing timely forecasts and a higher probability of being terminated for bold forecasts that deviate from the consensus. They also find that inexperienced analysts revise their forecasts more frequently. The relation between analysts' firm-specific experience and forecasting accuracy is debatable as opposing results emerged in explaining whether variations in forecast accuracy may be attributable to the number of years an analyst has followed a particular firm (Clement, Koonce, & Lopez, 2007). Other studies (Horton & Serafeim, 2009) find that the social network of analysts may have a negative impact on their forecasts.

As most investors are somewhat influenced by the recommendations of analysts in investment decision-making, it is imperative that these analysts' forecasts have a high level of reliability. Also, given the key role of the media as a vehicle that facilitates the dissemination of analysts' forecasts and recommendations, examining the correlation between analysts' popularity in the press, their tone and forecast accuracy may enable capital market participants make better investment decisions and increase their stock returns.

The remainder of this dissertation proceeds as follows: A background of prior literature bordering on factors that impact analysts' forecast accuracy and how they relate to their media exposure is presented in the next section. Section 3 describes the adopted methodology and how the variables are measured. The findings are discussed in section 5 and section 6 concludes with suggestions for future research.

LITERATURE REVIEW

Factors that affect forecast accuracy

Prior research give somewhat inconclusive results as to whether there are variations in the ability of sell-side analysts to accurately forecast particularly companies earnings and if so, the factors that may be associated with those variations. While Richards (1976), Brown & Rozeff (1980), O'Brien (1987), O'Brien (1990) and Butler & Lang (1991) find no evidence of differential forecasting abilities in their studies, Stickel (1992), Sinha, et al. (1997) and Clement (1999) document variations in analysts' forecast accuracy.

Based on Brown & Chen's (1991) research, All-American analysts in comparison to Non-All-American analysts are more accurate forecasters. Similarly, Stickel (1992) find's that Institutional All-American analysts issue more frequent forecasts, which are more accurate than those of other analysts. Also, stock prices' reaction to the upward forecast revisions of All-American analysts is more pronounced as compared to that of Non All-American analysts. More so, studies by Dugar & Nathan (1995) reveal that analysts' forecasts for firms that utilize investment banking services of the brokerage houses they work for are characterized by higher levels of optimism, although there is no significant difference in the returns earned by companies who follow the recommendations of investment banker analysts and that of those who follow the recommendations of other analysts. This is however challenged by Lin & McNichols (1998) who find no variations in the earnings forecasts produced by the two categories of analysts (those affiliated with a company's underwriters and unaffiliated analysts). By extending O'Brien's work and using a larger body of analysts, Sinha, et al. (1997) also identify differential forecast accuracy among analysts, which indirectly suggests that analysts' performance may improve over time. They however fail to give reasons for the differences.

Using time series analysis, Mikhail et al., (1997) show that an improvement in the firm-specific experience of analysts enhance their forecast accuracy. Their finding may however, not be generalizable because of the small sample size they use. Consistent with this conjecture, Clement (1999) runs a cross-sectional regression on a larger sample and a wider range of variables and observes that forecast accuracy has a positive correlation with analysts' experience and broker size and a negative correlation with the number of firms and industries the analysts follow. Contrarily, Jacob, et al. (1999) find no evidence that the accuracy of an analyst's forecast improves with his experience but do establish a relationship between employer size and forecast accuracy. In particular, they show that forecast accuracy has a positive relation with the degree of industry specialization of the brokerage houses that the analysts work for and a negative relation with the brokerage house turnover (Clement, 1999). More recent studies by Loh & Stulz (2011) suggest that analysts' media popularity may be associated with some of Clement's proposed variables. Thus, analysts who work for larger brokers and are as a result exposed to a wider range of resources are likely to have more media appearances.

Additionally, Lehavy et al (2011) perform a statistical regression on a 10-k filings' sample comprising over 33,700 observations from 1995 to 2006 to determine how readability is correlated with analysts' forecast accuracy. They measure readability as the number of complex words inherent in financial reports using Fog index and find that firms with more complicated financial reports are followed by a larger number of financial analysts. Also, the earnings forecasts for these firms are less accurate, more dispersed and rather characterized by a greater degree of uncertainty. This may be because more complicated financial reports tend to generate a wider range of analyst interpretations, giving rise to more uncertainty. More so, the Fox index that Lehavy et al (2011) use, ignores the quantitative complexity of the financial reports and as such may impede the practicality of their research finding. It measures only the qualitative complexity of the reports, which limit their findings.

Correlation between forecast accuracy, media exposure and sentiments

In recent years, various market participants have gained interest in the association between the press and the market. Among this growing body of literature are the works of Klibanoff, et al., (1998), Chan (2003), Tetlock (2007), Tetlock, et al., (2008), Fang & Peress (2009) and Bushee, et al., (2010).

Based on Klibanoff, et al's (1998) studies, closed-end funds' price reaction to country-specific news published particularly on the front page of *The New York Times* is more pronounced in comparison to when there is no news. Hence, they argue that some investors react more rapidly than they otherwise would in response to such news events. Using a quantitative approach, Tetlock (2007) investigates media content and documents that high trading volumes are predicted by low media pessimism whereas high pessimism predicts downward pressure on prices and a subsequent reversion to fundamentals in stock markets. Additionally, the level of optimism in firm-specific news according to findings of Tetlock, et al. (2008) not only predicts low earnings but also causes an abrupt underreaction of stock prices to such news stories. These findings suggest that the efficiency of stock prices may be influenced by the content of qualitative information reported by the media.

Nonetheless, there is much ambiguity among past papers regarding the extent of correlation between the frequency of an analyst's media appearances and his forecast accuracy. While researchers such as Chan (2003) demonstrate in his studies that the greater number of star analysts' status is based on their past research quality, implying that a positive correlation may exixts between the two variables, others including Fang & Peress (2009) argue that an analysts who has a relatively higher level of media popularity is more likely to issue less accurate forecasts as a result of the conflict of interest he may encounter. Chan's (2003) argument is however supported by Fang & Yasuda (2014) who make a comparison between the forecasts of All-American (AA) analysts with a high level of media appearance and those of other analysts for the period from 1994 to 2003 for some S&P Oil and Gas constituents and conclude that those analysts who have high media popularity are more likely to issue more accurate forecasts as well as give more reliable recommendations. Intriguingly, they find that AA analysts outperform the market by 6.12% and 2.59% in raw returns per year with regards to buy and sell recommendations respectively, reinforcing that analysts with a higher level of media exposure may consequently issue more accurate earnings' forecasts. There is a possibility, however, that the implied resultant forecast accuracy of high media exposure may be as a result of investors' reacting more strongly to the recommendations of celebrity analysts. This viewpoint is buttressed by Bonner, et al. (2007) who reveal that investors' response to the forecast revisions of analysts who are cited more frequently in the media is more pronounced due more to the popularity of these analysts and not necessarily to the exceptional quality of their performance.

Additionally, Barberis & Thaler's (2003) study of the investor's decision making process maintain that investor competence and confidence is boosted by the familiarity of their sources of information and may as a consequence, make investment choices that are favourable to those sources. Their research suggests that instead of analysts' media popularity being dependent on their ability to produce accurate forecasts, it is rather how well-known they are and their celebrity status that increases their forecast accuracy. This situation according to Arkes et al. (1991), is caused by investors' conviction that popular analysts' recommendations are more accurate.

Much as there is a substantial amount of literature on the determinants of forecast accuracy, only a few (Dyck & Zingales, 2002; Clement & Westphal, 2008) focus also, on the extent to which analysts' forecast accuracy and/or sentiments may explain their media popularity. That is, according to Barber & Odean (2008), whether the media prefers anaylsts with more expertise and accuracy or the media appearances of those analysts is based rather on other subjective factors. The general consensus of the majority of studies in this area suggests that analysts' media popularity is more atttributable to the accuracy of their forecasts than to their sentiments. Recent studies by Rees et al., (2012) reveal that among the major factors that determine the media coverage of analysts' is the quality of their forecasts, which may be because of the simple fact that reporters are more interested in information from those analysts who will enhance the intergrity of their stories.

I contribute to existing literature by determining whether the level of optimism expressed in the reports of sell-side analysts plays a significant role in the forecast accuracy of the analysts as well as their media popularity. This is the first paper that focuses on the relation between sell-side analysts' forecast accuracy, sentiments and media appearances for the S&P 500 oil and gas exploration and production constituents, to the best of my knowledge. If it happens to be the situation that there exist in fact very minimal correlation between the level of analysts' media exposure and their forecast accuracy, then it may be concluded that observed shifts in stock prices are merely investors' reactions to inaccurate signals.

METHOD

Test of hypotheses

Based on the objectives of this study, I test the following hypotheses;
H_1: Analysts who show more optimism in their reports are more accurate forecasters.
H_2: Analysts who show more optimism in their reports have higher media exposure.
H_3: Analysts who are more accurate forecasters have higher media exposure.

I primarily use Clement's (1999) approach of regression analysis to examine whether analysts' forecast accuracy is linked to the combination of their sentiments, experience, number of companies followed, firrm size and brokerage house size. According to Clement (1999), jointly analysing the aforementioned variables (with the exception of sentiments) is important because they are likely to be correlated. In order to determine the nature of the correlation between the variables, I run a first Ordinary Least Squares (OLS) regression with forecast accuracy as the dependent variable (Y) and media exposure, sentiments, analysts' experience, number of companies followed, firm size, brokerage house size, forecast horizon and number of forecast revisions as the independent variables (X's) then a second OLS regression with media exposure as the dependent variable and the same independent variables including forecast accuracy used in the first regression.

Dependent Variables

Proportional Mean Absolute Prediction Error

Similar to the method used by Clement (1999), analyst prediction error (hereafter APE) is a measure of the absolute difference between a firm's actual earnings and analysts' forecasted earnings, calculated as:

$$APE_{ijt} = | AEPS_{jt} - FEPS_{ijt} | \quad (1)$$

Where APE_{ijt} represents the absolute prediction error for analyst *i's* forecast of firm *j* in year t, $FEPS_{ijt}$ is the forecast EPS of analyst *i* for firm *j* for year *t*, and $AEPS_{jt}$ is firm *j's* actual earnings in year *t*. Adopting Clement's (1999) approach, I compare the absolute prediction error of each analyst and the mean absolute prediction error of all other analysts following the same firm in the same year to compute performance.

$$PMAPE = DAPE_{ijt}/\overline{APE_{jt}} \quad (2)$$

Where $DAPE_{ijt} = APE_{ijt}$ - $\overline{APE_{jt}}$, APE_{jt} is previously $\overline{APE_{jt}}$ represents the mean absolute prediction error of all analysts following firm *j* in year *t*. . Thus, the PMAPE of analyst i will be the fraction of his absolute prediction error in relation to the mean PMAPE of all analyst following firm *j* in year *t*. Consequently, PMAPE takes negative (positive) values representing better (worse) than average performance.

To maintain consistency with Clement (1999) and Clement & Tse (2005), only EPS estimates with a forecast horizon of at least 30 days are included in computing the PMAPE. In addition, Clement (1998 and 1999) observes that the probability of recognising systematic differences in analysts' forecast accuracy is higher when one controls for firm-year effects than controlling for firm-fixed effects and year-fixed effects. According to Clement (1999), firm-year effects are the results of factors such as strikes, mergers and disclosures, which increase the diffiulcty or ease for predicting a firm's earnings in some years than in others. Firm-year effects is controlled by subtracting the related firm-year average from the absolute prediction error. More so, heteroscedasticity (unequal variablity across the DAPEs over a period of time) is reduced when the DAPE is deflated by APE as there is greater variation in the DAPEs' of firms with large EPS than that those with small EPS (Clement, 1998). Note that I use "prediction" and "forecast" interchangeably to portray the same meaning.

Media Exposure

Inferring from the literature review, one may reasonably conclude that analysts' media popularity influences the accuracy of their forecasts. I expect that analysts who are cited more in the media would have more accurate forecasts. I measure an analyst's media exposure as the number of times the analyst appears in any of the media sources in Factiva in a particular year discussing a particular firm. That is,
$MedExp_{ijt}$ = Number of times analyst *i* is cited in Factiva discussing company *j* in year *t.*

Independent Variables

Analyst Sentiments

As discussed in the literature review, prior studies (Dyck & Zingales (2002), Clement & Westphal (2008)) suggest that there is a correlation between analysts' tone as measured by the number of pessimistic, optimistic or neutral words embedded in their reports and the frequency of the analysts' media appearances. Generally, they find that analysts who are popular in the press have a higher level of optimism in their forecasts. Using DICTION 7.0 Textual Analysis Software I run a sentimental analysis, which generates the total number of words, negative words, neutral words and number of positive words. These results are based on a context-specific word-list developed by Loughran & McDonald (2011) that contains words (positive, negative or neutral) generally agreed to have the corresponding effects on people. According to Rogers, et al., (2011), the use of computer textual analysis is theoretically justified on the basis that "a set of words has a generally agreed upon effect on readers".
I use two measures of sentiments in this dissertation as follows:

$$N\_OPTijt = (PWijt - NWijt)/TWijt \quad (3)$$

Where N_OPT_{ijt} is the net optimism tone of analyst *i* following firm *j* in year *t*, PW_{ijt} is the number of positive words and NW_{ijt} is the number negative words in analyst *i's* report for firm *j* in year *t*.

$$UNCSijt = UWijt /TWijt \quad (4)$$

Where $UNCS_{ijt}$ is analyst *i's* uncertainty score, following firm *j* in year *t* and UW_{ijt} is the number of neutral words in analyst *i's* report for firm *j* in year *t*. TW_{ijt} in equations (3) and (4) represent the total number of words in analyst *i's* report for firm *j* in year *t.*

The net optimism and uncertainty tones alone do not reflect an analyst's expression of optimism, pessimism or neutrality about a company he/she follows. Consequently, I compute the optimistic (neutral) sentiments as the difference between analyst *i's* net optimism (uncertainty) score and the mean of all analysts who follow the same firm in the same year. That is,

$$O\_Sent_{ijt} = N\_OPT_{ijt} - \overline{N\_OPT_{jt}} \quad (3')$$

Where O_Sent_{ijt} is analyst *i's* net optimism sentiment, following firm *j* in year *t.* N_OPT_{ijt} is as explained in equation (3) and $\overline{N\_OPT_{jt}}$ represents the mean net optimism of analysts following firm *j* in year *t*.

$$N\_Sent_{ijt} = UNCT_{ijt} - \overline{UNCT_{jt}} \quad (4')$$

Where N_Sent_{ijt} represents analyst *i's* neutral sentiment, following firm *j* in year *t,* $UNCT_{ijt}$ is as explained in equation (4) and $UNCT_{jt}$ is the mean uncertainty score of all analysts following firm *j* in year *t*.

General and Firm-Specific Experience (Analyst Ability)

While it is remains a fact that ability may not be observable, Clement (1999) suggests that certain indicators of ability may be observed through the activities of the analyst labour market. It is perceived that this market functions in a way such that weaker performers are compelled to exit the profession. The absolute error inherent in analysts' forecasts, according to Clement (1999) and Mikhail, et al. (1997), decreases with experience, implying that experience postivley affects forecast accuracy. A possible explanation is that analysts' general knowledge and skill increases with time. It is likely that as analysts become more experienced they may improve in associated job roles such as recognising trends in the economy and analysing financial statements. Similar to the method used by Clement (1999), an analyst's firm-specific experience is measured as the number of years the analyst issued at least one forecast for a particular firm in a particular year, and general experience as the number of years the analyst supplied at least one forecast for any of the firms within the S&P 500 index in year *t.* That is,

G_Exp_{ijt} = Number of years analyst *i* supplied a minimum of one EPS forecast for any of the firms within the S&P 500 index in year *t.*

F_Exp_{ijt} = Number of years analyst *i* supplied a minimum of one EPS forecast for firm *j* in year *t.*

Brokerage House Size (Analyst Resources)

Primarily, when analysts have more resources available to them, they are likely to work more effectively. Granovetter (1985) and Burt (1992) indicate that certain procedures and policies such as the quality of the sources of industry knowledge, training advantages and the amount of resources provided for analysts may differ from brokerage house to brokerage house, possibly resulting to variations in analysts' forecasting abilities. Thus, analysts' forecast accuracy may be influenced to some extent by the amount of resources at their disposal. Similarly, Stickel (1995) demonstrates that not only do large brokers have superior distribution channels, they also have distinctive research support networks and strong client relationships. According to Clement (1999), large brokers probably have superior resources that enhance the ability of their analysts to supply more accurate forecasts. Brokerage size is measured as the number of analysts working for a particular broker in a particular year. That is:

B_Size_{xt} = The number of analysts working for broker *x* in year *t*.

Number of Companies followed and Firm size (Portfolio complexity)

The general assumption is that following a large number of companies and industries is relatively more challenging. According to Clement (1999), individual firms in a larger portfolio are not devoted much attention. Given a circumstance where analysts are confronted with identical effort restrictions and diminishing returns to effort, the forecast errors of those analysts who follow a larger number of firms and industries will be relatively larger. On the contrary, it can be argued that analysts who follow more firms tend to forecast more repetitively thereby improving their forecasting abilities. The more an analyst forecasts, the more expertise he builds and hence the more accurate he will be.

Also, studies show that the size of the firm an analyst follows may have an impact on the analyst's forecast accuracy. For example, Lang & Lundholm (1996) identify a positive relation between firm size and forecast accuracy, implying that the larger the firm an analyst provides forecasts for, the higher the accuracy of his forecasts. This however contradicts the assumption that larger firms have more complex financial reports, which makes is more difficult to forecast those firms' EPS. Duru & Reeb (2002) provide evidence that the earnings of more internationally diversified portfolios are more complex to forecast. I however, do not include this proxy beacause the study is based on a sample of US companies.

N_Cos_{it} = The number of companies analyst *i* following firm *j* in year *t,* produced a minimum of one EPS forecast for.

F_Size_{jt} = The natural logarithm of firm *j's* market value in year *t*.

Forecast Horizon

In practice, the amount of information (in the form of indicators, outcomes and other analyst forecasts) available when predicting companies' earnings varies from analyst to analyst. It is therefore reasonable to assume that analysts with more information available to them will issue more accurate forecasts especially if their forecasts are published after that of other analysts. As such, I include a "forecast horizon" variable as a measure of the amount of information available to an analyst at the time of issuing his/her forecast. Following Horton & Serafeim's (2009) methodology, I measure forecast horizon as;

$$F\_Hoz_{ijt} = Actual\ EPS\ Announcement\ Date_{jt} - Last\ EPS\ Forecast\ Date_{ijt} \quad (5)$$

Where F_Hoz_{ijt} represents the forecast horizon. A shorter forecast horizon implies a more accurate forecast since that analyst is believed to have the most information as his/her forecast is issued closer to the actual earnings announcement date.

Number of Forecast Revisions

It is generally believed that analysts update their forecasts when they acquire new and relevant information. Analysts who update their forecasts more often are thus expected to be more accurate. As a consequence, I include a variable that measures the number of times an analyst revises his forecast within a year. Based on Kim's (2011) approach, I derive the number of forecast revisions as:

F_Rev_{ijt} = = The number of EPS forecasts issued by analyst *i* for firm *j* in year *t*.

Dummy Variables

A dummy variable is an artificial numerical variable used in a regression to represent subcategories in a sample. As the sample consist of fourteen companies from the S&P 500 Oil and Gas Industry and one company from the materials industry, I include one industry dummy with a value of 1 if firm *j* is a constituent of a particular industry in year *t* and 0 if otherwise to control for industry-specific effects. Additionally, I include year dummy variables with a value of 1 if an observation is for year *t* and 0 if otherwise to further control the firm-year effects since different economic activities happen in different years. One would expect the year of the global financial crises, preceding and/or post global financial crisis (2008 onwards) to have significant effects on analysts' forecast accuracy. Also the "dot com" bubble of 2000 is expected to have a negative effect on forecast accuracy.

Data

I collect analysts' annual earnings forecasts covering the period from January 1999 to December 2014 from the Institutional Broker Estimate System (I/B/E/S) Detail History tape. The "Detail file" under I/B/E/S contains company CUSIPS, company tickers, analysts' codes, fiscal period indicator, a measure indicator, estimate values (forecast EPS), forecast period end dates, announcement dates and times, activation dates and times, actual values (EPS) and announcement dates and times from the actual detail file. Analysts are identified by their unique codes (analyst codes), which remain unchanged irrespective of whether they move from one brokerage house to the other.

Analysts' reports (in pdf format) are collected from Thomson Reuters Investext®. Although the database provides data from as early as 1983, I download reports ranging from 1st January to 1999 to 31st December, 2014 to maintain consistency with the I/B/E/S earnings estimates. In total, 15,455 reports are downloaded for analysts in the sample who have EPS estimates in the I/B/E/S dataset. A number of analysts with earnings estimates in the I/B/E/S dataset have no reports in Investext and excluded from the sample (see Table 2). A major advantage of Investext is that it provides the full names of the analysts, which is very useful in retrieving their media appearances from Factiva. The I/B/E/S database provides only analysts' first names and the initials of their surnames and middle names.

From the Dow Jones Factiva database I collect all analysts' media appearances, following the fifteen S&P Oil and Gas companies that constitute the sample. Factiva provides access to a wide range of news and information sources including newspapers (*The New York Times* and *The Wall Street Journal*), magazines (*Dailey Variety* and *The Economist*), trade press, newswires (AFP, Reuters, Dow Jones Newswire), selected social networks (YouTube, LinkedIn, FlickR), A-list Blogs (Oil and Gas Lawyer Blog, MoneyBeat) and multimedia sources (BBC, ABC News, CNN, Fox Business, WSJ Live, Duetsche Welle) to mention but few. I search, with no imposed constraints, each analyst's number of appearances by specifying his/her full name (obtained from the individual reports collected from Investext) including all possible names associated with the full name in order to capture all the analyst's appearances. The names are separated with an "OR" in the search pane. For example, in a search for an analyst with full name Judson Edward Bailey, I include possible names Jud Bailey OR Jud E Bailey. Likewise, a search for Robert Muztafago will include Rob Muztafago. This is because reporters sometimes shorten the names of some of the analysts, which if not included may reduce the analyst's appearances. It is important to note that the first name of the analyst must come before any middle name and surname. To maintain consistency with all other databases used in this dissertation, the search is conducted for the period from 1st January 1999 to 31st December 2014.

FINDINGS

Forecast Accuracy

The findings show that analysts who exhibit smaller errors in their forecasts are cited in the media more frequently, which is supportive of the hypothesis that analysts with higher forecast accuracy are more popular in the press (H3: Analysts who are more accurate forecasters have higher media exposure).

Similarly, based on the results of net optimistic sentiment, analysts who express high levels of optimism in their reports exhibit smaller errors in their forecasts, which supports the hypothesis that optimistic analysts are more accurate forecasters (H1: Analysts who express more optimism in their reports are more accurate forecasters). This however, contradicts Hong & Kubik (2003) who argue that analysts sacrifice forecasting accuracy by expressing more optimism in their reports in exchange for better job opportunities. Furthermore, analysts who issue their forecasts closer to the actual earnings announcement date have a higher level of accuracy as they are believed to have more information. Also, analysts who revise their forecasts more frequently have a higher level of forecast accuracy than other analysts.

One thought-provoking finding is that the 2008 year dummy variable coefficient, which is the year of the global financial crisis is negative although that of the preceding year (2007) is positive. This implies that analysts forecast accuracy increased during the crises. A possible explanation for this odd finding may be that the effect of the crises started in the subsequent years as the coefficients for the 2009-2013 year dummy variables are positive. This shows that the effect of the crisis was more pronounced in the post-crisis years than in the actual year (2008). The result is however contradictory to Sidhu & Tan (2011) who find larger forecast errors of equity analysts and higher dispersion of errors during the year of the crisis.

Generally, I find that more accurate analysts appear more frequently in the media and express a lower level of optimism in their reports; probably because optimistic analysts are less accurate forecasters. Based on the hypotheses tested in this study, I expected optimistic analysts to have higher forecast accuracy and media popularity but the results suggest the opposite. Consistent however with prior research (Mikhail et al., 1997 and Clement, 1999), I find that forecast accuracy increases with experience, though not significant. Contrarily, Jacob, et al., (1999) find no evidence of such a relationship, though they establish a relation between forecast accuracy and size of the brokerage house an analyst works for. Excluding the “forecast horizon” and “number of forecast revisions” variables from the regression of forecast errors and the independent variables, forecast accuracy is found to increase with the amount of resources available to an analyst. More so, forecast errors is negatively correlated with brokerage house size, implying that analysts who work for larger brokers issue more accurate forecasts; also in line with Clement (1999).

While Clement (1999) finds forecast accuracy to decrease with the number of companies followed by an analyst, the results of this study show otherwise. Forecast accuracy is found to rather increase with the number of companies an analyst follows. This may be because analysts gain more expertise and become better forecasters as they forecast repetitively for a large number of firms. As the saying goes “the more frequently you do a particular thing, the better you become at doing it”. Consistent with Lang & Lundholm (1996), forecast accuracy is found to decreases with firm size; implying that analysts who follow larger firms issue less accurate forecast. This may explain the positive relation between forecast accuracy and the number of companies followed by an analyst. It may be the case that an analyst who follows a larger number of firms is able to do so because those firms are comparatively smaller. Furthermore, I find that forecast accuracy decreases with an analyst’s forecast horizon, a very significant factor and decreases with the number of times in a year the analyst revises his forecast, though not significant.

Media Exposure

In terms of media exposure, an analyst who is more popular in the press has smaller errors inherent in his forecasts, which supports the hypothesis that more accurate analysts have a higher number of media appearances (H_3: Analysts who are more accurate forecasters have higher media exposure). The negative coefficient of *WO*sent (not positive as expected) suggests that analysts who have higher media exposure express less optimism in their forecasts. Surprisingly, it appears that analysts who express higher levels of uncertainty in their reports are those cited more frequently in the media. Analysts who are popular in the press have shorter forecast horizons, follow a large number of smaller sized firms, are more experienced, revise their forecasts more frequently and have more resources are their disposal.

I find that analysts who are cited more frequently in the media are actually more accurate forecasters, though Fang & Peress (2009) argue that analysts with a high level of media popularity may issue less accurate forecasts as a result of the conflict of interest they are likely to encounter. Also, more experienced analysts are found not only to be more accurate forecasters but are also more popular in the press as one would expect, though the results are insignificant.

Contrary to my expectations, the results show that media outlets in fact give less audience to optimistic analysts, perhaps because their forecasts may not be reliable as they are characterized by larger errors. Rather, I find that analysts who express a high level of uncertainty in their reports appear more frequently in the media. Significantly, analyst media exposure is found to increase with the brokerage house size and number companies followed by an analyst, and decrease with the forecast horizon. In other words, analysts who are popular in the press work for larger brokers and thus have more resources, follow a larger number of companies and issue their forecast closer to the actual earnings announcement date.

The result of industry dummy showing a negative significant, though insignificant, implying that the differences in industrial factors affects may have an adverse effect on the media exposure of analysts who follow companies from different industries. The insignificance of the results may however be attributed to the fact that the sample size is relatively small.

It is quiet puzzling that none of the year dummy variables in the media exposure regression is significant, as one would expect the pre-financial crises years (2005-2007), the year of the financial crises (2008) and/or post crisis years (2009 onwards) to be significant. Again, this may be as a result of the small sample size not being representative enough to yield significant results. More so, the R^2 is very low (0.0401), meaning just 4.01% of the variations is explained. A higher percentage of the variations may be explained by a larger sample, which may also yield more significant results.

Overall, the findings are mostly consistent with prior literature with a few astounding discoveries, though mostly insignificant, which may be as a result of the small sample size used in the study. The financial crisis had an astonishing upward effect on analysts' forecast accuracy during the actual year of the crisis, which is 2008. The expected impact was more pronounced after that year. It has been seven years since the crisis and it appears that the world is still suffering the repercussions.

The results suggest that analysts' characteristics including their sentiments may be useful in explaining their forecasting performance variations as well as the level of media exposure received by the analysts. By modeling these characteristics, studies on capital market expectations may be improved to help investors and other market participants make better investment decisions.

CONCLUSION

I find that an analyst's forecast accuracy (as measured by the errors inherent in his forecasts) is negatively associated with the analyst's level of media exposure, experience, brokerage size, the number of times he revises his forecasts in a year and the number of companies followed by the analyst, and positively associated with the analyst's level of optimism expressed in his reports, forecast horizon and the size of the company he follows.

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