Which Analyst Characteristics Help Interpreting Less Readable Annual Reports?

Christof Beuselinck
IESEG School of Management and LEM
c.beuselinck@ieseg.fr
+33 320545892
3, rue de la Digue
59000 Lille (France)

Belen Blanco
University of Adelaide
belen.blanco@adelaide.edu.au
+61 8 8313 4922
Australia

Sofie van der Meulen
IESEG School of Management
s.vandermeulen@ieseg.fr
+33 320545892
3, rue de la Digue
59000 Lille (France)

Draft: March 30, 2023

Which Analyst Characteristics Help Interpreting Less Readable Annual Reports?

ABSTRACT: Using a sample of close to 175,000 one-year ahead analyst forecasts for US firms during the period 1995 to 2015, and for which we also observe annual report readability, we find that the better performing analysts are those with more general and firm-specific experience; are affiliated with the largest brokerage houses; and follow less companies compared to their peers. When it comes to forecasting performance of complex reporters, in particular, we find that analysts' general experience is less beneficial, but still results in a better performance. Interestingly, the large brokerage affiliation advantage entirely disappears when forecasting complex reporters' performance. Consistent with our hypothesis, we do find proof of the importance of good industry knowledge: when analysts follow only a few industries, and thus have more expertise in these industries, they are better able to interpret the complex reports. To validate our identification, we conduct a number of additional analyses, including a two-stage Heckman (1979) selection model that takes into consideration the endogeneity of analyst characteristics on portfolio choice composition. Results show that analyst-firm pairs are not random: analysts that typically choose to follow complex reporters are those with more experience, following more firms in less industries and with a large brokerage affiliation. Taken together with the results on analyst performance, our findings suggest that even though experience and broker affiliation drive analysts to follow complex reporters, these analyst-specific characteristics do not translate into better forecasting performance.

Keywords: Financial Report Readability, Analyst Forecasts, Relative Performance

Analyst Characteristics and Annual Report Complexity

I. Introduction

The increasing complexity of corporate disclosures has initiated a buoyant discussion on the usability of annual reports and other corporate communication reports. According to various sources (e.g., KPMG, 2014; EY, 2018), the average length of annual reports has risen dramatically and the message that it comprises is harder to interpret than ever due to the highly specific jargon used. The complexity of financial reports could be a natural consequence of our contemporaneous business complexity and the ever-increasing mandatory reporting and disclosure requirements. Puzzled by the actual determinants of this upward trend of annual report complexity (i.e., reports are said to become less readable over time), some indeed argue that complexity arises naturally over time and is geared by the meticulous disclosure rules that were developed over the past decades on topics like fair value accounting, derivatives and other financial transactions (KPMG 2011, Dyer et al. 2016, Guay et al. 2016). However, another stream of literature departs from the information-based agency problem perspective of complex financial statements and argues that managers may intentionally make financial reports complex in an attempt to hide negative information or to confuse external observers.

Indeed, one particular way how firms could make the information environment more opaque is by preparing complex (i.e., less readable) financial reports. Complex financial reports are less transparent because they require more time and effort from outsiders to become properly informed (e.g., Bloomfield 2002, Li 2008). Less readable financial reports make it also more difficult for external users to understand firm performance and the various strategic decisions of management resulting in a more opaque information environment. Building upon this tension and public interest, several studies have emerged on annual report readability and the quality of the resulting information. For example, there exist studies on readability related to earnings management, earnings persistence, stock market reactions around 10-K filing date, and stock price crashes (Luo et al., 2018; Ertugrul et al., 2017; Kim et al., 2019; Lang and Stice-Lawrence, 2015; Lawrence, 2013; Li, 2008; Lo et al., 2017; Rennekamp, 2012). In general, results of those studies support the conjecture that poor readability coincides with poorer information quality eventually channeling into inefficient price formation processes.

A particular set of studies is interested in how one specific financial intermediary, namely financial analyst, is forming opinions about firms with less readable reports compared to firms with more readable reports. Early work directly studies financial analysts' performance related to the informativeness of disclosures (Lang and Lundholm 1996; Healy et al. 1999), the use of segment disclosures (Botosan and Harris, 2000) and the effect of intangible asset information (Barth et al. 2001). While these studies generally support that better disclosure quality results in more analyst attention, they are not explicitly considering the complexity of the report. Nevertheless, a natural question is arising in this context, namely how professional sell-side analysts – known for their in-depth usage of a firm's financials (Brown et al. (2014) – proceed with more complex reporting.

Lehavy et al. (2011) investigated the behavior of sell-side analysts in relation to the readability of corporate information readability provided in 10-K reports. Their results are consistent with the prediction of an increasing demand for analyst services for firms with less readable communication and a greater collective effort by analysts. They also observe that less readable 10-Ks are associated with lower average accuracy, greater analyst dispersion, and a greater uncertainty in analyst earnings forecasts. While their results are insightful at large, they only provide aggregate evidence about analyst forecasting activity and preciseness in relation to reporting complexity. In other words, they are not directly investigating how specific analyst's skills set could potentially allow one analyst to deal better (or: worse) with less readable reports.

In the current study we try and close this gap by using Clement's (1999) relative forecast accuracy measure and relate it to analyst and portfolio characteristics of all analysts following the same underlying stock. Using a sample of close to 175,000 one-year ahead analyst forecasts for US firms during the period 1995 to 2015, where we also observe annual report readabilitymetrics , we find consistent with prior research that the better performing analysts are those with more general and firm-specific experience, affiliated with the largest brokerage houses and are on average following less companies. When it comes to forecasting performance of complex reporters, in particular, we find that analysts' general experience is less beneficial, but still results in a better performance. Interestingly, the brokerage affiliation advantage completely disappears when forecasting complex reporters' performance. This seems to suggest that either their analytical models are not appropriate for the complex reporters or that, given the generally larger number of firms to follow, they lack time to analyze complex reporting in detail. Consistent with our hypothesis, we do find proof of the importance of good industry knowledge: when analysts follow only a few industries, and thus have more expertise in these industries, they seem better able to interpret the complex reports.

To validate our identification, we conduct a number of additional analyses, including a two-stage Heckman (1979) selection model that takes into consideration the endogeneity of analyst characteristics on portfolio choice composition. Results show that analyst-firm pairs are not random: analysts that typically choose to follow complex reporters are those with more experience, following more firms in less industries and with a large brokerage affiliation. Taken together with the results on analyst performance, this seems to suggest that even though experience and broker affiliation drive analysts to follow complex reporters, it does not mean that these characteristics of the analyst will translate into a better forecasting performance.

We contribute to the literature in a number of ways. In particular, we add to the literature on annual report readability and a firm's information environment at large. In addition, we contribute to the literature on relative performance of individual analysts (e.g., Clement 1999; Farooq 2014). Prior literature has documented differences in analyst performance along innate characteristics like forecasting experience, portfolio complexity, analysts' brokerage house and industry expertise (Clement 1999; Gilsen et al. 2001; Boni and Womack 2006; Kadan et al. 2012; Jiang et al. 2015). To the best of our knowledge, we are the first study analyzing analyst-specific skills sets and their ability to see trough complex reporting. Finally, we also document the importance of analysts' profile on the decision to follow a firm. Prior research studying analyst-firm pairings mainly considered firm-level characteristics (e.g., Fortin and Roth 2007). Only a few have considered attributes of the analyst and the analyst's brokerage house (e.g., Liang, Riedl and Venkataraman 2008). With the current study, we gain deeper insights in the supply side of analyst research and examine a broader range of factors likely driving observed analyst-firm pairings.

The remainder of the paper proceeds as follows. The following section discusses prior research and builds hypotheses. In section III and IV, we describe the sample selection and research design, respectively. Section V presents empirical results and Section VI concludes the paper.

II. Literature Review and Hypotheses Development

Sell-side analysts convey important information to capital market participants through their forecasts and recommendations. Analysts have a prominent role in analyzing, interpreting and disseminating information to private and institutional investors, as well as to buy-side analysts (Frankel el al. 2006; Groysberg et al. 2012). For many years, little was known about the information or inputs analysts use in determining their forecasts. Indirect evidence suggested that analysts use their access to management and industry knowledge to signal idiosyncratic information to the investment public (Piotroski and Roulstone, 2004). More recent research by Brown et al. (2014) provides direct evidence. By surveying several analysts, aforementioned authors find that in forecasting firms' financials, analysts rely on inputs like10-K and 10-Q reports, conference calls, private communication with firm management, stock prices, and other analysts' reports but primarily on industry-wide information.[1]

It is therefore reasonable to assume that the readability of annual reports would affect the analyst forecasting behavior and outcomes at large. Evidence by Lehavy et al. (2011) already documents an increasing demand for analyst services for firms with less readable communication, as well as a greater collective effort by these analysts. More in particular, they observe that less readable 10-Ks are associated with more analyst following, lower average accuracy, greater analyst dispersion, and greater uncertainty in analyst earnings forecasts. What their study does not examine, however, is detailing which particular analyst-specific characteristics might help analysts in better dealing with and processing the less readable reports and can thus help overcome potential obfuscation strategies by corporations.

Clement (1999) for example documents that analyst-specific forecast accuracy is positively associated with analysts' ability and skill as well as with resources available to them. Moreover, he documents a negative association between individual forecast accuracy and portfolio complexity). Since the analyst labor market can be interpreted as a tournament game where strong performers continue in the game and poor performers quit (Clement, 1999), it is generally accepted that analyst experience levels proxy for its skillset and ability. This may be even more true, because analyst skills and knowledge are expected to improve with time. Also, analyst skills may be firm-specific and in that respect, it can be argued that analysts which follow a firm already over a long period of time, can better interpret peculiarities of firm-specific reporting behavior and potentially see through attempts of reporting obfuscation behavior. We argue that especially in the case of less readable (i.e., more complex) reporting,

[1] Although the survey was conducted in a post-RegFD period where the rules for selective disclosure of company information were tightened, survey respondents clearly indicated that (private) communication between management and analysts was more than ever common place and valued highly by firm management.

analyst general- and firm-specific experience may be helpful to help see through the complex annual reports.

This results in our first hypothesis (stated in the alternate form):

H1 (Ability hypothesis): *Ceteris paribus, analysts with greater ability and skills outperform other analysts more on firms with less readable reports compared to firms with more readable reports.*

It is widely accepted that larger brokerage houses can provide more and superior resources to support the forecasting accuracy of their affiliated analysts. Clement (1999) documents a positive relationship between broker-size affiliation and relative forecast accuracy.[2] In an international setting, Beuselinck et al. (2017) observe that brokerage size is positively related to the analyst forecast accuracy but only in a post-IFRS period. Their results suggest that large brokerage house affiliations work out particularly well when reporting formats are more replete with additional disclosures (as required under IFRS compared to local GAAP). Combined, this suggests that brokerage firm affiliation may be helpful in the interpretation and dissection of less readable annual reports. This leads to our second hypothesis (stated in the alternate form):

H2 (Resources hypothesis): *Ceteris paribus, analysts from large brokerage houses outperform other analysts more on firms with less readable reports compared to firms with more readable reports.*

Finally, portfolio complexity is expected to matter as analysts with more complex portfolios can devote less time and effort on a particular firm in that portfolio. Clement (1999) for instance shows that analysts with more firms in their portfolio and that are covering more industries are usually associated with lower individual forecast accuracy. Sonney (2009) finds

[2] This type of argument is similar to the logic applied in studies on auditing quality differences in Big-N to other audit firms and where the resources and the wider firms network of Big-N firms is helpful to provide the relevant expertise.

similar evidence for this in an international context and identifies sector diversification as the most detrimental component for individual analyst accuracy.

Since less readable annual reports by nature are harder to read and interpret, one may be particularly concerned that analysts with complex portfolios will not have sufficient time to dedicate to the more complex financial reports. At the same time, it may be argued that sector specialization can in fact be helpful for analysts in the context where they observe less readable 10-K, especially as the sector experience can help see through the convoluted reporting. In any case, portfolio complexity is expected to drive analyst accuracy down, and especially so when annual reports are less readable. These less readable reports require generally time and effort to be analyzed further, but analyst work is restricted in time and effort. This results into our third hypothesis H3:

H3a (Portfolio complexity hypothesis): *Ceteris paribus, analysts with more complex portfolios underperform other analysts more on firms with less readable reports compared to firms with more readable reports.*

III. Analyst Sample and 10-K Readability Observations

Our initial sample is based on the intersection of the I/B/E/S Detailed files, Compustat and the SEC's EDGAR filings database for fiscal year 1995-2015. The databases are joined based on SEC's Central Index Key (CIK) and Compustat GVKEY. Forecast observations without a match in Compustat and EDGAR are dropped from the sample.

We then impose a number of restrictions, both at the forecast and at the company level. First, we require that broker affiliation of the analyst is known and that there is at least one other analyst's forecast for the same firm in the same year. We only select the first, one-year ahead analyst forecasts per analyst-firm pair that falls within 90 days after prior year's 10K filing date (similar as Lehavy et al. 2011). Forecasts that are released earlier do not incorporate information from the 10K report, while forecasts that are released more than 90 days later most likely are affected by other announcements or documents published by the firm. At the firm level, we require the availability of annual EPS data in the I/B/E/S detailed actual files to compute forecast accuracy. Some observations are dropped because of missing data in Compustat. This screening process resulted in 293,590 forecasts or analyst-firm pairs over the period 1995 till 2015. Table 1 summarizes the sample selection procedures.

[Insert Table 1 here]

IV. Research Design

4.1 Measuring relative forecast accuracy

To capture differences in analysts' earnings forecast accuracy, we follow the analyst forecast literature and define forecast error of analyst *i's* forecast for firm *j* as follows:

$$FE_{ijt} = \left|EPS_{jt} - FEPS_{ijt}\right|$$

where FE_{ijt} is the absolute value of actual earnings per share (EPS_{jt}) announced by firm *j* for fiscal year *t* less analyst *i*'s last available one-year ahead forecast of earnings per share ($FEPS_{ijt}$) for that same firm *j* and fiscal year *t*. This forecast error is computed annually for each analyst-firm pair. Consistent with Clement (1999), we deduct the mean absolute forecast error in year t from an individual forecast firm *j* in year *t* to obtain a relative analyst performance measure which can be used across firms and across time. We multiply the measure by -1, so that higher values of this measure reflect more accurate forecasts. In particular, we define $RELACC_{ijt}$ relative forecast accuracy ($RELACC_{ijt}$) as:

$$RELACC_{ijt} = -\frac{FE_{ijt} - \overline{FE_{jt}}}{\overline{FE_{jt}}}$$

where $\overline{FE_{jt}}$ is the mean absolute forecast error across all analysts' first available forecast on firm *j*'s earnings for fiscal year *t*.

4.2. Measuring Readability

Following Bonsall et al. (2017) and Bonsall and Miller (2017), we use the Bog Index (BOG) as our primary measure of financial statement readability. The Bog Index captures important plain English attributes in the main text of the 10-K filings, excluding the exhibits[3]. It is a combination of three components: (1) a sentence Bog, (2) a word Bog, and (3) Pep. The sentence Bog captures the average overall sentence length across the entire document, with long sentences receiving a higher score. The word Bog expresses the complexity and the use of words within sentences. The use of specialist terminology and heavy words, as well as hidden verbs and passive voice results in a high word Bog. Finally, the Pep component accounts for good writing elements such as using interesting words, short sentences and sentence variety and can be regarded as a correction on the compiled sentence and word Bog. As a result, financial statements that are difficult to read will have an overall higher BOG score.[4]

4.3. Regression model

The following pooled regression model is estimated to test whether analysts' characteristics drive forecast accuracy in a different way for firms with less readable versus more readable 10-K reports.

$$\begin{aligned}RELACC_{ijt} = \ & \beta_1 GEXP_{ijt} + \beta_2 FEXP_{ijt} + \beta_3 NCOMP_{ijt} + \beta_4 NSEC_{ijt} + \beta_5 BSIZE_{ijt} + \beta_5 COMPLEX_{jt} \\ & + \beta_6 GEXP_{ijt} * COMPLEX_{jt} + \beta_7 FEXP_{ijt} * COMPLEX_{jt} + \beta_8 NCOMP_{ijt} * COMPLEX_{jt} \\ & + \beta_9 NSEC_{ijt} * COMPLEX_{jt} + \beta_{10} BSIZE_{ijt} * COMPLEX_{jt} + \beta_{11} FCAGE + \varepsilon_{ijt} \qquad \text{(Eq. 1)}\end{aligned}$$

The first five variables are determinants of relative analyst performance derived from prior work (e.g., Clement, 1999; Sonney 2009). These variables are related to the individual

[3] Exhibit 13 on annual or quarterly reports to securityholders is the only exhibit that is taken into consideration when calculating the BOG index.

[4] To verify the robustness of our results, we use alternative measures of financial statement readability that have been used in prior research. These measures are the Gunning Fog index, 10-K file size (Loughran and McDonald 2014a), and length of the 10-K report (Li 2008). All results are generally consistent with the main results reported in the paper although the Fog-results yield less clear relationships. The latter findings may not be surprising, as this measure has been criticized recently for being outdated and poorly specified in financial applications.

analyst's ability and experience (GEXP, FEXP), the analyst brokerage firm (BSIZE) to which the anayst is affiliated and the complexity of the analyst's portfolio of followed firms (NCOMP and NSEC)GEXP is analyst's general expertise and is measured as the number of years the analyst has been in the I/B/E/S database (starting from 1990), whereas FEXP is analyst's firm specific expertise or the time during which a particular company has been followed by an analyst, also expressed in number of years. Similar to the definition in Sonney (2009), BSIZE is a dummy variable that equals 1 if the analyst is working for one of the top size decile brokerage houses, where size is defined in terms of active analysts employed. NCOMP and NSIC reflect the number of companies and the number of sectors (defined in terms of SIC2 codes), respectively, followed by an analyst. Prior literature has found a positive relation between RELACC and GEXP, FEXP and BSIZE on the one hand, and a negative relation between RELACC and NCOMP. With regard to NSIC, the literature is inconclusive. Furthermore, the FCAGE variable is the time it takes an analyst to issue its first forecast after a 10K filing.

The readability of the financial reports in this model is introduced through the COMPLEX variable. Based on prior research, we know that values for the Bog index are highly dependent on time and industry (LeHavy et al. 2011). We therefore define complex or less readable reporters (COMPLEX=1) as firms that have a BOG index above or equal to the upper industry-year quartile. Firms with a BOG index below the lower industry-year quartile are labelled as less complex reporters (COMPLEX=0). We drop firm-observations with Bog index between the lower and upper quartile, as these are likely to be more comparable with regard to readability[5].

[5] Footnote: We run the analysis also using a median split and the results are qualitatively similar. Taking into account recent research on the use of dichotomization, we also run the (untabulated) analysis on the continuous, log transformed Bog index, but then additionally controlling for industry and firm fixed effects.

Our test variables are then introduced as the interaction between the set of determinants of relative forecast accuracy identified in prior research and the COMPLEX variable. Our hypotheses are based on the general belief that the factors found in prior literature to be determinant for relative accuracy of analysts, are even more determinant when it concerns firms with complex reporting. In other words, we expect β_6, β_7 and β_{10} to be positive and β_8 and β_9 to be negative.

As prior research suggests, we also control for forecast age by including the forecast's age in days as an independent variable. Forecast age more specifically is the number of days between the last year's 10K filing date and date at which the forecast was issued.

Finally, we control for firm-year effects by adjusting all independent variables (except for the COMPLEX variable) by their related firm-year means (similar as for the dependent variable).

V. Results

5.1 Descriptive forecast statistics on all firms

Panel A of Table 2 reports descriptive statistics on the sample of 293,590 forecasts over the sample period 1995 to 2015. Analyst follow on average 12 firms spread across 3 different sectors, have somewhat less than 7 years of general experience and follow the same firm for 3.5 years on average. Further, 58% of the forecasts come from large brokerage houses and forecasts are on average made 41 days after the last 10K filing date.

These 293,590 forecasts pertain to 35,579 unique firm-year observations. The Bog-index of these firms varies between 49 and 139, with an overall sample median of 84. In line with prior research, we compute industry and year statistics for this BOG index. Results are presented in panel B and C of Table 2. We clearly observe an increasing BOG index over the years, going from 77.16 in 1996 to 87.35 in 2014. With regard to the sector results, we can distinguish sectors where the BOG index is on average very high (eg. Sector 28 – Manufacturing Chemicals - with a Bog index of 90) versus those where the index is typically low (eg. Sector 52 - Building Materials - with a BOG index of 74).

[Insert Table 2 Here]

5.2 Replication of LeHavy et al.

Before reporting the model of interest, we first replicate the results from LeHavy et al (2011). LeHavy et al. show that the complexity in firm's annual reports is positively associated with the number of analysts following the firm and as well as with the dispersion amongst analysts and negatively associated with the accuracy in their forecasts. Their measure of complexity is the Fog index, whereas the forecast properties are measured using consensus data. In the current study, we use the BOG index and the detailed I/B/E/S forecast data to illustrate the same relation[6]. We run an OLS linear regression with the forecast properties as dependent variable and the BOG index as a continuous test variable. We additionally control for firm size (LOGSIZE), as well as industry and year fixed effects. Results are presented in Table 3. The first column reports the regression results with the number of analysts following as dependent variable. Similar as LeHavy et al., we find that firms with more complex firm reporting are associated with more analyst following (0.04; t=8.41). Next, in the second column, we find further evidence for more complex firm's reporting to be associated with more dispersed forecasts (1.78; t=2.26). Finally, in the last column we show that complexity in 10K reports is positively associated with the average forecast error, or more complexity in the 10K leads to less accurate forecasts (0.05; t=4.04). Overall, we show that the results in LeHavy et al. also hold in a larger, more recent sample period, using another proxy to measure 10K complexity or readability.

[6] Consensus data is computed every month. Using the first consensus data after prior year's 10K filing thus means that one considers forecasts issued within a month after the prior 10K filing. To make our results consistent with LeHavy, we selected the first, individual forecast of analysts that is issued within 90 days after the prior 10K filing of a firm.

[Insert Table 3 Here]

5.3. Descriptive forecast statistics for the final sample

As shown in Panel B and C of Table 2, readability of financial reports is highly dependent on industry and time. To distinguish complex from easily readable reporting by firms, we therefore use the year-industry stats (instead of an overall sample stat). In Table 4, we show univariate results for the analyst forecast data discerning between easily readable and complex reporters based on the year-industry quartiles. A BOG index below the year-industry specific Q1 quartile is considered as easily readable and above the Q3 quartile as complex reporting. We thus use 174,021 forecast observations in this and later analyses. We find that analysts following the more complex reporters are typically working for large brokerage houses, have more general experience and are more likely to follow firms in the same sector(s). Moreover, they also seem to issue their forecasts one day earlier on average compared to the average for the easily readable reports and they follow the firm for a shorter period.

Panel B documents the distribution of the variables of interest and other regression variables for this final sample of 174,021 forecast observations. By construction, if all analyst forecasts used to calculate these variables would be included, the mean of these variables should be zero. However, after variable construction and given the purpose of this study, we restrict further analysis to forecasts done within 90 days after prior year's 10K filing. These forecasts are most likely to incorporate information from that 10K report. As we can see from Panel B, the mean values are very close to zero (eg. mean RELACC= 0.00010). The median values show that this 90-day restriction results in selecting slightly better performing analysts from larger brokerage houses, following less firms and less sectors. However, we also conclude that there is a good mix within the sample on all variables, as evidenced by the negative Q1 (or below average analyst) and positive Q3 (or above average analyst) on all variables.

[Insert Table 4 Here]

Panel C reports Pearson correlations between the regression variables. The correlation between general and firm-specific experience (ρ= 0.56), as well as between number of companies and number of sectors followed (ρ= 0.58) seem to confirm that these are proxies of the characteristic ability respectively task complexity.

[Insert Table 5 Here]

5.4. Regression results

[Insert Table 6 Here]

Table 6 presents the results from the regression analysis. The first column shows the result from running an OLS regression like stated in the research design section. Consistent with prior research, we find that experience overall (GEXP and FEXP) has a positive impact on relative forecast accuracy. However, considering the interaction terms between the COMPLEX variable and these analyst characteristics, we find that the benefit from generalist experience is significantly less when forecasting earnings for complex reporters (-0.262, $p<0.05$). This is contrary to our expectations, but it seems to suggest that, when the annual report is more complex to read, experience hampers analysts in forming their opinion. With regard to analysts' specific firm experience, we do not find any significant difference between our two groups of reporters.

For the complexity of the analyst' portfolio, we find that more firms in the portfolio increase the complexity for the analyst and, as a result, end in less accurate forecasting (β_3= -0.233; $p<.0001$). This is again in line with prior research. We find no significant coefficient estimate for the interaction with COMPLEX, meaning that the impact of the number of firms followed on forecast accuracy is the same when forecasting for less and easy to read financial reports.

Complexity in the analyst's portfolio can also be expressed in terms of number of industries followed, with more industries followed interpreted as portfolios that are more complex. For this variable, we find a positive coefficient, contrary to Clement (1999). However, for the interaction with COMPLEX, we do observe a negative and significant parameter estimate of -0.468 (p= 0.02), consistent with our hypothesis. In other words, we find that complex reporting by firms in combination with firm followings in many different industries, negatively affects analysts' performance. This seems to suggest that when forecasting EPS for a less complex reporter, analysts seem to benefit from the knowledge they gain across different sectors. However, the complexity and multitude of data by following many different sectors, in turn seems to cause the analyst to perform less well when forecasting the performance of a less readable reporter.

Turning to the last variable of interest, BSIZE, we find that, consistent with prior literature, being affiliated with a large brokerage results in better forecasting performance (1.544; p= 0.0007). However, when predicting performance for firms with complex financial reports, this advantage seems to disappear completely (-1.966; p= 0.0016).

5.5. Robustness Check

As suggested in Panel A of Table 4, the type of analyst following complex reporters is significantly different from the analyst typically following a non-complex reporter. To mitigate econometric problems caused by endogeneity in our COMPLEX variable, we rerun our model using a 2SLS procedure. In the first stage, we model analyst's decision to follow a complex reporter in function of analyst characteristics. The dependent variable is our COMPLEX variable from our main regression model, as defined previously. Independent variables are the number of years of general experience (GEXP), the number of firms followed by an analyst

(NCOMP), the number of industries followed (NSEC), the top-decile broker affiliation of the analyst (BSIZE) and finally the average time it takes an analyst to issue a forecast (REPLAG). This results in the following 1st stage model:

$$\text{COMPLEX} = \alpha_0 + \alpha_1\,\text{GEXP} + \alpha_2\,\text{NCOMP} + \alpha_3\,\text{NSEC} + \alpha_4\,\text{BSIZE} + \alpha_5\,\text{REPLAG} + \varepsilon$$

Table 7 presents these results. We find that complex reporters are typically followed by analysts with more experience (0.008; p<.0001), following more firms (0.008; p<.0001) and being affiliated with the largest brokerages (0.041; p<.0001). They are typically focusing on a limited number of industries (NSEC= -0.077; p<.0001) and typically taking longer to issue their forecasts (0.001; p<.0001). The model results in an adjusted R-square of 75% (F-test=15,328), which confirms that our model is well specified. Results from the 2SLS procedure for our main regression of interest are reported in last two columns of table 6. Results are in line with the OLS results presented in the first columns of table 6. The only noticeable difference is with regard to the experience variables. The 2SLS results show that it is firm specific experience (and not general experience) that seems to negatively affect forecast accuracy on complex reporters.

6. Discussion and Conclusion

Studying analyst forecasts on US firms for the period 1995-2015, our study confirms earlier evidence that the better performing analysts are those with more general and firm-specific experience; are affiliated with the largest brokerage houses; and follow less companies compared to their peers. When relating the analyst performance to the readability of the US firms' annual reports, we furthermore observe that when forecasting earnings on the more complex reporters benefits of analyst's general experience seems to be less, but still significant.. Interestingly, on these more complex reporters, the large brokerage affiliation advantage seems to disappear. Consistent with our hypothesis, we do find proof of the importance of good industry knowledge: when analysts follow only a few industries, and thus have more expertise in these industries, they are not just performing overall better, but even more so for complex reporters. In untabulated analyses, we also measure portfolio complexity in terms of complexity of reporting by the firms in the portfolio.

To validate our identification, we conduct a number of additional analyses, including a two-stage Heckman (1979) selection model that takes into consideration the endogeneity of analyst characteristics on portfolio choice composition. Results show that analyst-firm pairs are not random: analysts that typically choose to follow complex reporters are those with more experience, following more firms in less industries and with a large brokerage affiliation. Taken together with the results on analyst performance, our findings suggest that even though experience and broker affiliation drive analysts to follow complex reporters, these analyst-specific characteristics do not translate into better forecasting performance.

References

Barth, M. E., R. Kasznik, and M. F. McNichols. 2001. Analyst coverage and intangible assets. *Journal of Accounting Research* 39 (1): 1–34.

Beuselinck, C., P. Joos, I. Khurana and S. van der Meulen. 2017. Which Analysts Benefited Most from Mandatory IFRS Adoption in Europe?. *Journal of International Accounting Research* 16(3): 171-190.

Bloomfield, R. J. 2002. 'The "incomplete Revelation Hypothesis" and Financial Reporting'. *Accounting Horizons* 16 (3):233–243.

Boni, L., and K. Womack. 2006. Analysts, industries, and price momentum. *Journal of Financial and Quantitative Analysis* 41(1): 85-109.

Bonsall, S. and B. Miller. 2017. The impact of narrative disclosure readability on bond ratings and the cost of debt. *Review of Accounting Studies* 22(2): 608-643.

Botosan, C. A., and M. S. Harris. 2000. Motivations for a change in disclosure frequency and its consequences: An examination of voluntary quarterly segment disclosures. *Journal of Accounting Research* 38 (2): 329–353.

Brown, P., J. Preiato and A. Tarca. 2014. Measuring country differences in enforcement of accounting standards: an audit and enforcement proxy. *Journal of Business Finance & Accounting* 41(1): 1-52.

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

Dyer, T., M. Lang, L. Stice-Lawrence. 2016. 'Do Managers Really Guide Through the Fog? On the Challenges in Assessing the Causes of Voluntary Disclosure'. *Journal of Accounting and Economics* 62(Issue 2-3): 270-276.

Ernst&Young. 2018. Annual Reporting in 2016-7: Broad Perspective, *E&Y Research Report*.

Ertugrul, M., Lei, J., Qiu, J., Wan, C., 2017. Annual report readability, tone ambiguity, and the cost of borrowing. Journal of Financial and Quantitative Analysis. 52 (2), 811–836.

Farooq, O. 2014. Investors' trading and relative performance of analysts during the crisis period. *Corporate Ownership and Control* 11(2).

Fortin, R., & Roth, G. 2007. Analyst Coverage Of Small Cap Firms In A Period Of Brokerage Firm Retrenchment. *Journal of Business & Economics Research 5*(12).

Frankel, R., S.P. Kothari and J. Weber. 2006. Determinants of the informativeness of analyst research. *Journal of Accounting and Economics* 41(1-2): 29-54.

Gilsen, S., P. Healy, C. Noe and K. Palepu. 2001. Analyst specialization and conglomerate stock breakups. *Journal of Accounting Research* 39(3): 565–582.

Groysberg, B., P. Healy, G. Serafeim and D. Shanthikumar. 2012. The stock selection and performance of buy-side analysts. *Management Science* 59(5): 1062-1075.

Guay, W., D. Samuels, and D. Taylor. 2016. 'Guiding through the Fog: Financial Statement Complexity and Voluntary Disclosure'. *Journal of Accounting and Economics* 62 (2):234–269.

Healy, P. M., A. P. Hutton, and K. G. Palepu. 1999. Stock performance and intermediation changes surrounding sustained increases in disclosure. *Contemporary Accounting Research* 16 (3): 485–520.

Heckman, J. 1979. Sample Selection Bias as a Specification Error. *Econometrica* 47(1): 153-161.

Jiang, D., A. Kumar and K. Law. 2015. Political contributions and analyst behavior. *Review of Accounting Studies*: 1-52.

Kadan, O., L. Madureira, R. Wang and T. Zach. 2012. Analysts' industry expertise. *Journal of Accounting and Economics* 54(2): 95-120.

Kim, J., Kim, Y., Zhou, J., 2017a. Languages and earnings management. Journal of Accounting & Economics 63 (2–3), 288–306.

Kim, C., Wang, K., Zhang, L., 2019. Readability of 10-K reports and stock price crash risk. *Contemporary Accounting Research* 36(2): 1184-1216.

KPMG, 2011. 'Disclosure Overload and Complexity: Hidden in Plain Sight'. *KPMG Research Report*, 56 pages.

KPMG, 2014. Room for Improvement - The KPMG Survey of Business Reporting. *KPMG Research Report*, second edition.

LeHavy, R., F. Li and K. Merkley. 2011. The Effect of Annual Report Readability on Analyst Following and the Properties of Their Earnings Forecasts. *The Accounting Review* 86(3): 1087-1115.

Li, F. 2008. 'Annual Report Readability, Current Earnings, and Earnings Persistence'. *Journal of Accounting and Economics* 45 (2):221–247.
Lang, M. H., and R. J. Lundholm. 1996. Corporate disclosure policy and analyst behavior. *The Accounting Review* 71 (4): 467–492.

Lang, M., Stice-Lawrence, L., 2015. Textual analysis and international financial reporting: large sample evidence. *Journal of Accounting & Economics* 60 (2–3), 110–135.

Lawrence, A., 2013. Individual investors and financial disclosure. *Journal of Accounting & Economics* 56 (1), 130–147.

Liang, L., E. Riedl and R. Venkataraman. 2008. The Determinants of Analyst-Firm Pairings. *Journal of Accounting and Public Policy* 27(4): 277-294.

Lo, K., Ramos, F., Rogo, R., 2017. Earnings management and annual report readability. *Journal of Accounting & Economics* 63 (3), 1–25.

Luo, J., Li, X., Chen H. 2018. Annual report readability and corporate agency costs. *China Journal of Accounting Research* 11(3): 187-212.

Piotroski, J., and B. Roulstone. 2004. The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. *The Accounting Review* 79(4): 1119-1151.

Rennekamp, K., 2012. Processing fluency and investors' reactions to disclosure readability. Journal of Accounting Research 50 (5), 1319–1354.

Sonney, F. 2009. Financial analysts' performance: Sector versus country specialization. *The Review of Financial Studies* 22(5): 2087-2131.

Tables

Table 1: Sample Composition

	Number of individual forecasts	Number of unique firm-years	Number of unique firms
Full population of individual forecasts on US firms between 1995-2015	3,764,529	126,966	18,418
Restrict to…			
forecasts for which forecast error can be computed	3,646,493	115,717	17,338
forecasts with a link to Compustat	2,902,506	86,040	12063
forecasts for firms with BOG index and 10-K filing date	1,824,440	45,468	7,032
forecasts where at least one other analyst is following the firm	428,295	45,231	7,011
first forecast issued within 90 days after last year's 10K filing date	295,802	36,069	5,906
forecasts for which additional data requirements hold	**293,590**	**35,579**	**5,877**

Table 2: Descriptives on analyst characteristics and annual report readbility

Panel A: Descriptives on analyst characteristics (based on 293,590 analyst-firm-year observations)

	Mean	Median	StDev	Min	Max
Forecast Age	41,18	43,00	22,58	1	90
Firm experience	3,50	3,00	2,60	1	19
General experience	6,93	6,00	4.17552	1	21
Number of companies followed	12,09	11,00	7.15725	1	122
Number of sectors covered	3,15	3,00	2.28163	1	38
Working for large broker	0,58	1,00	0.49409	0	1

Panel B: Average readability of annual reports per year (based on 35,579 firm-year observations)

Year	Number of firms	Average BOGindex	Year	Number of firms	Average BOGindex
1996	273	77.16	2006	2375	84.59
1997	682	78.62	2007	2418	84.78
1998	1241	80.97	2008	2437	85.36
1999	1308	81.31	2009	2447	85.69
2000	1228	80.69	2010	2379	86.18
2001	1197	80.27	2011	2335	86.29
2002	1429	81.50	2012	2361	86.36
2003	1904	82.82	2013	2335	86.81
2004	2128	83.33	2014	2396	87.35
2005	2231	83.93	2015	476	86.82

Table 2 - *Continued*

Panel C: Average readability of annual reports per sector (based on 35,579 firm-year observations)

Sic2	Number of firms	Average BOGindex	Sic2	Number of firms	Average BOGindex
10	151	80.02	48	972	85.98
12	94	84.83	49	1125	88.73
13	1385	81.94	50	595	83.42
14	58	85.19	51	325	83.92
15	175	81.47	52	64	73.89
16	167	82.63	53	260	77.65
17	78	87.47	54	172	77.98
20	658	78.71	55	265	82.68
21	34	81.79	56	529	78.90
22	117	79.51	57	169	78.62
23	283	79.96	58	526	77.56
24	147	78.79	59	676	80.11
25	183	81.29	60	2802	80.76
26	320	78.84	61	289	83.84
27	279	77.81	62	567	86.45
28	3022	90.91	63	1305	84.30
29	242	82.31	64	171	84.61
30	224	81.19	65	92	83.67
31	99	76.09	67	1343	86.52
32	143	81.75	70	76	80.34
33	461	83.44	72	108	80.04
34	348	81.64	73	3652	84.83
35	1919	84.72	75	83	85.90
36	2678	87.15	76	9	82.11
37	719	83.72	78	128	81.63
38	1899	89.90	79	335	81.70
39	221	80.10	80	529	87.88
40	99	83.89	81	12	82.83
41	13	88.08	82	176	83.28
42	301	81.20	83	55	86.36
44	171	82.55	86	1	82
45	245	81.07	87	542	85.46
46	85	85.84	99	42	85.38
47	139	82.68			

Table 3: Replication of the results in LeHavy et al

	Dependent variable					
	Number of analysts following		Dispersion		Forecast error	
Variable						
Intercept	-11,324	***	-91,772		-0,153	
	[-5.15]		[-0.25]		[-0.03]	
BOG	0,040	***	1,784	**	0,047	***
	[8.41]		[2.26]		[4.04]	
LOGSIZE	2,592	***	-9,358	***	-0,531	***
	[152.52]		[-3.30]		[-12.71]	
Time fixed effects	Yes		Yes		Yes	
Industry fixed effects	Yes		Yes		Yes	
R-Square	50,40%		0,36%		1.98%	

BOG is the bogindex measured for the last available 10K report. LOGSIZE is the number of outstanding shares multiplied with the share price at the end of the last available 10K report. Number of analysts measures the number of analysts that issued a forecast within 90 days after last year's 10K filing, whereas dispersion is the standard deviation between these forecasts, scaled by share price 60 days before last year's 10K filing date. Forecast error is measured as the average squared difference between each individual forecast and the actual EPS, scaled by the firm's share price 60 days before last year's 10K filing date.

Table 4: Descriptives on analyst characteristics and regression variables (n= 174,021)

Panel A: Descriptives on analyst characteristics

	COMPLEX= 0		COMPLEX= 1		t-value	
	Mean	StDev	Mean	StDev		
General experience	6,89	4,19	6,99	4,19	-5,17	***
Firm experience	3,54	2,64	3,49	2,59	3,69	***
Number of companies followed	12,09	7,25	12,06	7,10	1,04	
Number of sectors covered	3,35	2,39	3,02	2,19	29,47	***
Working for large broker	0,57	0,49	0,59	0,49	-6,92	***
Forecast Age	41,23	22,28	40,89	22,82	3,12	***

Panel B: Descriptive statistics on regression variables

	RELACC	GEXP	FEXP	NCOMP	NSEC	BSIZE	FCAGE
Q1	-0,204	-2,167	-1,000	-3,125	-0,857	-0,500	-9,167
Median	0,028	0,000	0,000	-0,375	-0,182	0,167	0,500
Mean	0,000	0,000	0,000	0,001	0,000	0,000	0,002
Q3	0,307	2,000	0,750	2,571	0,625	0,500	8,733

In Panel A we report descriptive statistics on the absolute value of the analyst characteristics, discerning between analysts following firms with complex reports versus more readable reports. In Panel B we show descriptive statstics for our regression variables, so for the firm-year demeaned variables. All variables are as defined in Appendix.

Table 5: Pearson Correlation Coefficients

	2	3	4	5	6	7
1. RELACC	0,0224	0,0156	-0,0084	-0,0030	-0,0005	0,1190
	<.0001	<.0001	0,001	0,205	0,849	<.0001
2. GEXP		0,5673	0,2395	0,1175	0,0077	0,0108
		<.0001	<.0001	<.0001	0,001	<.0001
3. FEXP			0,1007	0,0346	0,0076	-0,0158
			<.0001	<.0001	0,001	<.0001
4. NCOMP				0,5823	0,0627	0,0204
				<.0001	<.0001	<.0001
5. NSEC					-0,0715	0,0258
					<.0001	<.0001
6. BSIZE						-0,0275
						<.0001
7. FCAGE						1

This table presents the Pearson correlation coefficients for all regression variables. All variables are as defined in Appendix and firm-year mean-adjusted.

Table 6: Regression Results modelling Relative Forecast Accuracy

	OLS regression			2SLS regression		
	Parameter Estimate	Pr > |t|		Parameter Estimate	Pr > |t|	
GEXP	0,511	6,66	***	0,429	5,47	***
FEXP	0,202	1,65	*	0,447	2,99	***
NCOMP	-0,233	-5,25	***	-0,581	-10,39	***
NSEC	0,290	2,05	**	0,839	4,60	***
BSIZE	1,544	3,40	***	1,329	2,60	***
COMPLEX	0,002	0,01		-0,449	-0,53	
GEXP * COMPLEX	-0,262	-2,50	**	0,006	0,06	
FEXP * COMPLEX	0,003	0,02		-0,530	-2,87	***
NCOMP * COMPLEX	0,101	1,64		0,347	4,88	***
NSEC * COMPLEX	-0,468	-2,29	**	-0,874	-3,65	***
BSIZE * COMPLEX	-1,966	-3,15	***	-1,887	-2,93	***
FCAGE	0,397	50,11	***	0,396	49,47	***
N	174.021			174.021		
Adj-R2	0,015			0,015		

***, **, * : significant at the 1%, 5% and 10% level.

The general specification we estimate is : RELACCijt + β1ΓΕΞΠιφτ + β2ΦΕΞΠιφτ + β3ΝΧΟΜΠιφτ + β4ΝΣΕΧιφτ + β5ΒΣΙΖΕιφτ+ β6 COMPLEXjt + β7 GEXPijt * COMPLEXjt + β8 FEXPijt * COMPLEXjt + β9 NCOMPijt * COMPLEXjt + β10ΝΣΕΧιφτ * COMPLEXjt + β11ΒΣΙΖΕιφτ * COMPLEXjt + β12ΦΧΑΓΕιφτ + ειφτ. Subscripts *i, j,* and *t* refer to analyst, firm, and time, respectively; all variables are defined as in appendix. All independent variables except for COMPLEX are firm-year mean-adjusted. All coefficient estimates are multiplied by 100 for ease of interpretation.

Table 7: First Stage Regression results

	Parameter Estimate	Wald Chi-sq	Pr > ChiSq
INTERCEPT	0.118	48.55	***
GEXP	0.008	42.50	***
NCOMP	0.008	99.74	***
NSEC	-0.077	1026.02	***
BSIZE	0.041	16.96	***
REPLAG	0.001	33.30	***
Adj-R^2	0.745		

All variables are defined in Appendix. The general specification we estimate is: COMPLEX = $\alpha_0 + \alpha_1$ GEXP + α_2 NCOMP + α_3 NSEC + α_4 BSIZE + α_5 REPLAG+ ε

Appendix

Variable Definitions:

$GEXP_{ijt}$	=	number of years analyst *i* has been in the I/B/E/S database when he issues a forecast in year *t*, counting from 1990 onward,
$FEXP_{ijt}$	=	number of years for wich analyst *i* has been following firm *j* by year *t*;
$NCOMP_{ijt}$	=	number of companies for which analyst *i* has issued a forecast in year *t*;
$NSEC_{ijt}$	=	number of 2-digit sectors for which analyst *i* has issued a forecast in year *t*;
$BSIZE_{ijt}$	=	dummy variable that takes the value of 1 when the forecast originates from an analyst *i* who works in one of the top decile brokerage firms, and 0 otherwise;
AGE_{ijt}	=	number of days between firm *j*'s 10K filing date for year *t-1* and analyst i's forecast;
$COMPLEX_{jt}$	=	dummy variable that takes the value of 1 when firm j's reporting in year t is considered as a complex. Complex reporting means a BOG index of last year's 10K report above the upper industry-year quartile. The dummy takes a value of 0 when the BOG index is below the lower industry-year quartile.
REPLAG	=	average number of days analyst *i* takes to issue a forecast in year *t*