Gender and Analyst Reports

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Abstract

We examine gender differences in characteristics of sell-side analyst reports. We find that female analyst reports are shorter and more readable. Consistent with an "ethical standard" explanation, the textual sentiment of female analyst reports is less optimistic. Moreover, female analyst reports contain less financially oriented content, are more long-term oriented, and are less likely to be issued in response to coverage firm earnings announcements. Readability, length, and sentiment of female analysts' reports induce different market reactions than their male counterparts, yet female analysts improve report readability more and increase objectivity over their career than male analysts do. Our results provide evidence of gender stereotyping in the analyst profession.

JEL Classification: G10, G14, J16, M14, M41

Keywords: analyst reports, earnings announcements, gender, qualitative information, readability, sell-side analyst

1. Introduction

Analyst reports are a major information outlet through which analysts propagate their insights into covered firms. Prior studies in accounting and finance have established value relevance of both quantitative (Brav and Lehavy, 2003) and textual information (Huang, Zang, and Zheng, 2014) contained in these reports. Writing useful reports is an important requirement in the analysts' career advancement, especially when it comes to achieving a coveted All-Star rating. Psychology and linguistic studies have documented significant and consistent gender differences in writing abilities (Reynolds et al., 2015) and even writing styles (Argamon, Koppel, Fine, and Shimoni, 2003). The questions whether these differences can be observed in the language of analyst reports and whether these differences matter to investors remain unexplored.

In this paper, we attempt to fill this gap by comparing the language of sell-side analyst reports (hereinafter analyst reports) written by women to those written by men. Specifically, we examine whether gender differences exist in the writing characteristics of these reports, whether male and female analysts exhibit different attitudes toward covered companies in reports and focus on different topics, and whether equity markets react differently to reports written by analysts of different genders. We choose to focus on the textual characteristics of analyst reports for several reasons. First, writing skills have been consistently listed as one of the most valued skills on Wall Street (Weber and Cutter, 2019), evidenced by companies hiring more liberal arts graduates for their communication skills (Waller, 2016). Second, writing research reports is a primary task of analysts: written text serves as the foundation of their analysis (Asquith, Mikkhail, and Au, 2005) and is informative to the market (De Franco, Hope, Vyas, and Zhou, 2015; Huang, Zang, and Zheng, 2014). Finally, with the notable exception of Huang, Zang, and Zheng (2014), textual analysis of these reports is limited in the prior literature due to the absence of natural language processing tools to examine their qualitative characteristics on a large scale. This study provides an understanding of the informativeness of analyst reports within the context of gender underrepresentation (Kumar, 2010).

Using an extensive sample of analyst reports (more than 415,000 reports) from 1997 to 2017, we establish the existence of significant gender differences. Female analyst reports tend to be more readable and concise, and tend to be more conservative in their sentiment. Reports produced by male analysts tend to be more quantitative in nature and more short-term focused, while female analysts tend to be more focused on soft information and long-term indicators. Female sell-side analysts are also less likely to issue reports immediately following earnings announcements, and tend to produce information outside of earnings announcement window.

Prior studies show that ability and opinions of female sell-side analysts may be undervalued due to gender discrimination (Bloomfield, Rennekamp, Steenhoven, and Stewart, 2021; Kumar, 2010). To examine this effect, we compare market reactions to qualitative content of reports produced by female versus male analysts and find significant gender differences. Specifically, we find that while market participants do value clear and expressive analyst reports, they tend to have a more muted response when this readability and sentiment is produced by female analysts. Our analyses are robust to the inclusion of firm and analyst time variant characteristics as well as industry-by-year and brokerage-by-year fixed effects.

In our second set of tests, we examine the mechanism behind the observed analyst writing differences. If female analysts are subject to higher assessment standards than men (Green, Jegadeesh, and Tang, 2009), it may cause them to exert more effort throughout their career and result in more readable and more carefully written (i.e., not overly optimistic) reports. We, thus, compare how the readability and optimism of analyst reports for the two genders change during their career. We find that women and men tend to have a similar level of report readability at the beginning of their careers, but women tend to improve their readability more than men as their career progresses. We also find that female analysts exhibit a decrease in optimistic language over time. Next, we examine which gender exerts more effort to produce differentiated analyst research. For this test, we focus on the subsample of reports issued outside of earnings announcement windows, as these reports are more likely to be individualistic and not dominated by earnings news (Green, Jegadeesh, and Tang, 2009). We find that female analysts produce more readable and less optimistic research reports with more financial content and more long-term focus outside of earnings announcement windows compared to similarly timed reports produced by their male counterparts.

We make several contributions to the literature on the effect of gender in the financial intermediation. Gender differences in writing abilities have been studied in psychology (i.e., Hyde, 2005; Reilly, Neumann, and Andrews, 2019) and linguistics (Argamon, Koppel, Fine, and Shimoni, 2003). Linguistic gender differences have been examined in certain business settings, including earnings conference calls (Amicis, Falconieri, and Tastan, 2021; Brown et al., 2022; Klevak, Livnat, and Suslava, 2022) and annual reports (Nalikka, 2009; Kim and Chung 2014); our paper extends this strand of literature to the language of analyst reports. We also add to the literature of gender issues in the workplace, especially among high-paying professionals. Given the low representation of women in high-paying jobs, whether there exists gender discrimination or gender differences in ability has become a long-standing issue (Adams and Funk, 2012; Bertrand, Black, Jensen, and Lleras-Muney, 2019; Matsa and Miller, 2011). Finally, we contribute to the literature on financial analysts. Whether analysts' reports are informative is open to debate (Altınkılıç and Hansen, 2009; Bradley, Clarke, Lee, and Ornthanalai, 2014). Prior studies document that analyst gender is a dimension which predicts forecast boldness, stock recommendation favorableness, career advancement, and market reaction (Bosquet, de Goeij, and Smedts, 2014; Kumar, 2010; Green, Jegadeesh, and Tang, 2009; Li, Sullivan, Xu, and Gao, 2013). Our findings suggest that analyst gender also predicts writing styles with regard to textual sentiment, readability, and informativeness. Further, the market impact (i.e., coverage of firm stock return magnitude and abnormal trading volume) of these sell-side report textual features differs with analyst gender.

The rest of the paper is organized as follows. Section 2 is dedicated to literature review, Section 3 states our hypotheses, Section 4 describes our sample and variable selection, Sections 5 and 6 are dedicated to the empirical analysis, and Section 7 concludes.

2. Literature Review

2.1. Gender differences in communication

Hyde (2005) proposes the gender similarities hypothesis that “males and females are similar on most, but not all, psychological variables. That is, men and women, as well as boys and girls, are more alike than they are different” (p. 581). Regarding verbal performance, she reviews meta-analyses of gender differences in various cognitive attributes and finds that although gender differences in vocabulary and reading comprehension are trivial, moderate gender differences in writing performance exist. Gender differences in writing performance are also documented in other studies. For example, Reynolds et al. (2015) compare the performance of young persons from age 7 to 19 in Kaufman intelligence and achievement tests (Kaufman and Kaufman, 2004) and find that girls outperform boys in spelling and written expression with a moderate effect size (d=0.46), inconsistent with the gender similarities hypothesis.

If gender differences in writing result from gender stereotyping, gender differences are expected to decline as social expectations for females change (Feingold, 1988). However, Reilly, Neumann, and Andrews (2019) conduct large sample research on student achievement in writing from the National Assessment of Education Progress (NAEP) from 1988 to 2011 and find that gender differences are consistent over time at a medium level (d=0.55). Moreover, multiple studies document a developmental trend that female advantages in writing performance appear at a young age (i.e., 6 to 10 years old), widen until high school, and stabilize in adolescence (Scheiber, Reynolds, Hajovsky, and Kaufman, 2015; Reilly, Neumann, and Andrews, 2019).

In addition to female advantages in writing abilities, gender differences also exist in writing styles. Argamon, Koppel, Fine, and Shimoni (2003) examine a large sample of writing in the British National Corpus of books and articles. They find men use more noun specifiers and women use more pronouns.[1] They further argue that the results are consistent with earlier findings that women pay more attention to relationships than men do (Tannen, 1990).

2.2. Gender differences in analysts

Gender differences are substantial among sell-side analysts. First, women are significantly underrepresented. Prior studies show that women account for less than 15% of analysts in the Institutional Brokers Estimate System (I/B/E/S) database (Fang and Huang, 2017; Green, Jegadeesh, and Tang, 2009; Kumar, 2010). Second, female analysts exhibit heterogeneity in industry coverage distribution, with a relatively higher concentration in retail, clothing, textiles, and publishing industries while they are substantially underrepresented in coal, metals, automobiles, and defense (Green, Jegadeesh, and Tang, 2009; Kumar, 2010). Third, female analysts are more likely to cover large firms and are hired by larger brokerage houses (Brown et

[1] "Pronouns send the message that the identity of the 'thing' involved is known to the reader, while specifiers provide information about 'things' that the writer assumes the reader does not know." (Argamon, Koppel, Fine, and Shimoni, 2003, p. 323)

al., 2022; Kumar, 2010). Fourth, female analysts are more likely to be designated as Institutional Investor All-Stars (Fang and Huang, 2017; Green, Jegadeesh, and Tang, 2009; Kumar, 2010). Fifth, female analysts cover a smaller number of firms and rely more on independent research instead of earnings news (Green, Jegadeesh, and Tang, 2009).

Despite this underrepresentation, Kumar (2010) demonstrates that female analysts have greater average earnings forecast accuracy relative to male peers. Although gender differences in professional roles and industry selection preferences provide an explanation to female underrepresentation, whether a gender difference exists with respect to more complex outputs like sell-side analyst reports or market reactions to said reports is unclear (Fang and Huang, 2017; Green, Jegadeesh, and Tang, 2009; Kumar, 2010; Li, Sullivan, Xu, and Gao, 2013).

2.3. Analyst reports

Writing informative reports is a fundamental requirement for a job of financial analyst (Brown, Call, Clement, and Sharp, 2015; Hong and Kubik, 2003; Mikhail, Walther, and Wills, 1999). Analyst reports include both headline quantitative measures—earnings forecasts, stock recommendations, and price targets—and written analysis (Asquith, Mikhail, and Au, 2005; Huang, Zang, and Zheng, 2014; De Franco, Hope, Vyas, and Zhou, 2015; Huang, Lehavy, Zang, and Zheng, 2018). Prior studies find that these quantitative outputs are informative to the stock market (Brav and Lehavy, 2003; Li, Ramesh, Shen, and Wu, 2015). However, the main body of analyst reports is written analysis of the company which underlies the headline measures. As Tsao (2002) points out: “In the end, stock ratings and target prices are just the skin and bones of analysts' research. The meat of such reports is in the analysis, details, and tone. Investors who are willing to spend the time can easily figure out what an analyst really thinks about a stock by reading a research report.”

If the information in the report's text is fully reflected in headline quantitative measures, we do not expect to observe a significant market reaction when controlling for relevant quantitative information. However, prior studies show that sell-side analyst reports cover a wide range of financial and nonfinancial topics including performance, strategy, risk management, competitive position, stakeholders, and economic conditions (Asquith, Mikhail, and Au, 2005; Previts, Bricker, Robinson, and Young, 1994) and textual content in analyst reports is incrementally informative to the market (Asquith, Mikhail, and Au, 2005; De Franco, Hope, Vyas, and Zhou, 2015; Huang, Zang, and Zheng, 2014). This implies that text in analyst reports contains subtle, important information which is valuable to investors.

Further, investors may regard writing as the most valuable information embedded in an analyst report because investors do not simply *follow* analysts' conclusions but *refer to* information in analyst reports in order to construct their own investment decisions (Huang, Zang, and Zheng, 2014). According to *Institutional Investor* magazine's annual survey of institutional investors, writing useful reports is considered more important as an All-Star analyst voting criterion than stock recommendation profitability (Leone and Wu, 2007).

3. Hypothesis Development

Writing reports is a core task for sell-side analysts. Because information processing is costly (Hirshleifer and Teoh, 2003), complex text significantly increases information processing costs of readers (Lehavy, Li, and Merkley, 2011; Li, 2008; Lo, Ramos, and Rogo, 2017). To attract investor attention and increase influence, analysts have the incentive to issue more readable reports. Previous studies document that report readability is associated with analyst ability proxies (De Franco et al., 2015). Since females generally have an advantage of writing skills, we expect female analysts to issue better written reports (Reilly, Neumann, and Andrews, 2019).

Additionally, report writing entails a large amount of effort. Extant literature finds that women are more conscientious than men. Women conduct more organizational citizenship behavior and more discretionary work (Kmec and Gorman, 2010; Lovell et al., 199944). Moreover, female directors are found to have higher board input (Adams and Ferreira, 2009). More effort invested by female analysts may transfer to more readable reports.

Last, financial analysts have traditionally been regarded as a "boys club" profession (Fang and Huang, 2017). Given the potential discrimination, women choose to enter the industry may not be average women and are more likely to be more competent than their male counterparts—a "self-selection" phenomenon (Kumar, 2010). As a result, female analysts tend to have higher abilities on average. Moreover, female analysts face greater scrutiny by investors, which could lead them to put more effort into writing reports and thus issue more readable ones (Bloomfield, Rennekamp, Steenhoven, and Stewart, 2021; Hengel, 2022; Madera et al., 2019). Therefore, we hypothesize that:

Hypothesis 1. Female analysts issue more readable reports.

A higher evaluation standard may introduce a quantity-quality tradeoff for women. Prior studies report evidence consistent with this tradeoff that female analysts are less likely to revise earnings forecasts, issue fewer stock recommendations, but have higher forecast accuracy (Kumar, 2010; Li, Sullivan, Xu, and Gao, 2013). On one hand, women may reduce the number of outputs but, put more effort into each of them to increase quality (Hengel, 2022) and issue shorter reports as a result. Alternatively, to improve report quality, female analysts may spend more effort in issuing reports to support quantitative outputs and thus issue longer reports. We therefore examine the following tension:

Hypothesis 2a. Female analysts issue longer reports.

Hypothesis 2b. Female analysts issue shorter reports.

Investors are the primary consumers of analyst reports. Buy-side clients refer to industry knowledge and forecasts provided in analyst reports to make their own investment decisions (Brown, Call, Clement, and Sharp, 2015). Because sell-side analysts are particularly vulnerable to conflicts of interest, they develop more credibility with buy-side clients when they issue forecasts or recommendations that are less favorable than consensus (Brown, Call, Clement, and Sharp, 2015). Extant studies document that women have higher ethical standards than men (Dollar, Fisman, and Gatti, 2001; Franke, Crown, and Spake, 1997; Reiss and Mitra, 1998) and thus are less likely to be influenced by conflicts of interests that could lead to manipulation of report optimism. Specifically, the likelihood of issuing optimistic stock recommendations is significantly lower for female analysts, and the likelihood of issuing bolder forecasts is significantly higher for female analysts (Bosquet, de Goeij, and Smedts, 2014; Kumar, 2010). Therefore, female analysts may exhibit more negative sentiment in their reports.

Hypothesis 3. The tone of female analysts' reports is less positive than that of male analysts.

When writing reports, analysts gather a wide range of information. The information can be broadly classified into financial and nonfinancial information (Huang, Zang, and Zheng, 2014). Nonfinancial information is not included in a firm's financial reporting system (Stocken and Verrecchia, 2004). However, nonfinancial information, such as customer satisfaction, is value relevant (Cao, Myers, and Omer, 2012; Ittner and Larcker, 1998). Compared with financial information, nonfinancial information is more about relationships with stakeholders. Nonfinancial information may require more effort for analysts to collect and analyze because its disclosure by firms is not mandatory (Huang, Zang, and Zheng, 2014).

Cognitive differences between women and men suggest that information acquisition methods between the two can be different. Comparatively, women are characterized by a stronger focus on relationships (Tannen, 1990). For example, female writers encode a relationship with readers into text and use more pronouns, while men use more noun specifiers in formal writings (Argamon, Koppel, Fine, and Shimoni, 2003; Tannen, 1990). Newman et al. (2008) analyze text files from 70 studies with different contexts and find that women use more psychological and social process words while men were more likely to use more impersonal topics and refer to objects, events, and numbers. This suggests that reports by female analysts may contain proportionately lower financial content because of differences in cognition.

Hypothesis 4. Female analysts discuss less financial content in reports.

Another important dimension of analyst reports is forecast horizon. While the majority of forecasts are short-term oriented, long-term forecasts are also informative (Chen, Jung, Lim, and Yu, 2020; Chen, Shane, Yang, and Zhang, 2021). However, forecasting long-term activities such as innovation is difficult. Previous studies show that women are more conservative and risk-averse (Croson and Gneezy, 2009; Francis et al., 2015; Johnson and Powell, 1994) and are therefore expected to focus more on short-term performance. On the contrary, the perceived higher ability of female analysts could lead to lower unemployment risk and these analysts are expected to focus more on long-term related topics (Kumar, 2010; Clarke and Subramanian, 2006). Thus, we propose the following hypothesis:

Hypothesis 5. Female analysts have more long-term focus in reports.

Investors may put less weight on reports issued by female analysts due to gender stereotypes especially since gender can be easily inferred based on analyst name(s) within each report. For example, Bloomfield, Rennekamp, Steenhoven, and Stewart (2021) find that, in an experimental setting, female analysts are evaluated by investment professionals as less promotable when they exhibit unexpected behavior. Men, who account for a large proportion of the investor community, also exhibit bias against female analysts (Luo and Salterio, 2021). The ability and opinion of female analysts may be undervalued because the financial analyst profession is dominated by men. Moreover, subject to gender stereotypes, investors might also scrutinize female analysts' reports more carefully and perceive their credibility as lower.

Conversely, investor may attach more importance to female analysts' reports. The self-selection of female analysts leads to their superior performance in earnings forecasts. In a similar vein, if investors undervalue reports issued by female analysts, we expect female analysts to adapt to a higher standard required by investors and improve their analysis and writing skills over time (Hengel, 2022). This improved ability suggests that the market may react more strongly to female analyst reports. Due to these competing arguments, whether or not the market reacts differently to male and female analysts' report content is an empirical issue. Therefore, we propose:

Hypothesis 6a. Market reaction to female analyst text is stronger.

Hypothesis 6a. Market reaction to female analyst text is weaker.

4. Sample Selection and Variable Descriptions

4.1. Sample selection

We collect a large random sample of sell-side analyst reports issued between 1997 and 2017 from approximately two thousand firms that were/are members of the Russell 3000 index during this period from Thomson One Investext.[2] All analyst reports are downloaded as portable document format (PDF) files. For text-based PDF documents (i.e., text is searchable), we use *pdftotext* to convert them into text files; for image-based PDFs, we use *Tesseract*, an open-source

[2] A random sample is used due to data collection restrictions in Thomson One Investext.

optical character recognition (OCR) engine, to convert PDFs to plain text.[3] We use header information provided by Investext to match analyst reports and other datasets. Header information includes the title, report issue date, number of pages, analyst brokerage firm, analyst name, a unique number assigned to the report, and 6-digit firm NCUSIP. We remove non-English reports. Reports covering multiple stocks are also removed because it is difficult to distinguish firm-specific information (Huang, Zang, and Zheng, 2014). We remove reports issued by more than one lead analyst because gender-diverse team leads may introduce noise to our analysis of gender effects.[4]

We match analyst-company pairs in the report sample to I/B/E/S by analyst name and NCUSIP and further manually verify the matching with broker names. Unmatched reports are deleted from the report sample. We then match analyst reports with I/B/E/S earnings-per-share (EPS) forecasts, stock recommendations, and price target datasets.[5] For each valid forecast, I/B/E/S only records its announcement date (ANNDATS), the date on which the analyst issues a forecast, and review date (REVDATS), the most recent date on which the analyst confirms the forecast as valid. In other words, multiple reports may share the same record in I/B/E/S. We follow Huang, Zang, and Zheng (2014) and use the matching window spanning from two days before the announcement date to two days after the review date.[6] We only retain reports matched with at least one I/B/E/S earnings forecast, recommendation, or price target. We then take the intersection of the reports and CRSP/COMPUSTAT datasets to obtain stock return and financial data. Reports with less than 100

[3] https://github.com/tesseract-ocr/tesseract
[4] Fang and Hope (2021) find that 73% of annual earnings forecasts for U.S. firms from I/B/E/S over the period of 2013 to 2016 are issued by teams. However, the majority of analyst teams are led by one analyst who is in charge of the team. For example, RBC Capital Markets issued a report on Nov. 25th, 2013 and the analyst team consists of a senior analyst, Sunil Harshad "Nik" Modi, and three associates. The corresponding I/B/E/S record only lists Nik Modi as the unique analyst. We find that 98.4% of reports in our sample list one lead analyst.
[5] We use one-year-ahead EPS forecasts and one-year-ahead price target forecasts.
[6] Price target records in I/B/E/S do not have review dates and hence we only consider a matching window 5 days around the target release date.

words are excluded because they are less likely to convey value-relevant information to the market except for templated language. Last, we limit our sample to report observations without missing values for all variables. Our final sample consists of 415,744 reports related to 1,672 firms, 3,493 analysts, and 309 brokerages.

4.2. Gender determination

To determine analyst gender, we extract first names from full names in report header information and apply Gender API, a gender inference service based on more than 2 million names collected from government records and social networks.[7] Prior studies find that Gender API has superior accuracy compared with other algorithms (Bonham and Stefan, 2017; Santamaría and Mihaljević, 2018). Specifically, Gender API provides an accuracy score ranging from 0 to 100 to exhibit how reliable each gender guess is. All first names with a score less than 80 are manually checked using internet searches and S&P Capital IQ database. Our primary indicator variable of interest, *Female*, is set to 1 (0) for female (male) analysts.

Figure 1 presents the distribution of our report sample through time and across the two genders of lead analysts. We observe a sharp upward trend for the number of analysts' reports for both genders after 2000. However, the proportion of female analyst reports seems to be decreasing from 10%-15% in the early sample period to around 10% after 2008 . Overall, the percentage of female reports is consistent with prior studies on gender representation of financial analysts based on the I/B/E/S sample (Fang and Huang, 2017; Kumar, 2010).

[Insert Figure 1]

4.3. Textual variable construction

Following Hengel (2022), we measure analyst report readability with five widely used indices:

[7] https://gender-api.com/en/

Gunning Fog (*Fog*), Flesch-Kincaid Grade Level (*FKGL*), Flesch Reading Ease (*FRE*), Dale-Chall (*Dale*), and Simple Measure Gobbledegook (*SMOG*). Because more readable text obtains higher Flesch Reading Ease scores but lower scores for the other four indices, we multiply each of the four grade-level scores by negative one for easier interpretation. Thus, for the purpose of our analysis, all higher readability scores indicate that an analyst report is easier to follow. We also calculate a combined readability measure (*ReadPCA*), as the first principal component of all five readability indices.

We use three measures to examine reports length: a logarithm-transformed number of words in a report (*Word*), the log number of pages of a report (*Page*), and a combined one (*LenPCA*), calculated as the first principal component of *Word* and *Page*. Previous studies use report length as a measure of readability (Li, 2008; De Franco, Hope, Vyas, and Zhou, 2015), as well as a measure of effort put forth by analysts, especially when analysts have relatively less intention to obfuscate the information contained in the report (Twedt and Rees, 2012).

We use Loughran and McDonald (2011) dictionaries of positive and negative words to measure the sentiment of analyst reports. We measure the extent of report's optimism/ pessimism with *Pos*/*Neg*, as the ratio of positive/negative words to the total number of words in a report. We also calculate the overall sentiment of a report with net sentiment (*Net*) as the difference between total number of positive and negative words scaled by the total number of words in a report.

Additionally, we investigate reports' content across three dimensions: the extent of financial information, the proportion of numbers in a report, and analysts' timeframe in a report. We measure the extent of financial information (*Financial*) as the total number of financially-oriented words based on the Matsumoto, Pronk, and Roelofson (2011) dictionary scaled by the total number of words. Numerical information (*Number*) is the proportion of numerical information calculated following Campbell, Zheng, and Zhou (2021).[8] Finally, we measure analysts' time frame with two measures: the proportion of short-term (*ShortTerm*) and long-term oriented words (*LongTerm*) scaled by the total number of words in a report following Brochet, Loumioti, and Serafeim (2015).

4.4. Descriptive statistics

Table 1 shows descriptive statistics for the textual variables, as well as controls for report, analyst and firm characteristics. Continuous variables are winsorized at 1st and 99th percentiles. We observe that analysts' reports tend to use more negative words than positive ones: the mean of Pos is at 0.074, in comparison to 0.162 for *Neg*; this is consistent with analysts' role as external evaluators of company financial performance[9]. We also note that only 11 percent of reports in our sample are produced by female analysts (mean *Female* at 0.11), which is consistent with the observed gender imbalance in finance[10] and academic studies of female analysts (Fang and Huang, 2017; Kumar, 2010; Brown et al., 2022):

[Insert Table 1]

Table 2 reports the correlation between the indicator for female analysts and our textual variables. We note that *Female* is positively correlated with all readability measures, indicating that women tend to produce reports that are easier to follow. Women analysts also tend to produce shorter reports (negative correlations between *Female* and *Word/ Page*). We also observe that all readability and length measures are highly correlated with each other, indicating that readability and length are consistent across these measures. Female variable is also positively correlated with net tone, long-term oriented words, and short-term oriented words and negatively correlated with

[8] *Number* also contains numerical information embedded in report tables, which is not included in other measures.
[9] In contrast, managers tend to exhibit an overall positive sentiment in their communications to the market (Suslava 2021).
[10] Lack of gender diversity in the investment profession is a well-established social phenomenon. A recent study by the CFA Institute finds that women represent only 18 percent of its charterholders, a striking statistic given that 57 percent of college graduates and 48 percent of business majors are women (CFA Institute, 2016).

numerical and financial content. However, the correlations with net tone, short-term sentiment, and numerical content are economically small.

[Insert Table 2]

5. Empirical Analysis

5.1. Univariate analysis

Table 3 shows the comparison of the textual measures by gender. First, we observe that female analysts issue more readable reports than male analysts; this observation is consistent across all five readability measures, as well as our combined *ReadPCA* measure. The results are statistically significant at 1 percent level with t-statistics ranging from 8.89 to 27.17. Second, we note that women tend to issue shorter reports based on both the number of words (*Word*) and the number of pages in their report (*Page*). Given that prior studies use report length as another measure of readability (Li, 2008; De Franco et al., 2015), our results for both length and readability measures seem to indicate that women tend to produce clearer analyst reports.

Our measures of report sentiment also exhibit significant gender differences. It appears that women tend to use significantly fewer positive and negative words in their reports: the differences for *Pos* and *Neg* are negative and significant at 1 percent level. The overall sentiment of analyst report tends to be more optimistic for women analysts: the difference between two genders for *Net* is positive and significant at 5 percent level.

Looking at the report topics, female analysts tend to use significantly fewer financial words (the difference for *Financial* is negative and significant at 1 percent level), and fewer numbers in their report (the difference for *Number* is negative and significant at 5 percent level). Finally, while the number of short-term oriented words is the same between the two genders, women tend to use a higher proportion of long-term oriented words: the difference for *LongTerm* is positive and significant at 1 percent level.

We note significant gender differences across various analyst-level characteristics. For instance, 23.4% of female analyst reports are written by Institutional Investor All-Star analysts compared with only 17.5% of male analyst reports (*AllStar*). Female analysts are associated with fewer years of forecasting experience (*GenExp*), less firm-specific experience (*FirmExp*), larger brokerage houses (*Broker*), a smaller number of firms covered (*FirmCover*), and more reports issued per year (*Frequency*). Finally, we observe significant gender differences in terms of firm characteristics. Female analysts tend to cover larger and more complex growth firms: the difference for *BM* is negative and significant, while the differences for *Size* and *Segment* are positive and significant. Overall, our observations are consistent with prior studies that female analysts tend to have less experience, are more likely to cover larger firms and be hired by larger brokerage houses (Kumar, 2010).

[Insert Table 3]

5.2. Analyst report readability and length

Next, we test H1 and H2 in a multivariate setting, using the following regression models:

$$Readability = \alpha + Female + EA + AnalystControls + Firm\ Controls + \varepsilon \qquad (1)$$

$$Length = \alpha + Female + EA + AnalystControls + Firm\ Controls + \varepsilon \qquad (2)$$

Our dependent variables for Model (1) are our five measures of report readability (*Fog, FKGL, FRE, Dale*, and *SMOG*), and for Model (2) – our measures of length (*Word* and *Page*). Our main variable of interest is the indicator variable for analyst gender (*Female*). If women produce more readable/ shorter reports, we expect it to load positively/ negatively and significantly for the measures of readability/ length. In all specifications, we include firm-year and brokerage-year fixed effects, and standard errors are clustered at the firm level for all OLS models.

The results are reported in Table 4. In Panel A, we observe that female analyst reports are more readable in terms of all five readability measures. The coefficients on *Female* load positively and significantly for columns (1) through (5). Columns (6) and (7) report our results for the measures of report length. Negative and significant coefficients on *Female* for both *Word* and *Page* indicate that female analyst reports are, on average, shorter than those of male analysts. In terms of economic significance, the coefficients indicate that women use, on average, 4% fewer words and 5% fewer pages than their male counterparts. In Panel B, we re-estimate our model using the first principal components of the five readability measures (*ReadPCA*) and two measures of length (*LenPCA*) and obtain similar results.

Overall, our results support H1 and H2b and indicate that, controlling for analyst and firm characteristics, female analysts tend to issue shorter and more readable reports. We interpret this pattern as a quality versus quantity tradeoff for female analysts.

[Insert Table 4]

5.3. Analyst report sentiment

Next, we examine gender differences in the sentiment of analyst reports. We use the same regression specifications as in Models (1) and (2), and use three measures of sentiment as the dependent variables: proportion of positive words (*Pos*), proportion of negative words (*Neg*) and net sentiment (*Net*). If women are more conservative in their reports than men, we expect *Female* to load negatively for *Pos* and *Net*, and positively for *Neg*. We add a control for the favorability of analyst revisions (*RevFavor*) calculated as the total number of upward revisions minus the total number of downward revisions among earnings forecasts, stock recommendations, and price target revisions (*RevFavor*).

The results are reported in Columns (1)-(3) of Table 5. We note that *Female* loads negatively and significantly at 1 percent for *Pos*. In terms of economic significance, the coefficient indicates that women analysts use 0.3% or approximately 6 fewer positive words per report, than their male counterparts. This is similar to the textual analysis results in recent accounting studies (Levy, Shalev, and Zur, 2018; De Franco, Shohfi, Xu, and Zhu, 2022). We find no significant gender differences for negative sentiment (*Neg*) and net tone (*Net*).

Overall, our findings seem to support our argument that female analysts are less likely, than males, to use more positive sentiment in their reports. This is also consistent with prior findings that female analysts tend to be more ethical and, as a result, less likely to curry favor with firm management.

[Insert Table 5]

5.4. Analyst report content

Analysts may have their own unique forecasting and information production approaches. One taxonomy of information is that which is recognized by financial reporting systems (Huang, Zang, and Zheng, 2014). Because nonfinancial content encompasses a broad scope of topics and is thus difficult to capture, we employ an indirect approach by examining the percentage of financial content with two measures: the proportion of financial words (*Financial*) and the proportion of numbers (*Number*) in the analyst reports.

In Columns (4) and (5) of Table 5, we report OLS regression results of *Financial* and *Number* on *Female* using the same model specifications as in our sentiment regression tests. We find that female analyst reports include fewer financial terms and use less numbers: *Female* loads negatively and significantly at 1 percent level for both *Financial* and *Number*. In terms of economic significance, women tend to use 2 percent fewer financial terms and 15 percent fewer numbers than men in the analyst reports. These results also provide some indirect evidence that female analysts might be producing more nonfinancial information compared to male analysts.

We further explore nonfinancial content of analyst reports by looking at the reports' language around forecast horizon. Forecast horizon can be affected by performance measures stipulated in an accounting system which is essentially short-term oriented (Marginson and McAulay, 2008). In other words, financial content is more related to short-termism and nonfinancial content is more related to long-termism. Given our findings that female analysts tend to mention fewer financial terms and numbers in their reports, they might be more interested in nonfinancial information that tends to be long-term oriented.

In our next set of tests, we examine whether women analysts are more likely to use short-term or long-term oriented words than men. In Columns (6) and (7) of Table 5 we use *ShortTerm* and *LongTerm* as our dependent variables and apply the same regression specifications as in the previous tests. We note that in Column (6) *Female* loads negatively and significantly on *ShortTerm*, indicating that women tend to mention fewer short-term horizon words and phrases than men. In contrast, *Female* loads positively and significantly on *LongTerm*, suggesting that women tend to focus on more long-term time horizon than men when writing their reports. These results seem to provide some additional explanation as to why women tend to be less focused on financial and numerical results than men.

[Insert Table 5]

5.5. Gender differences in market reaction to the report content

Focusing on the *quantitative* information produced by analysts, prior studies find that female analyst forecast revisions elicit stronger market reactions (Kumar, 2010). In our next set of tests, we examine whether gender differences also exist in market reaction to the *qualitative* content of analyst reports. We focus on the immediate market reaction after the analyst report is released and use the following regression specification:

$$CARabs = \alpha + Female \times Netabs + Female \times ReadPCA + Female \times LenPCA$$
$$+ Female + Netabs + ReadPCA + LenPCA + AnalystControls + \varepsilon \quad (3)$$

Our dependent variable is the absolute value of cumulative abnormal returns (*absCAR*). We calculate *CAR* as the Fama-French 3 factor and momentum factor-adjusted cumulative abnormal return over the [0,+1] analyst report release window. Our main variables of interest are the interaction terms of our *Female* analyst gender indicator and three textual measures: absolute value of sentiment (*NetAbs*) and our combined measures of readability (*ReadPCA*) and length (*LenPCA*). If market participants react differently to the sentiment, readability, and length of analyst reports produced by women, we expect to see significant coefficients for these interaction terms. Finally, we add a control for the number of total sell-side analyst reports for the target firm over the [0,+1] window (*Concentration*), as the market may react more strongly when more reports are issued.[11]

Column (1) of Table 6 reports the results. When we look at the textual measures of sentiment, readability and length, we note that they all load significantly, indicating that market participants tend to react to the qualitative aspects of analyst reports. We note positive market reactions to *Netabs* and *ReadPCA*, suggesting that analyst reports with stronger sentiment and more clear content elicit a stronger immediate market reaction. We note a negative reaction to the report length, indicating that more lengthy reports might be associated with weaker reactions at the time of its release, as investors might need more time to digest the content of these reports.

Next, we examine whether market reacts to the analysts' gender. We note that the interactions for *Female*×*Netabs* and *Female*×*ReadPCA* are statistically significant at 5 and 10 percent levels,

[11] We also conduct a firm-day level regression analysis by aggregating reports for the same firm on the same day and using the fraction of reports issued by female analysts in place of the analyst-level gender indicator variable. Results are similar.

respectively. Therefore, it appears that investors do care about the analysts' gender when reacting to report's readability and sentiment. Looking at the sign, we note that the association is negative, and, in effect, is diminishing the positive effects of *Netabs* and *ReadPCA* variables. This seems to suggest that the sentiment and the clarity of reports written by female analysts induce weaker market reactions from the investors.[12]

Our next set of tests examines whether this result holds in both earnings news window and outside it. Although analysts react to and issue reports for various company events, quarterly earnings announcements are a primary determinant of report issuance. Additionally, prior studies find that the two genders behave differently outside of earnings news window (Green, Jegadeesh, and Tang, 2009). Following Ivković and Jegadeesh (2004), we calculate the number of trading days relative to quarterly earnings announcement dates (EAD) and examine the distribution by gender in Figure 2. The results indicate that while both female and male analyst reports cluster in the first trading week relative to EAD, women are less likely to issue reports immediately around EAD.

[Insert Figure 2]

Next, we divide our sample into reports issued within two days of earnings announcement (EAD) and those outside of the two-day window (non-EAD) and re-run Model (3) regression for each sub-sample separately. Columns (2) and (3) of Table 6 report the results. We note that while the interaction terms *Female*×*Netabs* and *Female*×*ReadPCA* continue to load negatively for both EAD and non-EAD windows, the statistical significance is concentrated outside of earnings announcement. In other words, investors respond less strongly to the clarity and sentiment of reports written by women than men outside of EAD window, potentially as there is more scrutiny

[12] In untabulated analysis, we exclude the reports in earnings announcement windows and re-run models in Table 6. Our inferences are unaltered.

of analyst reports outside of busy earnings days. As a robustness test, in columns (4) through (6) of Table 6, we repeat our analysis using abnormal trading volume (ATV) as a dependent variable and find consistent results.

Overall, our results of market reactions indicate that market participants pay attention to the readability, sentiment and length of the analyst reports. However, when it comes to reports written by women, the market reaction is less pronounced. This seems to indicate that female analyst reports might be undervalued in the marketplace, which is consistent with prior evidence of gender discrimination in finance.

6. Additional Analyses

6.1. Time trend of analyst report characteristics

Given the higher standard females must meet when being evaluated, women exhibit a superior learning curve and adjust writing style both proactively and gradually (Hengel, 2022). Figure 3 plots the median report readability over the career of analysts. This graph shows that there is a downward trend in readability for male analysts while the readability of female analysts varies more over time. Figure 4 shows a general downward trend for female analysts relative to male counterparts with respect to Loughran and McDonald (2011) positive tone.[13]

[Insert Figure 3]

[Insert Figure 4]

To explore whether female analysts improve their writing ability over time, we include interaction terms between *Female* and the number of years since the analyst's first report date in our sample (*Career*). Results are reported in Table 7. The positive interaction in column (1)

[13] In unreported figures, we use the sub-sample of analysts that were active for the entire sample period to account for survivorship bias and find a similar trend.

suggests that female analysts' writing quality improves over time, though they start their career with similar writing ability compared to male analysts. The influence of experience on writing quality is higher for female analysts. However, as suggested by results in Column (2) female analyst report length does not significantly change with experience. Next, we explore whether career progression affects report sentiment. Our results in Columns (3)-(5) suggest that female analysts use less positive language as their careers progress, possibly reflecting more objective analysis from a higher ethical standard.[14]

[Insert Table 7]

6.2. Analyst report characteristics and issuance around earnings announcements

Previous studies argue that forecasts not issued around earnings announcement dates are more likely based on independently sourced research instead of earnings news (Green, Jegadeesh, and Tang, 2009). To examine this in the context of gender, we include an indicator which is equal to 1 if a report is issued within two days of an earnings announcement (*EA*) and interact this variable with analyst gender. If female analysts have better writing skill or dissimilar style based on their individually produced information (i.e., not directly earnings announcement related), gender differences across *EA* reports should be larger.

In Panel A of Table 8, we find that reports issued around earnings announcement dates are more readable. However, the interaction of *Female* and *EA* in column 1 shows that the advantage of female report readability is lower (higher) for reports (not) driven by earnings announcements, consistent with our prediction. Column 3 of Panel A suggests that female analyst reports issued outside of earnings announcement windows are less positive in sentiment.

[14] In untabulated results, we also observe small decreases (increases) in financial (numerical) content over time for feme analysts. There are no significant career related differences in short- or long-term report content across analyst gender.

We examine additional textual features by gender around earnings announcements in Panel B of Table 8. Column 1 shows that female analyst reports issued outside of earnings announcements also contain more financial information, suggesting that these reports have incremental value in additional to the substantial financial information contained in earnings announcements (Landsman and Maydew, 2002). Additionally, column 4 of Panel B shows female analyst reports around earnings announcements are more long-term in nature. This long-term focus balances corporate management's fear that short-term earnings results can induce large price declines in a firm's stock (Hotchkiss and Strickland, 2003).

6.3. Work length dispersion

Female analysts may choose to distribute their effort differently across firms from their male counterparts, which is likely observed in firm-specific variations in report length. To examine this possibility, we create a Herfindahl–Hirschman Index (*HHI*) for analyst report length. Specifically, we first calculate the average number of words in reports for each of the firms an analyst covers in each year and then calculate the *WorkHHI* at the analyst-year level based on the average number of words in reports on each firm. For example, an analyst who covers 10 firms and only writes reports on one firm would have *WorkHHI* of 100 while an analyst who covers 10 firms and writes an average of 100 words on each firm would have *WorkHHI* of 10. While univariate comparisons in Table 3 show that female analysts concentrate more of their effort on specific firms, no gender difference in report length dispersion is observed in untabulated multivariate results.

6.4. Text-recommendation consistency

Previous studies find that analysts may issue inconsistent stock recommendations and earnings forecasts to balance the interests of coverage firms and investors (Malmendier and Shanthikumar, 2007). If female analysts are less influenced by conflict of interest, we expect to observe that female analysts issue more consistent reports. We construct an indicator variable—*Consistency*—which is equal to 1 if both analyst recommendation and report tone are above each sample mean. In untabulated multivariate results, we find no gender differences in *Consistency*.

6.5. Propensity score matching

Because analyst characteristics are significantly different between female and male analysts, we conduct a one-to-one analyst-level propensity score matching with replacement based on the analyst variables. We re-run all analyses of readability, tone, time horizon, and market reaction for the matched sample and these untabulated results largely hold.

7. Conclusion

Motivated by existing evidence of gender differences in analyst headline quantitative outputs (e.g., earnings estimates, recommendations, etc.), we compare the textual characteristics of reports between female and male analysts. Controlling for quantitative measures including earnings forecasts, stock recommendations, and price targets, we find female analysts issue more readable reports and improve report readability over time relative to male counterparts. However, female analyst reports are shorter, consistent with a "quality over quantity" approach. The textual sentiment of female analyst reports is also less optimistic, suggesting that they are more resistant to conflicts of interest than their male counterparts. Moreover, female analyst reports contain more nonfinancial content and are more long-term oriented. Market reactions (abnormal returns and trading volume) to female analyst report characteristics (readability and absolute sentiment) are different from their male counterparts.

In additional tests, we compare the changes in report characteristics between female and male analysts over their career and find that female analysts tend to improve readability and use less positive language. Also, reports written by female analysts outside of earnings announcement windows are more readable, contain more financial information, and are less long-term focused.

Overall, our findings contribute to a better understanding of how gender differences in writing abilities and gender stereotyping collectively affect gender differences in analyst report text characteristics and market reactions. Future research may attempt to explore how female and male analysts consider various topics when compiling their reports.

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Appendix A – Variable definitions

Variable	Definition
Readability	
Fog	The Gunning-Fog index
FKGL	The Flesch-Kincaid Grade Level index
FRE	The Flesch Reading Ease index
Dale	The Dale-Chall index
SMOG	The Simple Measure Gobbledegook index
ReadPCA	First principal component of the five readability indices
Length	
Word	Logarithm of the number of words in the report
Page	Number of pages of the report
LenPCA	First principal component of the two length measures
Sentiment characteristics	
Pos	Percentage of positive words in the report based on Loughran and McDonald (2011) dictionary
Neg	Percentage of negative words in the report based on Loughran and McDonald (2011) dictionary
Net	The difference between *Pos* and *Neg*
Topics	
Financial	Percentage of financially oriented words based on Matsumoto, Pronk, and Roelofsen (2011).
Number	Ratio of numerical content to words, in percentage (%)
ShortTerm	Percentage of short-term oriented words developed by Brochet, Loumioti, and Serafeim (2015).
LongTerm	Percentage of long-term oriented words developed by Brochet, Loumioti, and Serafeim (2015).
Report characteristics	
EA	Indicator variable equal to 1 if the firm issues an earnings announcement over the [-2,+2] window centered on report date.
Concentration	The number of reports for the target firm over a [0,+1] window relative to the report date.
SameDayAnaReport	Number of reports issued on the same day by the analyst
CAR	The cumulative abnormal return over the [0,+1] window relative to the report date based on Fama-French 4-factor model
Runup	The cumulative abnormal return over the [-10,-1] window relative the report date based on Fama-French 4-factor model
ATV	The standardized cumulative abnormal trading volume over the [0,+1] window relative to the report date

Analyst characteristics	
Female	Indicator variable equal to 1 if the author of the report is female and 0 otherwise
RevFavor	Number of upward earnings forecasts, stock recommendations, and price target revisions minus the number of downward revisions made by the analyst on the coverage firm prior to the report date
AllStar	Indicator variable equal to 1 if the analyst is ranked as an *Institutional Investor* All-Star in the current year
GenExp	The number of years between the analyst's first forecast date on I/B/E/S and the report date
FirmExp	The number of years between the analyst's first forecast date for the firm and the report date
BrokerSize	The number of analysts issuing earnings forecasts from the report analyst's brokerage house in the report year
IndCover	The number of Fama-French 48 industries covered by an analyst in the prior calendar year of the report
FirmCover	The number of firms covered by an analyst in the prior calendar year of the conference call.
Frequency	Number of reports issued by the analyst in the report year
Accuracy	Earnings forecast accuracy defined as negative one times the difference between absolute forecast error and mean absolute forecast error, scaled by the mean absolute forecast error from Clement (1999).
WorkHHI	HHI of firm-level aggregated average report length across covered firms for each analyst-year
Consistency	Indicator variable equal to 1 if both analyst recommendation and report tone are above each sample mean
Firm characteristics	
BM	The book value of equity to market value of equity at the end of last fiscal year end
Size	Logarithm of firm market value at the end of last fiscal year
Segment	Number of unique 4-digit SIC industry operating segments within the firm
InstOwn	The percentage of institutional ownership at the end of last fiscal year end

Figure 1 – Distribution of analyst reports by gender and year

This figure plots the percentage of reports by female analysts by year and the number of analyst reports by gender and year.

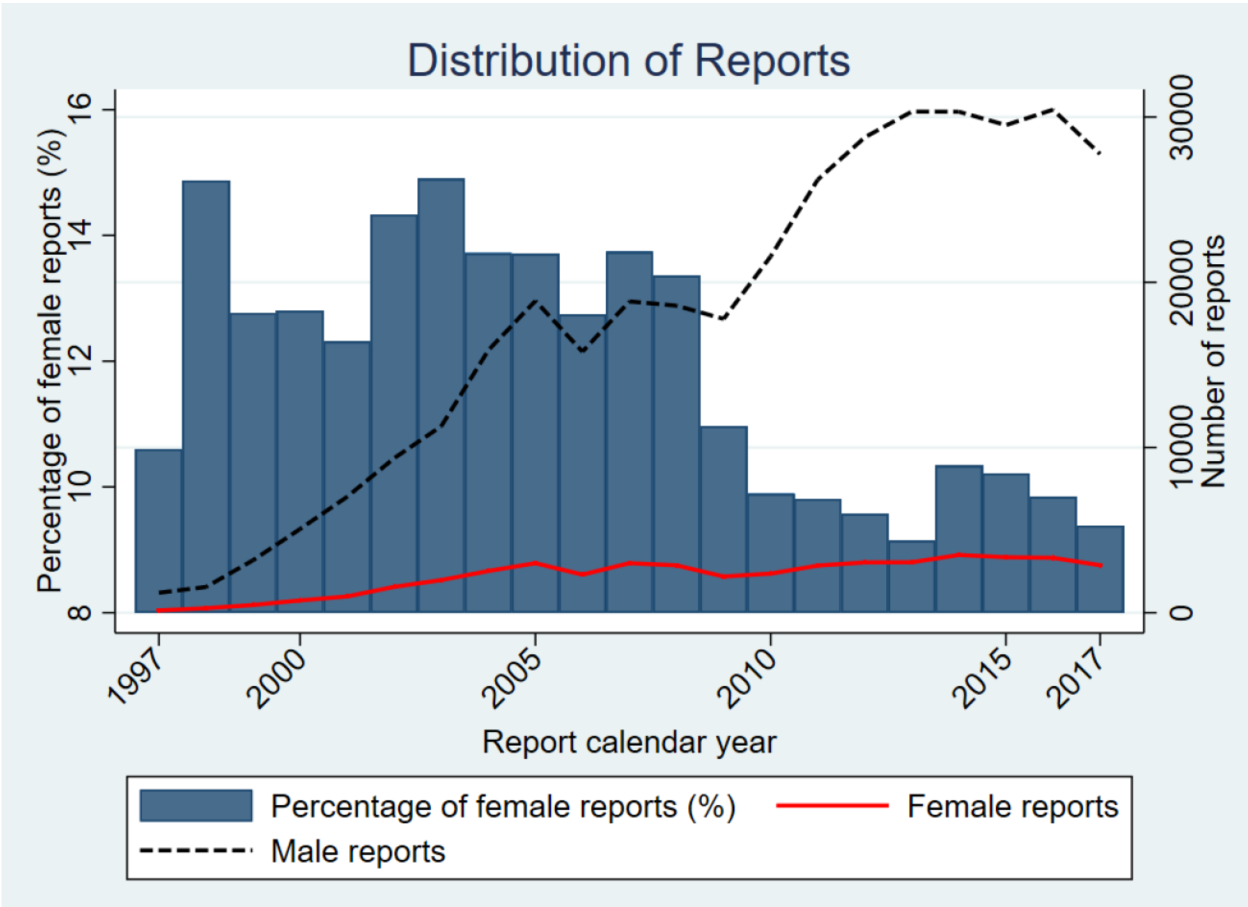

Figure 2 – Reporting timing distribution

This figure reports the report timing distribution of reports by gender around quarterly earnings announcement dates.

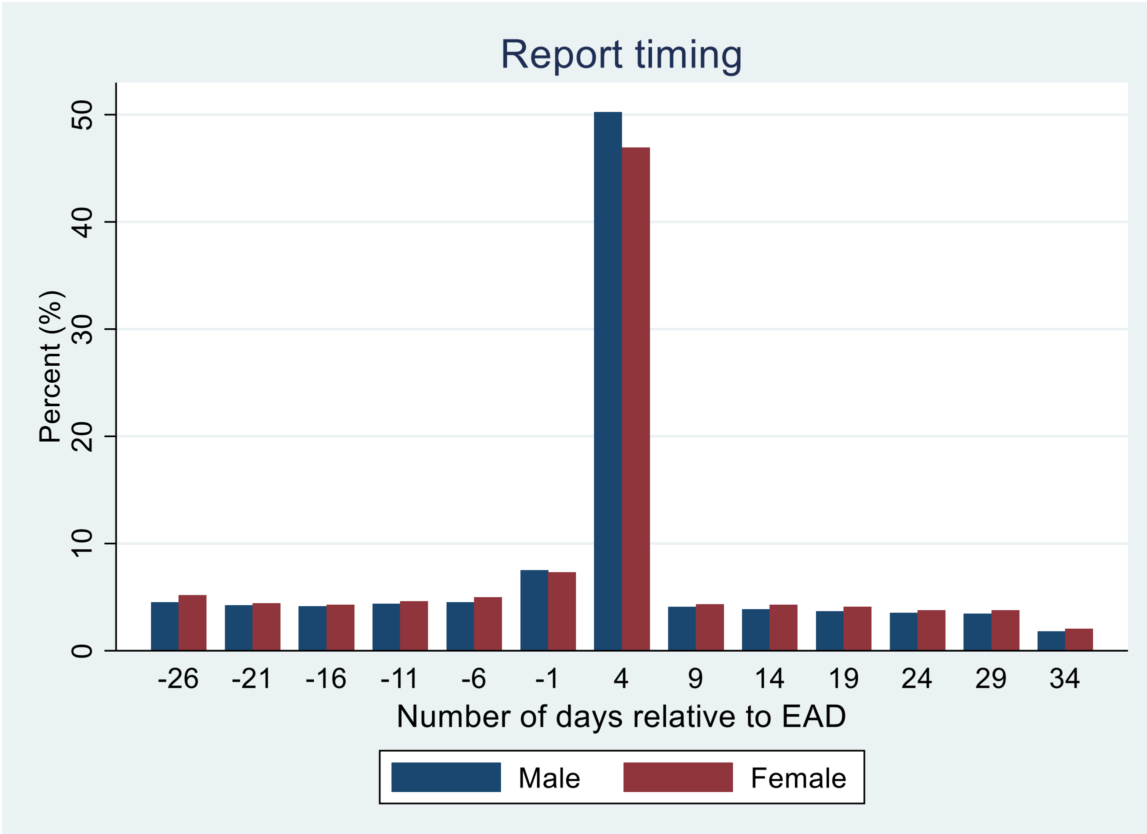

Figure 3 – Report readability by career progression

This figure reports median readability over the career of female and male analysts using the first principal component of the five readability measures (*ReadPCA*).

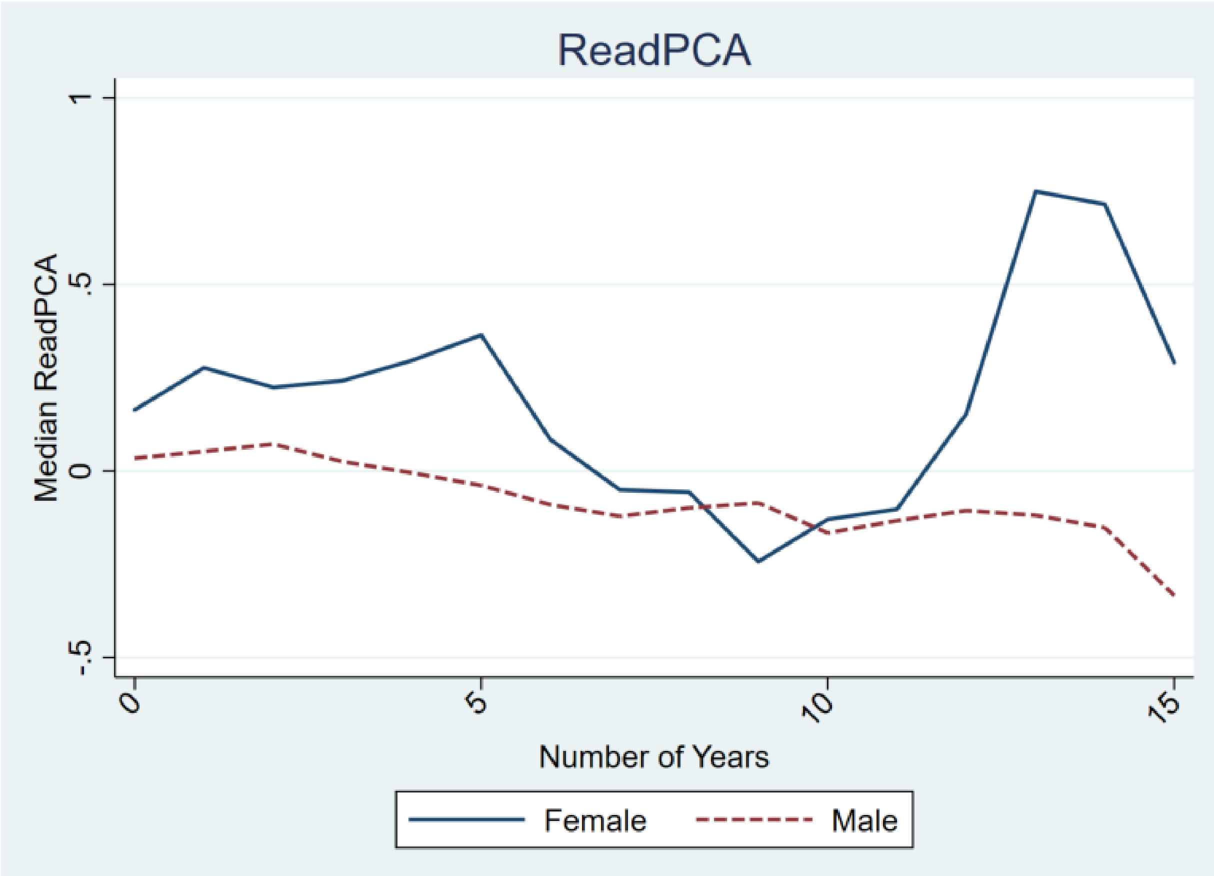

Figure 4 – Report tone by career progression

This figure reports Loughran and McDonald (2011) positive sentiment (*Pos*) over the career of female and male analysts.

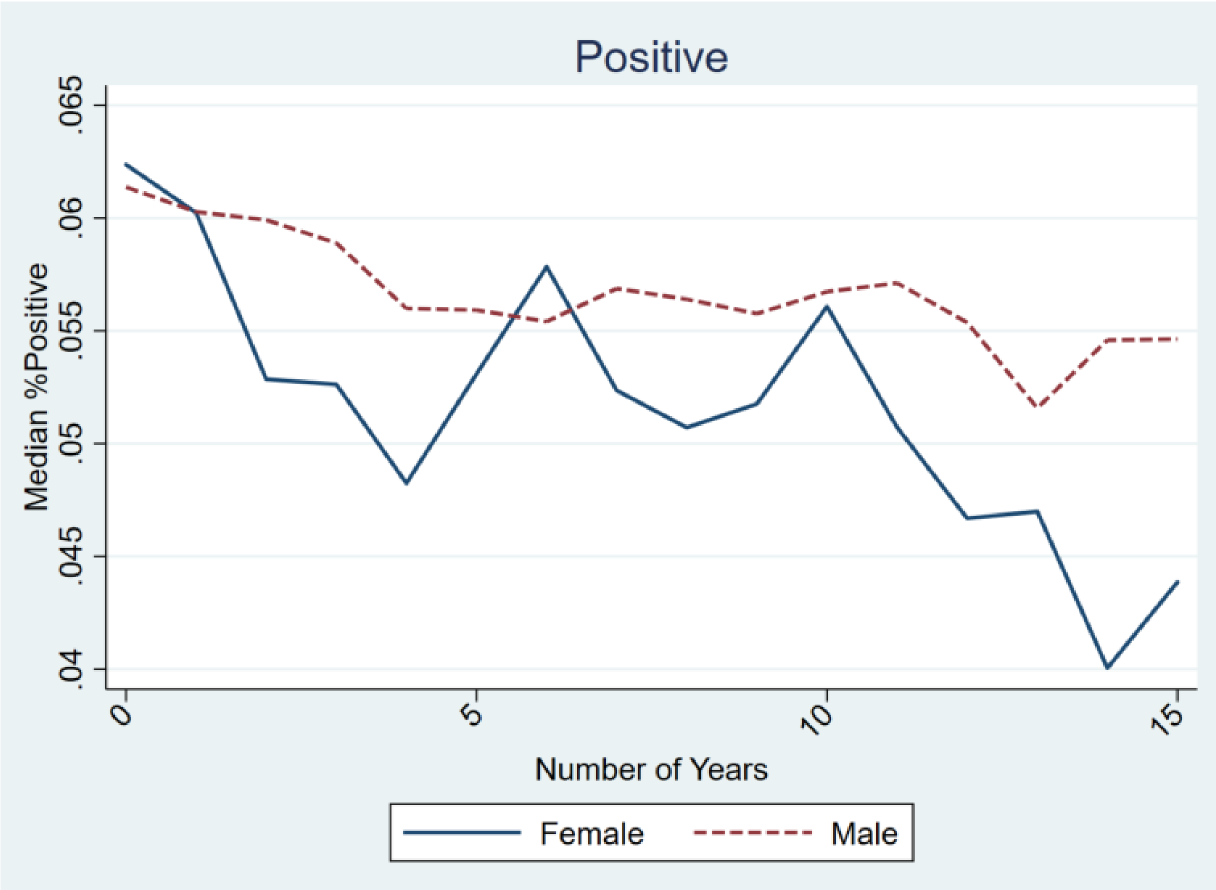

Table 1 - Summary statistics

Table 1 reports summary statistics of key variables used in the analysis. The total number of observations is 415,744. The time period used is 1997 to 2017. See Appendix A for variable definitions.

	Mean	Std. Dev.	Min	p25	Median	p75	Max
Readability							
Fog	-15.270	4.083	-50	-16.734	-15.035	-13.303	-0.224
FKGL	-11.825	3.473	-30	-13.253	-11.671	-10.056	3.515
FRE	56.233	10.016	-20	51.054	56.035	61.204	100
Dale	-10.620	0.866	-20	-10.964	-10.598	-10.168	-3.929
SMOG	-12.914	1.819	-40	-13.915	-13.087	-12.095	-3.129
ReadPCA	0	1.934	-19.988	-0.896	-0.031	0.947	9.808
Length							
Word	8.026	0.759	4.605	7.652	8.132	8.524	12.042
Page	1.838	0.648	0	1.609	1.792	2.197	5.759
LenPCA	0	1.376	-5.191	-0.656	0.131	0.856	7.821
Sentiment characteristics							
Pos	0.074	0.074	0	0.022	0.057	0.104	0.398
Neg	0.162	0.114	0	0.090	0.142	0.209	0.626
Net	-0.089	0.133	-0.559	-0.152	-0.078	0.000	0.298
Topics							
Financial	0.805	0.570	0	0.333	0.714	1.146	2.824
Number	0.056	0.045	0.005	0.022	0.039	0.080	0.203
ShortTerm	0.017	0.037	0	0	0	0.021	0.234
LongTerm	0.035	0.054	0	0	0.015	0.048	0.289
Report characteristics							
RevFavor	-0.134	1.274	-3	-1	0	1	3
EA	0.471	0.499	0	0	0	1	1
SameDayReport	4.238	4.318	1	1	2	6	31
SameDayAnaReport	1.614	1.288	1	1	1	2	35
CAR	-0.049	6.432	-23.656	-2.515	0.040	2.630	20.577
Runup	0.044	8.080	-27.739	-3.601	0.180	3.889	25.968
ATV	1.182	1.826	-11.791	-0.087	1.040	2.292	15.029
Analyst characteristics							
Female	0.112	0.315	0	0	0	0	1
AllStar	0.182	0.386	0	0	0	0	1
GenExp	14.08	8.887	0.786	6.153	13.219	21	33.334
FirmExp	4.339	4.590	0	1.121	2.770	5.942	22.893
BrokerSize	64.511	48.419	1	24	49	101	290
IndCover	2.999	1.977	1	1	2	4	10
FirmCover	16.182	7.102	1	12	16	20	38
Frequency	57.317	45.965	4	26	45	74	242
Accuracy	0.011	0.686	-2.468	-0.305	0	0.528	1
WorkHHI	26.605	19.830	6.339	14.402	20.382	33.412	100
Consistency	0.453	0.498	0	0	0	1	1
Firm characteristics							
BM	0.456	0.369	0.028	0.203	0.358	0.599	2.076
Size	7.937	1.861	0.180	6.655	7.861	9.221	13.183
Segment	1.515	0.874	1	1	1	2	7
InstOwn	0.735	0.265	0	0.626	0.805	0.919	1.163

Table 2 – Correlation matrix

Table 2 reports correlations between female, readability, length, and topic variables. See Appendix A for variable definitions.

Variables	*Female*	*Fog*	*FKGL*	*FRE*	*Dale*	*SMOG*	*Read PCA*	*Word*	*Page*	*Len PCA*	*Net*	*Financial*	*Number*	*Short Term*
Female	1.000													
Fog	0.029	1.000												
FKGL	0.032	0.974	1.000											
FRE	0.031	0.855	0.843	1.000										
Dale	0.014	0.308	0.230	0.412	1.000									
SMOG	0.041	0.811	0.816	0.895	0.292	1.000								
ReadPCA	0.035	0.954	0.943	0.953	0.428	0.921	1.000							
Word	-0.013	-0.130	-0.170	-0.046	0.104	-0.094	-0.099	1.000						
Page	-0.021	-0.139	-0.174	-0.058	0.071	-0.118	-0.115	0.894	1.000					
LenPCA	-0.017	-0.138	-0.177	-0.053	0.090	-0.109	-0.110	0.973	0.973	1.000				
Net	0.004	-0.072	-0.050	0.033	-0.025	0.017	-0.021	0.099	0.089	0.096	1.000			
Financial	-0.026	-0.344	-0.330	-0.052	0.150	-0.131	-0.199	0.136	0.208	0.177	0.158	1.000		
Number	-0.004	-0.354	-0.360	-0.035	0.204	-0.102	-0.192	0.324	0.300	0.321	0.100	0.496	1.000	
ShortTerm	0.001	-0.026	0.004	0.015	-0.054	0.018	-0.004	-0.070	-0.013	-0.042	0.078	0.066	-0.022	1.000
LongTerm	0.028	-0.001	0.009	0.100	0.093	0.074	0.056	-0.059	-0.033	-0.047	0.084	0.141	0.055	0.175

Table 3 – Univariate test statistics

Table 3 reports two-sample t-test results between female and male analysts. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Appendix A.

	Female (n = 46,396)	Male (n = 369,348)	Difference	t-stat
Readability				
Fog	-14.940	-15.312	0.371	18.478***
FKGL	-11.515	-11.863	0.349	20.399***
FRE	57.114	56.122	0.992	20.124***
Dale	-10.586	-10.624	0.038	8.897***
SMOG	-12.706	-12.940	0.234	26.174***
ReadPCA	0.190	-0.024	0.214	22.456***
Length				
Word	7.999	8.030	-0.031	-8.164***
Page	1.799	1.843	-0.044	-13.692***
LenPCA	-0.068	0.008	-0.076	-11.229***
Sentiment characteristics				
Pos	0.071	0.074	-0.003	-7.566***
Neg	0.158	0.163	-0.005	-8.411***
Net	-0.087	-0.089	0.002	2.814**
Topics				
Financial	0.762	0.810	-0.048	-16.974***
Number	0.055	0.056	-0.000	-2.688**
ShortTerm	0.017	0.017	0.000	0.849
LongTerm	0.039	0.034	0.005	18.102***
Report characteristics				
RevFavor	-0.117	-0.136	0.020	3.116**
EA	0.440	0.475	-0.035	-14.277***
SameDayReport	4.334	4.226	0.107	5.051***
SameDayAnaReport	1.768	1.595	0.173	27.283***
CAR	-0.109	-0.042	-0.067	-2.117*
Runup	0.058	0.042	0.016	0.412
ATV	1.164	1.184	-0.020	-2.241*
Analyst characteristics				
AllStar	0.234	0.175	0.059	31.103***
GenExp	12.978	14.218	-1.240	-28.364***
FirmExp	4.080	4.372	-0.291	-12.890***
BrokerSize	70.779	63.723	7.056	29.618***
IndCover	2.794	3.025	-0.231	-23.709***
FirmCover	14.826	16.353	-1.527	-43.745***
Frequency	60.978	56.857	4.122	18.212***
Accuracy	-0.003	0.013	-0.016	-4.665***
WorkHHI	29.387	26.255	3.131	32.100***
Consistency	0.465	0.451	-0.014	-5.155***
Firm characteristics				
BM	0.408	0.462	-0.054	-30.005***
Size	8.064	7.921	0.143	15.609***
Segment	1.613	1.502	0.110	25.669***
InstOwn	0.733	0.736	-0.002	-1.771

Table 4 - Analyst report readability and length

Table 4 reports the results for readability and length. Panel A reports OLS regression results for each readability and length measure. Panel B reports results using the first principal component for the readability and length measures. Standard errors are clustered at firm level. The time period is 1997 to 2017. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Appendix A.

Panel A: OLS regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	*Fog*	*FKGL*	*FRE*	*Dale*	*SMOG*	*Word*	*Page*
Female	0.148**	0.138**	0.537***	0.028***	0.090***	-0.041***	-0.048***
	(0.065)	(0.061)	(0.187)	(0.010)	(0.031)	(0.014)	(0.014)
EA	0.180***	0.149***	1.082***	0.042***	0.134***	0.023***	0.001
	(0.022)	(0.019)	(0.043)	(0.004)	(0.008)	(0.005)	(0.005)
AllStar	0.140***	0.125***	0.286**	-0.010	0.030*	0.037***	0.038***
	(0.041)	(0.038)	(0.112)	(0.010)	(0.018)	(0.011)	(0.009)
GenExp	0.010***	0.010***	0.035***	0.002***	0.005***	0.001**	0.000
	(0.003)	(0.002)	(0.006)	(0.000)	(0.001)	(0.000)	(0.000)
FirmExp	0.007	0.006	-0.001	0.000	0.001	-0.003***	-0.003***
	(0.005)	(0.004)	(0.011)	(0.001)	(0.002)	(0.001)	(0.001)
IndCover	-0.047***	-0.045***	-0.132***	0.002	-0.017***	0.001	0.001
	(0.014)	(0.012)	(0.030)	(0.003)	(0.005)	(0.002)	(0.002)
FirmCover	-0.002	-0.002	0.007	-0.000	0.000	0.001	0.000
	(0.003)	(0.003)	(0.007)	(0.001)	(0.001)	(0.001)	(0.000)
Frequency	0.000	0.000	0.001	0.000	0.001**	-0.001***	-0.001***
	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Accuracy	-0.023**	-0.022***	-0.061***	0.001	-0.009**	0.004***	0.002
	(0.009)	(0.008)	(0.022)	(0.002)	(0.004)	(0.001)	(0.001)
BM	-0.051	-0.032	-0.288	-0.053	-0.018	0.090***	0.065**
	(0.168)	(0.137)	(0.367)	(0.034)	(0.068)	(0.029)	(0.026)
Size	0.108	0.079	0.236	-0.035	0.071*	0.047***	0.031**
	(0.095)	(0.078)	(0.227)	(0.022)	(0.041)	(0.014)	(0.013)
Segment	-0.072	-0.082	-0.069	-0.003	0.011	0.005	0.003
	(0.099)	(0.074)	(0.227)	(0.018)	(0.050)	(0.017)	(0.015)
InstOwn	-0.131	-0.188	-0.313	0.066*	-0.096	0.019	0.027
	(0.158)	(0.130)	(0.411)	(0.040)	(0.071)	(0.025)	(0.021)
Constant	-16.041***	-12.309***	53.954***	-10.419***	-13.545***	7.623***	1.583***
	(0.859)	(0.691)	(2.015)	(0.183)	(0.372)	(0.125)	(0.116)
Observations	415,744	415,744	415,744	415,744	415,744	415,744	415,744
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Broker-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.307	0.362	0.345	0.344	0.393	0.431	0.372

Panel B: OLS results using principal component analysis

VARIABLES	(1) *ReadPCA*	(2) *LenPCA*
Female	0.094***	-0.090***
	(0.033)	(0.028)
EA	0.142***	0.023**
	(0.008)	(0.010)
AllStar	0.054***	0.076***
	(0.020)	(0.020)
GenExp	0.006***	0.001
	(0.001)	(0.001)
FirmExp	0.002	-0.005***
	(0.002)	(0.002)
IndCover	-0.023***	0.002
	(0.006)	(0.004)
FirmCover	-0.000	0.001
	(0.001)	(0.001)
Frequency	0.000	-0.002***
	(0.000)	(0.000)
Accuracy	-0.011**	0.006**
	(0.004)	(0.003)
BM	-0.043	0.155***
	(0.076)	(0.055)
Size	0.045	0.077***
	(0.045)	(0.027)
Segment	-0.021	0.008
	(0.047)	(0.031)
InstOwn	-0.066	0.047
	(0.074)	(0.044)
Constant	-0.387	-0.654***
	(0.400)	(0.236)
Observations	415,744	415,744
Firm-Year FE	Yes	Yes
Broker-Year FE	Yes	Yes
Adjusted R^2	0.341	0.401

Table 5 - Analyst report sentiment and content

Table 5 reports the OLS regression results for sentiment or topic of analyst reports. Standard errors are clustered at firm level. The time period is 1997 to 2017. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Appendix A.

VARIABLES	(1) *Pos*	(2) *Neg*	(3) *Net*	(4) *Financial*	(5) *Number*	(6) *ShortTerm*	(7) *LongTerm*
Female	-0.003***	-0.003	-0.000	-0.022***	-0.153***	-0.000**	0.001***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.023)	(0.000)	(0.000)
EA	-0.001**	-0.005***	0.004***	0.116***	0.283***	0.001***	0.002***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.013)	(0.000)	(0.000)
RevFavor	0.001***	-0.001***	0.002***	-0.005***	-0.021***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)	(0.000)	(0.000)
AllStar	-0.003***	-0.001	-0.002	-0.016***	-0.201***	0.001***	-0.001***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.022)	(0.000)	(0.000)
GenExp	-0.000**	-0.000	-0.000	-0.000***	-0.002*	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
FirmExp	0.000	0.000*	-0.000	-0.003***	-0.027***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
IndCover	0.000*	-0.001*	0.001***	0.007***	0.005	0.000*	-0.001***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.006)	(0.000)	(0.000)
FirmCover	-0.000	0.000	-0.000	0.001***	0.018***	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Frequency	-0.000	-0.000	0.000	-0.000***	-0.001***	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Accuracy	-0.000	0.001**	-0.001***	0.005***	0.017*	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.009)	(0.000)	(0.000)
BM	-0.001	0.006	-0.006	-0.017	0.035	-0.000	-0.001
	(0.003)	(0.004)	(0.005)	(0.021)	(0.170)	(0.001)	(0.002)
Size	-0.003**	0.001	-0.004	-0.005	0.042	-0.000	-0.000
	(0.002)	(0.003)	(0.003)	(0.011)	(0.086)	(0.001)	(0.001)
Segment	0.000	-0.001	0.002	-0.002	0.048	-0.002**	0.001
	(0.002)	(0.003)	(0.004)	(0.012)	(0.081)	(0.001)	(0.001)
InstOwn	-0.005	0.002	-0.008	-0.009	0.176	-0.002	0.000
	(0.004)	(0.005)	(0.006)	(0.026)	(0.222)	(0.002)	(0.003)
Constant	0.107***	0.156***	-0.052**	0.813***	4.877***	0.022***	0.035***
	(0.014)	(0.021)	(0.026)	(0.098)	(0.740)	(0.007)	(0.009)
Observations	415,744	415,744	415,744	415,744	415,744	415,744	415,744
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Broker-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.254	0.426	0.384	0.338	0.293	0.245	0.318

Table 6 – Market reaction

Table 6 reports OLS regression results for the absolute value of *CAR [0,+1]* (*CARabs*) and abnormal trading volume (*ATV*). The time period is 1997 to 2017. Standard errors are clustered at the firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in Appendix A.

	Full	Non-EAD	EAD	Full	Non-EAD	EAD
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*CARabs*	*CARabs*	*CARabs*	*ATV*	*ATV*	*ATV*
Female × Netabs	-0.513**	-0.649***	-0.347	-0.157**	-0.224***	-0.138
	(0.257)	(0.225)	(0.542)	(0.076)	(0.075)	(0.141)
Female × ReadPCA	-0.028*	-0.032*	-0.042	-0.005	-0.002	-0.015**
	(0.017)	(0.019)	(0.027)	(0.005)	(0.006)	(0.008)
Female × LenPCA	-0.025	0.030	-0.033	0.012	0.029***	0.005
	(0.028)	(0.028)	(0.052)	(0.010)	(0.011)	(0.014)
Female	0.023	0.039	0.046	-0.012	-0.005	0.002
	(0.066)	(0.067)	(0.098)	(0.018)	(0.021)	(0.026)
Netabs	0.853***	0.739***	1.148***	0.191***	0.221***	0.185***
	(0.116)	(0.130)	(0.187)	(0.038)	(0.044)	(0.050)
ReadPCA	0.018**	0.011	0.045***	0.001	-0.001	0.008**
	(0.008)	(0.009)	(0.012)	(0.002)	(0.003)	(0.003)
LenPCA	-0.032***	-0.072***	0.073***	-0.007*	-0.016***	0.014**
	(0.012)	(0.013)	(0.023)	(0.004)	(0.004)	(0.006)
EA	0.652***			0.477***		
	(0.088)			(0.028)		
Concentration	0.229***	0.405***	0.181***	0.115***	0.186***	0.070***
	(0.016)	(0.032)	(0.013)	(0.004)	(0.007)	(0.004)
AllStar	0.057	0.054	0.065	0.003	0.025	-0.019
	(0.052)	(0.064)	(0.070)	(0.019)	(0.024)	(0.021)
Frequency	0.000	-0.001	0.001	-0.001***	-0.002***	-0.001**
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Accuracy	0.163***	0.155***	0.146***	0.014*	0.024**	-0.005
	(0.024)	(0.030)	(0.035)	(0.008)	(0.010)	(0.010)
Constant	11.750***	10.872***	13.296***	1.466***	1.657***	1.419***
	(0.308)	(0.382)	(0.362)	(0.081)	(0.095)	(0.097)
Observations	415,744	219,722	196,022	415,744	219,722	196,022
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Brokerage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm/Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.136	0.134	0.143	0.227	0.176	0.193

Table 7 – Time trend of analyst report readability, length, and tone

Table 7 reports OLS regression results of the impact of analyst career on the readability, length, and tone measures. Robust standard errors are reported in parentheses. The time period is 1997 to 2017. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined Appendix A.

VARIABLES	(1) *ReadPCA*	(2) *LenPCA*	(3) *Pos*	(4) *Neg*	(5) *Net*
Female × Career	0.014**	-0.008	-0.001***	0.001***	-0.001***
	(0.006)	(0.005)	(0.000)	(0.000)	(0.000)
Female	0.021	-0.052	0.001	-0.007***	0.007***
	(0.046)	(0.042)	(0.001)	(0.002)	(0.002)
Career	0.009***	-0.003	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
EA	0.142***	0.022**	-0.001**	-0.005***	0.005***
	(0.008)	(0.010)	(0.000)	(0.001)	(0.001)
RevFavor			0.001***	-0.001***	0.002***
			(0.000)	(0.000)	(0.000)
AllStar	0.055***	0.077***	-0.002***	-0.001	-0.002
	(0.020)	(0.020)	(0.001)	(0.001)	(0.002)
IndCover	-0.022***	0.002	0.000	-0.001*	0.001***
	(0.006)	(0.004)	(0.000)	(0.000)	(0.000)
FirmCover	0.000	0.002*	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Frequency	0.000	-0.002***	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BM	-0.033	0.149***	-0.001	0.005	-0.005
	(0.075)	(0.055)	(0.003)	(0.004)	(0.005)
Size	0.051	0.075***	-0.003**	0.001	-0.004
	(0.044)	(0.027)	(0.002)	(0.003)	(0.003)
Segment	-0.023	0.008	0.000	-0.001	0.002
	(0.047)	(0.031)	(0.002)	(0.003)	(0.004)
InstOwn	-0.057	0.044	-0.005	0.001	-0.007
	(0.074)	(0.044)	(0.004)	(0.005)	(0.006)
Constant	-0.402	-0.633***	0.106***	0.157***	-0.055**
	(0.399)	(0.236)	(0.014)	(0.021)	(0.026)
Observations	415,744	415,744	415,744	415,744	415,744
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
Broker-Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.341	0.401	0.254	0.426	0.384

Table 8 – Analyst report issuance around earnings announcement

Table 8 reports OLS regression results of the impact of report issuance around the earnings announcement on the readability or length measures and the topic variables. Robust standard errors are reported in parentheses. The time period is 1997 to 2017. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined Appendix A.

Panel A: Readability, length, and sentiment					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	*ReadPCA*	*LenPCA*	*Pos*	*Neg*	*Net*
Female	0.119***	-0.108***	-0.004***	-0.003	-0.001
	(0.041)	(0.037)	(0.001)	(0.002)	(0.002)
EA	0.148***	0.018*	-0.001**	-0.005***	0.004***
	(0.009)	(0.010)	(0.000)	(0.001)	(0.001)
Female × EA	-0.054*	0.038	0.002*	0.001	0.001
	(0.031)	(0.029)	(0.001)	(0.001)	(0.002)
RevFavor			0.001***	-0.001***	0.002***
			(0.000)	(0.000)	(0.000)
AllStar	0.054***	0.076***	-0.003***	-0.001	-0.002
	(0.020)	(0.020)	(0.001)	(0.001)	(0.002)
GenExp	0.006***	0.001	-0.000**	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
FirmExp	0.002	-0.005***	0.000	0.000*	-0.000
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
IndCover	-0.023***	0.002	0.000*	-0.001*	0.001***
	(0.006)	(0.004)	(0.000)	(0.000)	(0.000)
FirmCover	-0.000	0.001	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Frequency	0.000	-0.002***	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Accuracy	-0.011**	0.006**	-0.000	0.001**	-0.001***
	(0.004)	(0.003)	(0.000)	(0.000)	(0.000)
BM	-0.043	0.155***	-0.001	0.006	-0.006
	(0.076)	(0.055)	(0.003)	(0.004)	(0.005)
Size	0.045	0.077***	-0.003**	0.001	-0.004
	(0.045)	(0.027)	(0.002)	(0.003)	(0.003)
Segment	-0.021	0.008	0.000	-0.001	0.002
	(0.047)	(0.031)	(0.002)	(0.003)	(0.004)
InstOwn	-0.066	0.047	-0.005	0.002	-0.008
	(0.074)	(0.044)	(0.004)	(0.005)	(0.006)
Constant	-0.391	-0.651***	0.107***	0.156***	-0.052**
	(0.400)	(0.236)	(0.014)	(0.021)	(0.026)
Observations	415,744	415,744	415,744	415,744	415,744
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
Broker-Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.341	0.401	0.254	0.426	0.384

Panel B: Content				
	(1)	(2)	(3)	(4)
VARIABLES	*Fin*	*Number*	*ShortTerm*	*LongTerm*
Female	-0.006*	-0.158***	-0.000	0.000
	(0.004)	(0.029)	(0.000)	(0.000)
EA	0.119***	0.282***	0.001***	0.002***
	(0.002)	(0.013)	(0.000)	(0.000)
Female × EA	-0.036***	0.010	-0.000	0.002***
	(0.005)	(0.038)	(0.000)	(0.000)
RevFavor	-0.005***	-0.021***	-0.000	-0.000***
	(0.001)	(0.005)	(0.000)	(0.000)
AllStar	-0.016***	-0.201***	0.001***	-0.001***
	(0.003)	(0.022)	(0.000)	(0.000)
GenExp	-0.000***	-0.002*	-0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)
FirmExp	-0.003***	-0.027***	0.000	0.000***
	(0.000)	(0.002)	(0.000)	(0.000)
IndCover	0.007***	0.005	0.000*	-0.001***
	(0.001)	(0.006)	(0.000)	(0.000)
FirmCover	0.001***	0.018***	-0.000***	0.000***
	(0.000)	(0.001)	(0.000)	(0.000)
Frequency	-0.000***	-0.001***	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Accuracy	0.005***	0.017*	0.000	-0.000***
	(0.001)	(0.009)	(0.000)	(0.000)
BM	-0.017	0.035	-0.000	-0.001
	(0.021)	(0.170)	(0.001)	(0.002)
Size	-0.005	0.042	-0.000	-0.000
	(0.011)	(0.086)	(0.001)	(0.001)
Segment	-0.002	0.048	-0.002**	0.001
	(0.012)	(0.081)	(0.001)	(0.001)
InstOwn	-0.009	0.176	-0.002	0.000
	(0.026)	(0.222)	(0.002)	(0.003)
Constant	0.811***	4.877***	0.022***	0.035***
	(0.098)	(0.740)	(0.007)	(0.009)
Observations	415,744	415,744	415,744	415,744
Firm-Year FE	Yes	Yes	Yes	Yes
Broker-Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.338	0.293	0.245	0.318