Do Images Provide Relevant Information to Investors? An Exploratory Study*

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Abstract

We introduce the concept of "visual-readability" in annual reports and innovate by using machine-learning algorithms to construct visual-readability measures. We create a novel measure of content reinforcement, representing the information content investors can extract from images, complementing and reinforcing particulars contained in the textual narrative. An increase in visual prevalence and in the degree to which images convey reinforcing information is associated with greater (lower) analyst forecast accuracy (disagreement) in subsequent quarters. Effects of *visual readability* are distinct from those of textual readability. Using Kelly and Ljungqvist (2012)'s identification, we find that firms increase the use of visuals when facing an exogenous drop in analyst coverage. Our metrics are further associated with lower risk, lower cost-of-equity, and higher credit ratings during the subsequent year. In the age of information overflow, our results highlight the importance of *visual readability* for information assimilation.

Keywords: Visual readability, annual reports, images, image information content, information dissemination, content reinforcement, textual readability, analyst forecast accuracy, analyst disagreement.
JEL Classification: D83, G12, G14, M41

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1 Introduction

Information dissemination by firms reduces information processing costs (Drake, Roulstone, and Thornock, 2016; Blankespoor, 2019) and enhances price efficiency (Blankespoor, Miller, and White, 2014; Gao and Huang, 2020; Gibbons, Iliev, and Kalodimos, 2021). Improved readability of financial reports lessens information asymmetry, and boosts forecasting accuracy and investment efficiency (You and Zhang, 2009; Lehavy, Li, and Merkley, 2011; Lawrence, 2013; Biddle, Hilary, and Verdi, 2009).

To improve readability, firms have included increasingly lengthier narratives accompanied by more, graphs, charts, and images in their disclosures over time. While finance and accounting scholars have extensively researched the role of *textual* readability (e.g., the *FOG* index, Li, 2008), and the frequency of graphs/charts in firms' 10-K filings (Christensen, Fronk, Lee, and Nelson, 2020), they have not examined the impact of images included in their annual reports on information firm outcomes and the information environment. This paper partially addresses this literature gap by examining whether visuals and images in particular, provide incremental information content to annual reports' textual information. We focus on annual reports (rather than SEC filings) because they are subject to fewer guidelines and restrictions on images and are referred to by analysts.[1]

The case of American Science and Engineering, Inc., depicted in Figure 1 illustrates the richness and informativeness of image displays in annual reports. Beyond reading textual descriptions of the firm's technology in the annual report, stakeholders can glean clearer and potentially augmented and more impactful information from the report-contained images.[2] These improvements give rise to a better information environment and can facilitate information assimilation due to a reduction in information processing and other cognitive constraints.[3]

[1] Annual reports are far richer in graphical and image content than 10-K filings and are usually read by most stakeholders as firms post them on the investor relation section of their website. Discussion with analysts indicates that they look to annual reports to understand companies' priorities and what they want to promote. The SEC 2008 Report "Guidance on the Use of Company Web Sites," requires the format of information on firm web sites to be focused on "readability, not printability" and recognizes that "allowing companies to present data in formats different from those dictated by our forms or more technologically advanced than EDGAR may be beneficial to investors." https://www.sec.gov/rules/interp/2008/34-58288.pdf.

[2] A March 3, 2020 Wall Street Journal article relays how, beyond satisfying regulatory requirements, companies engage a broad set of stakeholders by including graphics, videos, and other visual elements in their communications. https://www.wsj.com/articles/companies-find-ways-to-keep-their-annual-reports-from-being-a-bore-11583231402

[3] Scholars have acknowledged the effects of limited investor attention or processing capacity, especially when information is abundant or complex.(Tversky and Kahneman, 1973; Hirshleifer, Lim, and Teoh, 2009, 2011). The psychology literature demonstrates that visuals can mitigate such effects. Experiments show that visual ease can contribute to processing fluency (Alter and Oppenheimer, 2009).

To be responsive to the SEC's plea for "readability not printability," we focus on "visual readability," a term we coin to refer to the enhancement of visual information assimilation via two potentially overlapping channels. The first is attention, through which the use of visuals can mitigate investors' cognitive constraints (Stenning and Oberlander, 1995; Alter and Oppenheimer, 2009). The second, a channel we newly explore, is "content reinforcement," through which visuals reinforce concepts inherent in the narrative.[4] We provide evidence on both channels.

One challenge facing researchers is the systematic identification of images and other visual elements (team photos, charts/graphs, maps, and infographics). We overcome this challenge by combining machine learning algorithms and heuristic rules to objectively identify distinct visual elements. That is, our methodology allows us to identify whether a visual element is an image, a chart, a map, an infographic or a team/management photo. We conjecture, however, that page-level visual representation best captures readers' focal experience and therefore identifies visual content at the annual report page level. Therefore, after classifying pages into non-visual pages (those that do not contain visual elements) and visual pages (those that do), we use our algorithms to decompose the latter into five categories: visual pages with predominantly images (henceforth image-pages), visual pages with predominantly team/management photos (team-pages), and visual pages with predominantly charts, infographics and/or maps (charts-pages, maps-pages, and infographics-pages). We find that 74.3% of the reports in our sample (annual reports for S&P 1500 firms from 2002 to 2019) include pages with at least some visual elements, 72.5% of reports include image-pages, 40.7% include team-pages, and 10.5% include pages with predominantly charts, maps, or infographics.[5] Visual use does not seem to be concentrated in any specific industries.

We create two sets of measures: visual prevalence and content reinforcement measures. To reflect the intensity of visual use, or visual prevalence, we create the following measures: *IMGC* the number of image-pages; *TC* the number of team-pages; and *CMIC* the union of the numbers of charts-pages, maps-pages, and infographics-pages. We also separately create *AVC*, which is the union of *IMGC*, *TC*, and *CMIC*. These visual prevalence measures, in capturing the reader's overall exposure to visuals, are intuitive and geared towards capturing investor attention (i.e., the attention

[4] As an example of lab experiments addressing the nexus between pictures and text in other contexts, see (Glenberg and Langston, 1992).

[5] The 10.5% of firms we identify as using predominantly charts, maps, or infographics pages likely represents a lower bound on the number of actual charts, infographics, and maps in reports, since our visual identification analysis is conducted at the page level.

channel). If visuals inform, greater visual prevalence would be associated with better information assimilation.

Our novel content reinforcement measure, *RFC*, is designed to capture the content reinforcement channel, and reflects the degree to which information contained in images enhances the assimilation of important concepts conveyed in the text. We measure reinforcement following Ronen, Ronen, Zhou, and Gans (2023), by processing all image-pages through Google's Vision API, which identifies labels based on the content of the images. We ascertain the degree to which the algorithm's image labels correspond to the words in the annual report narrative (text). In this paper, *RFC* is then constructed as the total number of informative image labels that match words within an annual report's narrative. We also consider variants of this measure, in which we capture reinforcement to other pertinent textual narrative produced by the firm. Higher values of *RFC* represent stronger reinforcement, or higher mapping between the image information content and the textual narrative information content.

We examine the impetus for firms' inclusion of image-pages in annual reports and find that greater news coverage over the fiscal year is positively associated with the number of image-page (and visual pages in general) in the subsequent annual report. Growth in total assets over the year is also positively associated with the prevalence of subsequent-year image-use, seemingly to highlight expansion with visual aids. However, we detect no relationship between the firm's annual advertising expenses and image-pages, suggesting firms do not merely view visuals as a marketing tool. Overall, the evidence is consistent with firms using visuals to convey information.

We contribute to the literature by documenting the association between visual readability and analyst earnings forecast accuracy. While Lehavy et al. (2011) finds that lower *textual* readability of 10-K filings results in lower analyst forecast accuracy, to our knowledge, no work to date has highlighted the impact of *images*. Notably, our work focuses on the impact of images in *annual reports*, which tend to include visuals, and which our results indicate are an additional source of information in forming analyst forecasts.[6]

[6] 10-K filings are known to be a major source of analysts' information set (Previts, Bricker, Robinson, and Young, 1994; Rogers and J, 1997; Gibbons et al., 2021). We reached out to analysts to get a sense of how they use annual reports in their analysis. Consistent with Gibbons et al. (2021), analysts read the 10-K financial statements as quickly as possible to update their models and publish ratings/recommendations as soon as earnings are released. But, at the same time, analysts look at the annual reports to understand companies' priorities and what they want to promote. Thus, annual reports can have long-term value in forming earnings forecasts throughout the year. We explore the horizon dimension using analyst annual earnings forecasts.

We find that both visual use and content reinforcement in the annual report of year t are negatively associated with forecast errors in subsequent quarters. That is, analysts exhibit higher accuracy for stock A relative to stock B if the former is associated with more visuals or greater content reinforcement. Using our measure of relative analyst forecast accuracy, *WAFE*, which contrasts forecast errors across stocks covered by each analyst in a given quarter, we find that the effect of visual readability is comparable to that of textual readability. Notably, of the five different visual element pages (image-pages, team-pages, maps-pages, charts-pages, and infographics-pages), only image-pages (*IMGC*) exhibit statistically and economically significant with analyst forecast errors.[7] Finally, consistent with our individual analyst findings, we find that both visual prevalence measures (*IMGC* and *AVC*) and content reinforcement (*RFC*) result in lower forecast dispersion across analysts.

In order to further ascertain the ability of *RFC* to measure the information content reinforcement of images, we construct two additional *RFC* measures, RFC_{BUS}, and RFC_{MDA} (as well as variants thereof), capturing the reinforcement of image content to the textual narrative of the firm's 10-K business description (10-K Item 1) and to the firm's MD&A (10-K Item 7), respectively. Like *RFC* which captures the reinforcement of image content to the textual narrative of the *annual report*, these additional measures are also associated with higher forecast accuracy. Using Natural language processing (NLP) algorithms, we also compute *RFC* measures based on "important sentences." The combined results support our conjecture that firms use visuals to facilitate information assimilation.

We conjecture that the use of visuals can help mitigate cognitive and attention constraints analysts face, especially when attention is limited (Hirshleifer, Levi, Lourie, and Teoh, 2019; Bourveau, Garel, Joos, and Petit-Romec, 2022) with greater benefits for more constrained analysts. Consistent with our conjecture, we find that the effect of visuals is greatest when analysts cover more stocks, multiple industries, and when the text of the 10-K report is more complex.

Textual readability has been found to affect firm outcomes such as cost-of-equity and cost-of-

[7] Since our analysis is conducted at the page level, and we do not focus on the impact of individual infographics, charts, maps, or other elements, our results do not contradict those of the literature that finds that infographics other non-image graphics are often used by firms and would likely affect investor decisions. However, by controlling for the effects of these visual elements in our tests, our results do enforce the notion that when page-level (by dominant image type on a page) analysis yields results highlighting the importance of our classification and the relevance of *images* to analyst information production. Also, the relatively small number of dominant infographic-and other non-image pages would obscure the results of tests using pages with visual elements other than image-pages.

debt (Rjiba, Saadi, Boubaker, and Ding, 2021). Consequently, we explore whether *visual readability* affects outcomes related to the firm's information environment, captured by the standard deviation of returns, market beta, and cost-of-equity. We find that an increase in visuals in the annual report of year t is associated with lower risk, a lower beta, and as a result, a lower cost-of-equity over the subsequent year. Bonsall and Miller (2017) find that less (textually) readable financial disclosures are associated with less favorable bond ratings. We find that the impact of visual readability is strongest for high-yield bonds, where information is more valuable (Hotchkiss and Ronen, 2002). In particular, visuals are associated with a lower likelihood of a downgrade during the subsequent year. This suggests that firms increase their information dissemination efforts to mitigate negative information.

Given these results, it is fair to conclude that firms use visuals to better disseminate information to investors. In our tests we control for other information dissemination channels such as 8-K disclosures, earnings calls transcripts, and firm corporate events marketed via investor relations, and find visuals to carry relevant information. However, we acknowledge that the use of images is an endogenous decision potentially driven by unobservables. To address this issue, we exploit Kelly and Ljungqvist (2012)'s brokerage closure identification strategy. We conjecture that once firms lose coverage, they are incentivized to increase visuals (images) in reports to substitute for the loss of information production. Our results confirm that firms indeed increase their use of images when they face an exogenous drop in analyst coverage. Pre- and post-event analysis increases the possibility of an inference of causality.

While visuals appear to enhance the readability of a firm's financial report, firms may also use visuals as a marketing tool to boost their image or engender positive sentiment (hype). However, in our analysis, we find that the correlation between firm advertising expenses and visual use is low. In addition, our findings, that both visual prevalence and information reinforcement result in higher analyst accuracy lend credence to an information-based story. Further, we find no evidence of reversals in subsequent year returns and in fact, document a positive association between visuals and subsequent year ROA.

Indeed, our overall set of results is consistent with an information story, where visuals facilitate the assimilation of information by readers. In our tests, we control for a battery of firm characteristics, textual readability measures, and other dimensions of firm information dissemination.

In addition, our identification strategy supports the use of visuals as a substitute for lost analyst coverage. Thus, while we cannot fully rule out the possibility that our findings are largely driven by the firm's general (non-visual) information dissemination efforts, our results indicate that visuals and in particular, the reinforcement of their information content to textual narrative, do provide incremental value.

Our paper contributes to the established literature on readability. In this study, we focus on *visual* readability (i.e., the use of visuals to facilitate information dissemination), as opposed to *textual* readability (how complax the textual narrative is). Our visual readability measures add value above and beyond the text-based readability measures used in the literature. We show that through visual prevalence and content–reinforcement, visual readability helps increase analyst forecast accuracy and decrease analyst dispersion. We further find that the economic significance of visual readability is as important as the economic significance of textual readability.

Of equal importance, our paper contributes to the young and growing literature that explores the use of visual information in financial settings, as well as the existing literature linking visuals in other settings (e.g., marketing, computer science, and psychology- see Section 2 for a review of the literature). To the best of our knowledge, we are among the first to explore the impact of visuals contained in financial reports on stakeholders.[8] Additionally, distinct from other papers, we innovate by quantifying the information content embedded in images, and examining its impact beyond the general use of images. We link the use of images to a broad set of firm outcomes and show that the use of images contributes to the information environment, and promotes efficiency, as captured by analyst disagreement and forecast errors.

Finally, this paper is the first to employ two sets of novel methodologies to process visual material and tease out the distinct elements that facilitate the computation of our metrics.

The rest of the paper is organized as follows. Section 2 reviews related literature. Section 3 describes the data, explains the construction of our visual measures, and provides summary statistics. Section 4 explores the determinants of visual use in annual reports. Section 5 (6)

[8] A contemporaneous paper by Christensen et al. (2020) shows that firms have increased the disclosure of both qualitative and quantitative infographics in 10-Ks. Our analysis is not restricted to infographics. Instead, it encompasses all visual content, including actual images. Another contemporaneous study by Deng, Gao, Hu, and Zhou (2020) explores the use of visuals in annual reports in an event study setting. Their paper differs from ours in scope, variables of interest, methodology, and main research questions. Their one visual measure is a dummy variable of *first-time* use of graphics in annual reports and find positive return reactions and an increase in institutional holdings.

explores the association between visual readability and analyst earnings forecasts (firm outcomes). Section 7 uses brokerage closures as an identification strategy, and Section 8 concludes. Appendix A describes the data collection process. Appendix B provides additional details on the visual classification methodology, and Appendix C provides variables definitions and additional analysis.

2 Review of the Literature on the Use of Visual Information

The most basic and intuitive visual aids are graphs, charts, and maps. Studies examine impacts of these aids on readers' financial and investment decisions in various contexts. Lusardi, Samek, Kapteyn, Glinert, Hung, and Heinberg (2017) find that visual tools can increase the comprehension of information. Shaton (2017) finds that household investment decisions depend on how information is displayed. Dilla, Janvrin, and Jeffrey (2013) find that the use of graphical displays of Pro Forma earnings information impacts even professional investors. Cox, de Goeij, and Van Campenhout (2018)'s survey experiment finds a graphic of net expected return reduces the additional (preventable) fees by up to 20%, and that the visualizations' effectiveness depends on experience and familiarity with investing.

Researchers have also studied the role of color in financial reports and decision-making (Chan and Park, 2015; Bazley, Cronqvist, and Mormann, 2021). Bazley et al. (2021) find that when financial data are presented in red, individuals' risk preferences, expectations of future stock returns, and trading decisions are impacted. Infographics were effective in highlighting information, according them greater weight in decision-making. See for example, Bertrand and Morse (2011).

Along with graphs and other visual aids, images have emerged prominently in financial reporting both in the United States and elsewhere. For example, Lee (1994), Davison and Skerratt (2007), Beattie and Jones (2000), Beattie and Jones (2008), Beattie (2014), and Davison (2014) document the use of well-known images of art masterpieces as well as commissioned artwork in firms' annual reports.[9] Lee (1994) attributes the increased use of images in financial reports to a desire to "participate in consumer engineering," wherein firms use stylized images to induce impressions of rationality, establish the identity of the corporate personality in the minds of consumers, and influence or manipulate corporate stakeholders. Davison and Skerratt (2007) find that UK companies

[9]For example, British Land, Zumtobel, and WPP commissioned cartoons from Ronald Searle, Anish Kapoor and Diego Rivera, respectively. Images of masterpieces appearing in annual reports include Vermeer's The Art of Painting (Ernst and Young's 2001 Annual Review), and Frith's, Life at the Seaside (British Land Annual Report 2006).

with high values of intangible assets were more likely to employ visual and stylistic elements in their financial reporting. Ang, Hellmann, Kanbaty, and Sood (2020) note that while graphs have been used for impression management, research on photographs (images) in financial reports is scarce in the accounting and finance literature.

A few studies do explore the relationship between the aesthetics of images and investor decisions. For example, in an experimental study, Townsend and Shu (2010) show in an experimental study that the aesthetic of the first two pages of annual reports (more pictures, images, and more color) increases the likelihood of investing in the firm. The authors attribute this finding to increased pride of ownership in the company and a resulting increase in valuation. In different contexts, Duarte, Siegel, and Young (2012), for example, report that an impression of trustworthiness in photographs of potential borrowers on peer-to-peer lending sites can impact the probability of loan funding; Trustworthiness of clients affects auditors fees (Hsieh, Kim, Wang, and Wang, 2020) and trustworthiness and dominance of sell-side analysts are associated with lower forecast errors (Peng, Teoh, Wang, and Yan, 2022).

Pope and Sydnor (2011), Gonzalez and Loureiro (2014), and Ravina (2019) analyze how lending platforms use borrower appearance characteristics, such as race, gender, and attractiveness, in their lending decision making. Zhang, Lee, Singh, and Srinivasan (2017) demonstrate that image quality can affect Airbnb booking volume; and Hu and Ma (2020) find that more positive startup pitch videos (i.e., happy, warm, passionate) increases funding probability. Other studies have have examined the effect of facial expressions, demographics, or beauty on job placement (Malik, Vir Singh, Lee, and Srinivasan, 2017), CEO compensation (Graham, Harvey, and Puri, 2017; Halford and Hsu, 2020), mutual fund performance (Ganji, Kale, and Kale, 2021); firm value (Blankespoor, Hendricks, and Miller, 2017; Halford and Hsu, 2020), and in entrepreneurial ventures (Warnick, Davis, Allison, and Anglin, 2021).

A few other contemporaneous studies examine whether and how imagery affects stock price reactions. Obaid and Pukthuanthong (2021) construct a daily market level sentiment index using news photos and find that photo pessimism predicts return reversals. Nekrasov, Teoh, and Wu (2021) look at the existence of images in firm earnings announcement Tweets and whether the presence itself of images affects retail attention, as captured by the number of retweets, and Google Search volume. Higher attention leads to higher price reactions on the earnings announcement days, but the effects subsequently reverse. Gu, Teoh, and Wu (2023) find that an investor sentiment measure they construct from StockTwits GIFs is positively correlated with same-day stock returns and predicts subsequent (two-week) stock return reversals. Obaid and Pukthuanthong (2021), Nekrasov et al. (2021), and Gu et al. (2023) focus on sentiment and attention. We complement these lines of inquiry by 1. analyzing images appearing in financial reports, and 2. focusing instead on both different explanatory and outcome variables. Specifically, we consider not only the existence of images but also at the type of visual content and the information content of images (whether they are reinforcing or not) as explanatory variables and analyst forecast errors, forecast dispersion, and other capital market measures as outcome variables.

As noted above, this study focuses on the information reinforcement content of images in addition to their prevalence. Our emphasis is on the objective quantification and impact of images' information content rather than on the emotional appeal or demographic characteristics. Comparing images' information content with text-embedded content, we show how informative images contribute to *visual readability* and affect investors' ability to analyze the firm information and firm outcomes.

3 Data, Visual Metrics, and Summary Statistics

In this section, we describe the annual report data we use, discuss the construction of our visual measures (Section 3.1), describe the other data sets and variables we rely on (Section 3.2), and provide summary statistics of visual measures and other firm characteristics (Section 3.3).

3.1 Annual Report Data and Visual Metrics

3.1.1 Annual Report Data

We scraped all digital annual reports available for S&P 1500 firms that were available on AnnualReports.com from 1989 (when data were first available) to 2019. From the 19,656 reports initially retrieved, we drop the 1989-1992 period due to small sample size (28 reports in total). We further exclude: 165 reports for which pdf files were either broken or could not be otherwise extracted, 588 duplicate reports, 134 reports with less than 5 or greater than 500 pages, and 512 reports lacking the fiscal year of coverage. The resulting sample comprises 18,229 reports covering the years 1993-2019.

Table A.1 of Appendix A details this data construction process. Panel B of Table A.1 shows that the number of reports in our sample rises steadily over our sample period, potentially due to digitization as well as to changes in the information environment. We convert each page into an 'image' file format to facilitate image-processing. The 18,229 reports (before applying additional filters) comprise a total of 2,096,775 annual report pages. Two factors led us to analyze data starting in 2002 (instead of 1993). First, the relatively small number of firms providing digitized reports prior to the year 2000 raises sample selection concerns, particularly if mostly higher quality firms were able to apply new technologies (ahead of other firms). Second, given our focus on readability and the information environment, and since the likelihood is low that investors will focus on annual reports of firms that have no media coverage, we require that firms are covered by at least one news article in a given year. Since our media coverage data starts in 2002, our final sample comprises annual reports spanning 2002 to 2019.[10]

3.1.2 Visual Classification

Annual report pages that include visuals of any kind often contain a mix of different visual elements, combining images, graphs, charts, maps, infographics and/or text. Some pages may contain many of one type of visual element, and others may provide a mix. We assume readers assimilate the combined information on a page holistically and that page-level visual representation therefore best captures readers' focal experience; that is, we assume readers simultaneously consider and synthesize not only each individual element on a page, but other factors such as the size, layout, and position of the visual elements, as well as their potential interactions. Indeed, since design companies offer annual report design services at the page level, not not the individual level, page-level view also likely best reflects the firm's intent.[11] We therefore conduct our investigation at the annual report *page* level.

In fact, analysis at the individual image level would likely skew the importance of each image

[10]The 2019 data available to us at the time we conducted the analysis is incomplete since the data were provided with a lag. Consequently, we exclude 2019 when we report time-series statistics. Additionally, the year the annual report refers to may not correspond to the fiscal year. In such instances we use Compustat fiscal year data. For example, Walmart's 2020 Annual Report covers the year ending January 31, 2020, corresponding to its 2019 fiscal year. Thus for this report, we use the 2019 Compustat data.

[11]Design services and templates for annual reports provide design layouts at the page level. See for example Adobe instruction for design at the page level–https://www.adobe.com/creativecloud/business/teams/resources/how-to/annual-report-design.html, and Visme, a representative software package for creating annual reports: Free Annual Report Maker - Design Reports Online — Visme.

beyond the reader's experience. Since report pages may contain a mix of visual elements, each varying in number, shape, positioning, and size, each visual element's impact is likely to vary depending on the mix of other visuals included on the same page; a full-page sized image can impact differently from a thumbnail appearing within a mix of other images on a page or within a mix of charts, infographics, or maps. In Figure B.1 of Appendix B, the image of the cat likely captures the viewer's focal point and attention more than the small medicine dropper in the top right thumbnail image – analysis conducted at the image level as opposed to the page level would have counted each thumbnail as prominently as the larger central image, and would not capture either the relative size of the images or notably, their interaction and relative positioning.[12]

We combine machine learning algorithms and heuristic rules to split the 2,096,775 annual report pages contained in our sample into non-visual pages (those containing only text), and visual pages (those containing any visual elements). For the 137,453 visual pages in the sample, we categorize the visual elements we identify on those pages into 5 distinct categories: images, excluding team photos (IMG); team or management photos (T); charts/graphs ($CHAR$); infographics ($INFO$); and maps ($MAPS$). This allows us, importantly, to overcome the challenge of systematically identifying images as distinct from other visual elements. Finally, using our algorithms, we categorize visual report pages by the visual element that is most prevalent on the page (image-pages, team-pages, charts-pages, maps-pages, and infographics-pages). Appendix B provides additional details on our visual classification methodology as well as on the calculation of visual measures.

3.1.3 Visual Measures

We construct two broad sets of visual measures. The first captures visual prevalence, or the intensity of visual use, and the second captures content reinforcement. The concept of visual prevalence is intuitive and straightforward. Evidence from the psychology literature suggests that visuals facilitate the flow of information and can ease cognitive constraints (e.g., Larkin and Simon, 1987; Stenning and Oberlander, 1995; Glenberg and Langston, 1992; Alter and Oppenheimer, 2009). Thus, we expect increased use of visuals to increase investor attention to information and facilitate

[12] Additionally, we are unable to extract individual elements from a page if it is uploaded by the firms as a combined file (.pdf or .img) of several individual image files, thus potentially underrepresenting the individual elements, hence distorting the analysis. This also hampers the researchers' ability to identify individual elements of visual representation- for example, we are unable to identify with reasonable precision or consistency, pages that have only images versus those that have other elements within.

information processing, leading to positive effects. Our visual prevalence set includes the following measures: *IMGC* (the number of image-pages); *TC* (the number of team/management photos-pages); *CMIC* (the union of the numbers of charts-pages, maps-pages; and infographics-pages), and *AVC*, the union of *IMGC*, *TC*, and *CMIC*.[13] *AVC* thereby represents the number of pages with any of these visual elements, i.e, pages that are not comprised of only text.

The other measure, *RFC*, captures the content-reinforcement channel (capturing the degree to which visual information content reinforces textual narrative). To construct *RFC*, we follow a two-step procedure, as in Ronen, Ronen, Zhou, and Gans (2023). First, we determine whether the visual content on report pages is informative. To do so, we process each of the image-pages through Google Vision and analyze the algorithm-generated image labels that associate visual items with confidence levels.[14] Figure 3 presents an example of labels generated by the algorithm for an image of a woman surrounded by a pile of shoes. The top label is "footwear," with a confidence of 98%. Other labels pick up on the other items shown in the image, including the woman's smile, happiness, and the fact that the image represents fashion, as well as more details regarding the specific footwear types.

We filter out image-pages for which the labels are categorized as uninformative to obtain our final set of image-pages with "informative" labels.[15] We require that image-pages be classified as informative before determining reinforcement with the textual narrative.

Finally, we construct (*RFC*) by calculating the number of informative image labels from informative image-pages that match the annual report's text. Higher values of *RFC* represent stronger reinforcement (mapping between the image information content and the textual narrative information content). Appendix B.2 provides details on this process and also lists the 100 most prevalent informative labels in our sample. These words largely relate to core business operations of the company. Figure 4 presents examples of reinforcing image-pages of four companies' annual reports along with their reinforcing labels which match the text ("Vehicle" and "Motor vehicle for PACCAR Inc., "Furniture" for Ethan Allen Interiors, "Health Care Provider" for Teleflex Inc, and

[13] The categories of charts-pages, maps-pages, and infographics-pages are combined to construct the *CMIC* measure because of the low incidence of their pages.

[14] https://cloud.google.com/vision.

[15] To correctly classify images, we train Google Vision on a sub-sample of images to derive a bag of words that consistently capture uninformative labels. These are used as stop labels to filter out uninformative labels, based on the top three generated labels for each report page image. Appendix B.2 provides further detail on this process. Figure B.2 provides examples of uninformative images.

“Property” for Toll Brothers Inc).

In addition to *RFC*, we also calculate reinforcement measures with respect to the textual narrative in the business description and MD&A sections of the firm's 10-K filing: RFC_{BUS} and RFC_{MDA}, respectively, as well as three combinations of the latter: RFC_{BUSMDA}, in which we consider reinforcement to the combined text of the business and MD&A sections; $RFC_{BUSMDA+}$, in which matches are considered twice if they appear in both, and RFC_{BUSMDA_IFBOTH}; in which matches are kept only if the image label matches a word that appears in *both* sections of the 10-K.

Figure 5 provides an illustrative example of how image-page labels may correspond similarly or differently to each of these different textual narratives. The first image page, for example, from the 2005 annual report of Texas Roudhouse Inc, produces ten Google Vision labels. Panel B lists the labels and their probabilities, along with a breakdown of which narrative text each label matches. The word “dish” matches only the annual report text, but the word “food” matches all three narrative texts (the annual report, the business description, and the MD&A section of the firm's 10K filing).[16]

3.2 Other Data

We construct our other variables from several data sources. Stock prices, shares outstanding, and trading volume are from CRSP. Data on book value, long-term debt, total assets, sales, ROA, and advertising expenses are from Compustat. Institutional holdings are from Thomson Reuters S34 files. Credit ratings are from Mergent FISD. Data on the number of news articles for a given firm are from RavenPack, which starts in 2002. We include only articles with a relevance score of 100. Finally, data on analyst coverage, analyst quarterly earnings forecasts, and analyst dispersion are from IBES.

3.3 Summary Statistics

Our sample consists of 15,477 firm-year observations from 1,363 unique firms for the period January 2002 to December 2019. To be included in the sample, a firm must be part of the S&P 1500 Index and must have been covered in the media at least once during the year. See Appendix A for details regarding the data collection process.

[16] If this were the only image-page in the report, the reinforcement measures for this report would be as follows: RFC= 8; RFC_{BUS}= 7; RFC_{MDA}=2.

[Table 1]

Table 1 reports the summary statistics of our visual measures and classifications. On average, the annual reports in our sample are 118 pages long. Panel A of Table 1 provides the distribution of the visual prevalence and reinforcement measures. The mean number of image-pages ($IMGC$) per report is 5.14 (6.9% of the average number of pages), the mean number of team-photos is (TC) is 0.95 and the mean number of pages that are dominantly charts, maps and/or infographics is 0.12. Therefore, AVC is 6.2, with a standard deviation of 8.94. The mean number of RFC (text-reinforcing image labels) per report is 4.38, with a standard deviation of 6.49. Table 1 also presents the distribution of the additional reinforcement measures and their variants. Their means are 2.86, 1.81, 3.27, 3.56, and 1.14 for RFC_{BUS}, RFC_{MDA}, RFC_{BUSMDA}, $RFC_{BUSMDA+}$, and RFC_{BUSMDA_IFBOTH}, respectively.

Panel B of Table 1 reports similar statistics for the set of 11,607 annual reports that contain any visual elements (not merely text). The average number of AVC, $IMGC$, TC, and $CMIC$ in the restricted sample are 8.27, 6.84, 1.26, and 0.166, with standard deviations of 9.46, 8.52, 1.90, and 0.49, respectively. The reinfircement measures are 3.81, 2.41, 4.36, 4.79, and 1.52, respectively for RFC, RFC_{BUS}, RFC_{MDA}, RFC_{BUSMDA}, $RFC_{BUSMDA+}$, and RFC_{BUSMDA_IFBOTH}.

Panel C shows that the use of visual elements is pervasive across (GICS) sectors, with AVC ranging from 4.17 per report (Commercial Services) to 8.89 (Consumer Services), $IMGC$ ranging from 3.55 (Commercial Services) to 7.57 (Consumer Services), and TC and $CMIC$ displaying similar patterns. RFC ranges from 2.28 (Information Technology) to 8.04 (Consumer Staples), and, as is the case for the visual prevalence measures, the reinforcement measures are also not concentrated in specific sectors.

[Table 2]

Table 2 reveals a fairly monotonic increase in the number of annual reports that include visual elements over time, from 297 in 2002 to a maximum of 827 in 2018. This is consistent with an overall increase in the number of reports in the sample – from 361 in 2002 to a maximum of 1,164 in 2018. On average, 74.3% of reports include visual elements. Notably, 72.5% include images-pages. In contrast, only 40.7% of reports include team/management photo-pages and 10.5% include pages with charts, infographics, or maps. This is consistent with Christensen et al. (2020) who find that 6.5% (25.8%) of firms used infographics in their 10-K reports in 2003 (2020). This contrast highlights the heavy reliance by firms on image-pages, which we focus on in our study.

[Table 3]

Table 3 reports summary statistics of the main firm variables and their correlations with the various visual measures. Panel A reports the statistics of the selected firm variables. The average (median) stock market capitalization (total firm assets) is \$11.66 (2.67) billion (\$15.65 (3.12) billion). The average percent of institutional investors' holdings of outstanding shares is 67.5%. The percentage change in institutional holdings over the fiscal year is zero on average, with a standard deviation of 4.5%. On average, firms in our sample are covered by 129.5 news articles over the fiscal year. RavenPack's filters ensure that these articles are solely about the firm. The average ROA, cost-of-equity capital, and cost-of-debt capital are 12.3%, 11.4%, and 5.3%, respectively. On average, each firm in our sample is covered by 10 analysts.

Panel B of Table 3 reports the correlations across our visual classification measures and textual-based readability measures. All measures are demeaned to capture within-firm correlations. The 0.97 correlation between *AVC* and *IMGC* confirms the importance of images as distinct from other visual elements; *AVC* and *TC* and *AVC* and *CMIC* are less correlated, at 0.55 and 0.22, respectively. Our content reinforcement measure, *RFC*, has a correlation of 0.57 with *IMGC*, suggesting that firms may use images with content reinforcement in mind. The correlations between *IMGC* and the measures capturing reinforcement to the textual narrative of the 10-K sections, RFC_{BUS}, and RFC_{MDA}, are 0.47 and 0.39, respectively. The correlation between our visual measures and the *FOG* readability measure is virtually zero, which suggests that the visual-based measures capture aspects that differ from those captured by standard text-based readability measures and generally improve readability and understanding.

Lastly, Panel C of Table 3 reports the correlation across the various control variables. As in Panel B, we demean the variables by firm. *LnAssets* and *LnSize* are highly correlated, and as expected, both are positively correlated with news coverage.

4 Determinants of the Use of Visual Information

In this section, we explore the determinants of visual prevalence. We discuss the results for *IMGC*, since *IMGC* is highly correlated with *AVC* and is the base for the *RFC* measure. For completeness, we report results for *AVC* and *RFC* in Appendix C. The regression specification takes the following form:

$$IMGC_{j,t} = \alpha + \beta \cdot IMGC_{j,t-1} + \sum_{k=1}^{K} \gamma_k \cdot X_{k,j,t} + f_j + y_t + \epsilon_{j,t}, \tag{1}$$

where *IMGC* is the number of images-pages in the annual report of firm j in year t, and $IMGC_{j,t-1}$ is *IMGC* of the previous fiscal year (*LDEP*); k denotes the specific explanatory variable; t denotes the fiscal year; and j denotes the firm. The set of explanatory variables includes the number of annual report pages (*Pages*), the natural logarithm of the total number of news articles over fiscal year t (*LnNews*), the natural logarithm of the number of firm discretionary 8-K filings (*701_801_DISCLOSURE*), the cumulative stock returns over fiscal year t (*AnnRet*), the return on assets for the fiscal year t (*ROA*), the fiscal year level of institutional holdings (*InstHold*), the annual advertising expenses normalized by annual sales (*AdvExpToSale*), the natural logarithm of the firm's assets (*LnAssets*), the natural logarithm of book-to-market ratio (*LnBM*), the daily standard deviation of returns over the fiscal year (*SdRet*), and the average daily turnover over the fiscal year (*Turnover*). Finally, we include firm fixed effects (f_j) and report–year fixed effects (y_t). To facilitate economic interpretation, we Z-Score adjust both the dependent variable and our variables of interest.[17]

[Table 4]

Table 4 reports the results. We find a positive association between the number of news articles about the firm over the fiscal year and the number of image-pages, suggesting that the increased media coverage reflects events that are included in the annual report and the visuals contained therein. In terms of economic significance, a one standard deviation increase in the *LnNews* results in an increase of about 3% in *IMGC*, in *IMGC* standard deviation units. An increase in 8-K filings results in an increase of about 2.2%.

[17] We exclude the stock market capitalization (*LnSize*) from these regressions because of the high correlation between *LnAssets* and *LnSize*. Replacing *LnAssets* with *LnSize* yields similar coefficients to those of *LnAssets*. However, given that we control for firm annual return, *LnAssets* better captures the changes in firm operations.

Annual returns (*AnnRet*) are positively correlated with the use of images; a one standard deviation increase in *AnnRet* results in an increase of about 2% in the use of images, and, similarly, a one standard deviation increase in *ROA* is associated with an increase of about 3% in *IMGC*, suggesting better market or accounting performance spurs the firm to enhance its use of images to highlight its success.

The use of visuals in annual reports may be part of the firm's advertising efforts. If so, one might expect to find a positive relationship between the firm's advertising expenses and the use of images. Our results indicate that *IMGC* is uncorrelated with adverting expenses, suggesting that the prevalence of image-pages is not merely a reflection of the firm's general marketing efforts. Also, consistent with the correlations reported in Table 3, the association between *IMGC* and *FOG* is negative, but insignificant both statistically and economically.

Within columns 5-7 of Table 4, we include other firm characteristics, such as firm assets that reflect growth in firm activity. Notably, an increase in total assets is associated with an increase in *IMGC*; The association appears to be economically significant: A one standard deviation increase in assets results in an increase of 13% in *IMGC*. We find that *LnBM* is negatively associated with *IMGC* suggesting that higher growth (low *LnBM*) leads to higher use of visuals. Interestingly, *SdRet* and *Turnover* are negatively associated with *IMGC*.

Table C.2 of Appendix C presents results for the determinants of *AVC* and *RFC*. The results are qualitatively similar to those for *IMGC*. Overall, the combined results suggest firms endeavor to convey relevant information by using imagery. In the next sections, we explore the relationship between visual use, analyst forecast errors, forecast dispersion, and a battery of firm outcomes.

5 Analysts' Earnings Forecasts and Visual Readability

Proceeding from a maintained hypothesis that analysts review annual reports in addition to 10-Ks – the latter typically do not contain images – we use annual reports as the platform based on which we investigate the impact of imagery on information environment variables.[18] Our examination parallels Lehavy et al. (2011)'s usage of the *FOG* index to study the relation between textual

[18] Conversations with an equity analyst revealed that although analysts primarily prioritize reading the 10-K financial statements as quickly as possible after earnings announcements are released to update their models and publish ratings/recommendations, they do examine the annual reports to understand companies' priorities and what they want to promote (which naturally tends to be positive). Another analyst reported that analysts do not want to be at a disadvantage- since they know other analysts may examine the annual reports, they would likely follow suit.

readability and analyst earnings forecasts. Our focus on visual use (or readability) complements the studies on readability and deepens our understanding of how users of annual reports assimilate financial information.

5.1 The Accuracy of Analysts' Quarterly Earnings Forecasts

We examine the relationship between visual readability and analyst quarterly earnings forecast errors by constructing a within-analyst quarterly forecast accuracy measure (*WAFE*) based on forecast errors across stocks covered by each analyst in a given quarter. The measure, a variant of the *PMAFE* measure used by Clement (1999) and Jame, Johnston, Markov, and Wolfe (2016), is defined as:

$$WAFE_{i,j,q} = \frac{(AFE_{i,j,q} - \overline{AFE_{i,q}})}{\overline{AFE_{i,q}}}, \tag{2}$$

where $AFE_{i,j,q}$ is the absolute forecast error of analyst i's forecast of firm j's earnings for fiscal quarter q of the year t+1 scaled by the stock price at the end of the previous quarter ($|Forecast - Actual|/Price_{j,q-1}$), and $\overline{AFE_{i,q}}$ is the mean absolute scaled earnings forecast error of analyst i across all stocks covered during quarter q. The regression specification takes the following form:

$$\mathit{WAFE}_{i,j,t+1} = \alpha + \beta \cdot \mathit{VIS}_{j,t} + \sum_{k=1}^{K} \gamma_k \cdot X_{k,j,t} + f_j + A_i \times y_{t+1} + \epsilon_{i,j,t+1}, \tag{3}$$

where $\mathit{WAFE}_{i,j,t+1}$ is the average of the four quarterly within- analyst forecast errors, ($WAFE_{i,j,q}$), for year t+1; *VIS* is the selected visual measure, f_j is the firm fixed effect; and A_i *times* y_{t+1} is the analyst–year fixed effects.

We require that at least two stocks be followed by each analyst i in quarter q. We control for the time lapse between the forecast date and the date of the actual earnings announcement (*DaysToEarnAnn*) – the shorter the lapse, the more accurate the forecast is expected to be. We also include the *FOG* index so as to contrast the partial effects and economic significance of visual and textual readability. As in Table 4, other firm control variables include: the number of annual report pages (*Pages*), the natural logarithm of the total number of news articles over fiscal year t (*LnNews*), the cumulative stock returns over fiscal year t (*AnnRet*), the return on assets for the fiscal year t (*ROA*), the fiscal year institutional holdings (*InstHold*), the annual advertising expenses normalized by annual sales (*AdvExpToSale*), the natural logarithm of the firm's assets

(*LnAssets*), the natural logarithm of book-to-market ratio (*LnBM*), the daily standard deviation of returns over the fiscal year (*SdRet*), the average daily turnover over the fiscal year (*Turnover*), and the stock market capitalization as another measure of firm size (*LnSize*). We also control for analyst dispersion (*Analyst Disp*), which may affect analyst accuracy.

Table 5 reports the results for both the visual prevalence measures (*AVC* and *IMGC*) and the reinforcement measure (*RFC*), and displays the control variables. To ease economic interpretation, we standardize the dependent variable and the visual measures (i.e., to have a mean of zero and a standard deviation of one). As a result, the coefficients represent the effect of a one standard deviation change in X on the dependent variable in standard deviation units.

[Table 5]

Panel A reports results from panel regressions of analyst forecast errors on visual prevalence (measured by *AVC*). All specifications yield a negative and statistically significant coefficient, with greater visual prevalence associated with higher forecast accuracy in the subsequent year. The effect is economically significant; a one standard deviation increase in *AVC* is associated with roughly a 2.5% increase in accuracy, measured in terms of the standard deviation of $WAFE$ (column 5).

Panel B reports results using the number of image-pages (*IMGC*) as the visual prevalence measure. To capture the partial effect of *IMGC*, we control for the number of other visual pages (*TC* and *CMIC*). Notably, since most firms do not include more than one page each, we use fixed-effects (i.e., dummy indicators) instead of continuous measures, to capture differences between firms that use *TC* and/or *CMIC* and those that do not. The results for *IMGC* are qualitatively similar to those reported for *AVC*, ranging from -2.4% to -3.4% depending on the specification used. Panel C reports results using the reinforcement measure (*RFC*). Again, the coefficient is negative and statistically significant across most specifications, indicating that the larger the degree of reinforcement between the image content and the narrative text of the annual report, the higher the analyst forecast accuracy.

Control variables also load as expected. The coefficient of *DaysToEarnAnn* loads positively; consistent with earlier forecasts being less accurate. Institutional holdings load negatively, consistent with better governance. News and growth in assets both load positively, consistent with accuracy loss, potentially due to expanded operations making earnings harder to predict. Notably, firm advertising expenses have a positive and significant coefficient pointing to lower forecast accuracy and suggesting that the benefits of advertising are somewhat foggier than those emanating from other activities.

Consistent with Lehavy et al. (2011), *FOG* has a positive and statistically significant coefficient, suggesting that lower 10-K readability is associated with higher analyst forecast errors. A one standard deviation increase in *FOG* is associated with a 2.1% decrease in analyst accuracy (column 5).[19] The economic significance of our visual prevalence and content reinforcement measures is comparable to that of *FOG*. Finally, *Analyst Disp* also loads positively, suggesting that stocks for which analyst forecast dispersion is higher also exhibit higher forecast errors.

5.2 Information Reinforcement with other Pertinent Narrative Text

In addition to *RFC*, we also consider reinforcement measures with respect to the textual narrative in the business description and MD&A sections of the firm's 10-K filing. We posit that these sections include important information content regarding the firm and that therefore, image labels-to-text matches using these sections of narrative text can complement our main results by providing an informal gauge of reinforcement to curated and directly meaningful words.

[Table 6]

Table 6 reports results for the analysis conducted in Table 5 using reinforcement measures based on RFC_{BUS}, RFC_{MDA}, and their variants. Panel A shows that each of these five measures is negatively and statistically associated with analyst forecast errors. The economic significance of the associations appears to be at least as high as that of *RFC* (shown in Table 5), consistent with the notion that these reinforcement variants are useful in picking up words deemed to be of importance to the firm.

For robustness, Panels B-D provide results for other variations of our reinforcement measures. In Panel B, we consider reinforcement measures calculated at the image-page level. In Panel C, we consider measures of reinforcement to 'Important Sentences' of the 10K sections, calculated using NLP algorithms to summarize the texts of the business and MD&A sections into 10 key

[19] An alternative to the *FOG* measure for textual readability is the 10-K file size (Loughran and McDonald, 2014). Our results on the effect of visuals on analyst accuracy are qualitatively similar using this alternate measure.

important sentences.[20] Panel D considers the reinforcement measures calculated at the image-page level, matched to the "Important Sentences" described above. The results for all panels echo the results in Panel A: image content that reinforces textual narrative in the annual report and/or the 10-K filings is associated with reduced analyst forecast errors.

5.3 Visual Readability and Analyst Cognitive Constraints.

In this subsection, we present evidence that supports the attention/cognitive constraint channel of visual use. Like other investors, analysts have limited information processing capacity or attention (Hirshleifer et al., 2019; Bourveau et al., 2022), which we conjecture can be relaxed by visual readability. We consider three facets of cognitive constraints: the number of stocks covered by analysts, their industry concentration, and the textual complexity of the 10-K report. Table 7 reports results for *AVC* and *RFC*, and Table C.4 reports results for *IMGC*. The results are qualitatively similar (for all panels) to those for *AVC*.

[Table 7]

Panel A explores the relationship between visuals and analyst coverage. For each sub-sample in each panel, the three columns correspond to columns 1, 3, and 5 of Table 5. The "High COV" ("Low COV") sub-sample is comprised of the top (bottom) analyst tercile in terms of the number of stocks that an analyst follows (stock coverage). Consistent with our conjecture, the results for *AVC* suggest visuals are associated with significantly smaller forecast errors for the top tercile (those who cover more stocks, (coefficient = -0.024 ; t-stat= -2.65)), but not for the bottom tercile, which is roughly zero (coefficient = 0.000 ; t-stat= 0.01). *RFC* results are qualitatively similar, with significant results only for the top tercile (coefficient = -0.017 ; t-stat= -2.18).

In Panel B, we present results for "High COV" analysts, ranked by their industry concentration. We conjecture visual readability would have a greater impact on analysts covering a *wide* range of industries, as they may face bandwidth constraints. For each analyst, we calculate the maximal fraction of stocks per industry covered. "Low Industry Concentration" ("High Industry Concentration") indicates that the analyst is in the bottom (top) tercile of industry concentration. Consistent with our conjecture, results for *AVC* indicate that visuals are associated with

[20] The average number of matched labels to important sentences across the *BUSMDA* based measures is around 1, with a standard deviation of about 1.5. The correlations between *IMGC* and RFC_{BUS_IS}, RFC_{MDA_IS}, and $RFC_{BUS\_MDA\_IS}$ are 0.24, 0.16, and 0.26, respectively.

significantly smaller forecast errors in low industry concentrations (coefficient = -0.054 ; t-stat= -4.17), but not in the bottom tercile (coefficient = -0.017; t-stat= -1.00). While the coefficients for *RFC* are more negative for the "Low Industry Concentration" group than the "High Industry Concentration" group, the differences are small.

Panel C explores the relationship between visual readability and textual readability. The "High FOG" ("Low FOG") sub-sample is comprised of stocks that appear in the top (bottom) tercile of stock textual readability. Consistent with our conjecture, *AVC* results indicate that visuals are associated with significantly smaller forecast errors for the top tercile (textually complex stocks, (coefficient = -0.055 ; t-stat= -2.77)), but not for the bottom tercile (coefficient = -0.014 ; t-stat= -1.03). Again, results for *RFC* results are consistent with those for *AVC*.

Overall, the tests reported in Table 7 and Table C.4 support the cognitive limitation conjecture. That is, visuals and their reinforcement are most valuable when analysts face constraints in either the number of stocks or industries they cover, or the complexity of the 10-K narrative. Notably, our finding, that visual readability is more important when textual readability is low, may be consistent with a substitution effect – when the textual narrative in the 10-K is more obscure, analysts may resort more to the annual report (and its images) for insights.

5.4 Visual Readability and Firm Information Dissemination

Visual readability may be correlated with other information disseminated by the firm. In the above analysis, we control for firm characteristics and textual readability. In this sub-section we further control for other firm-disseminated information events that may be correlated with visual use. We include two sets of controls.

The first set includes firm information events such as firm disclosures and investor conference events. To capture firms' discretionary disclosures, we use 8-K filings (Items 7.01 and 8.01, Segal and Segal, 2016).[21] For corporate events, we rely on Bloomberg's firm event calendar that records all scheduled firm corporate activities. We use the Bloomberg function "EVTS" and focus on

[21] While there are multiple items that can be filed with an 8-K filing, six items account for more than 96% of the cases (Ben-Rephael, Da, Easton, and Israelsen, 2022). Of those, we focus on two items that are related to firm disclosure that are somewhat subject to discretion: Item 7.01 ("Regulation FD disclosure") and Item 8.01 ("other events that are not specifically called for by Form 8-K" that the firm considers to be of importance). The other four items specifically define what triggers a filing: Item 1.01 ("entry into a material definitive agreement"), Item 2.02 ("results of operations and financial condition"), Item 5.02 ("departure/election of directors or principal officers"), and Item 5.07 ("submission of matters to a vote of security holders").

"TV/Conference/Presentation" (primarily investor conferences, including prescheduled press conferences), "Analyst Marketing," and "Corporate Access" (consisting of firm corporate access events and analyst marketing events). We also control for the number of firm press releases throughout the year.

The second set of control variables includes measures extracted from year-end earnings call transcripts, which we analyze to capture any soft, or additional, information. After downloading transcripts from S&P Global, we construct textual measures based on the management and Q&A transcript using the Loughran and McDonald dictionary (Loughran and McDonald, 2016) including the difference between the number of positive and negative words scaled by their sum (SENT), the fraction of uncertainty words (UNC), and strong modal words (SMODAL).

[Table 8]

Table 8 reports the results for *AVC* and *RFC*. Column 1 replictes the results of Column 5 of Table 5 for reference. Columns 2 and 3 show that both discretionary disclosure and corporate events are negatively and significantly associated with analyst forecast errors, consistent with both types of events conveying useful information. *SENT* loads negatively; one interpretation is that accuracy is lower when sentiment is negative. Results for *RFC* are qualitatively similar, as are those for *IMGC*, which for parsimony, are presented in Appendix C. Importantly, the conclusion that visuals convey unique and valuable information is unaffected by these controls. Indeed, visuals convey content that is incremental to firms' otherwise-disseminated information.

5.5 Analyst Forecast Dispersion

Having established significant associations between visuals and analyst forecast accuracy, we turn our attention to analyst forecast dispersion (across analysts per covered firm). We calculate analyst dispersion as the standard deviation of the analysts' quarterly earnings forecasts normalized by the absolute mean of these forecasts, and use the following model:

$$AnalystDisp_{j,t+1} = \alpha + \beta \cdot VIS_{j,t} + \sum_{k=1}^{K} \gamma_k \cdot X_{k,j,t} + f_j + y_{t+1} + \epsilon_{j,t+1}, \tag{4}$$

where $AnalystDisp_{j,t+1}$ is the average of $AnalystDisp_{j,t+1,q}$ over the four quarters for firm j in year *t+1*. *VIS* is the selected visual measure, f_j is the firm fixed effect, and y_{t+1} is the year fixed effect. We control for lagged analyst dispersion, and other control variables are as in Table 5.

[Table 9]

Table 9 reports results for *AVC*, *IMGC* and *RFC*. We find a negative relationship between both visual prevalence measures (*AVC* and *IMGC*) and the dispersion of analyst forecasts, suggesting that the use of visuals lessens disagreement across analysts. Consistent with previous evidence in the literature, lower textual readability (high *FOG*) results in more dispersion. Notably, the economic significance of *AVC* and *IMGC* is comparable to that of *FOG*.

RFC is also negatively and significantly associated with analyst forecast dispersion, as are the other reinforcement measures, RFC_{BUSMDA}, $RFC_{BUSMDA+}$, and RFC_{BUSMDA_IFBOTH}, which are presented in Table C.5 for parsimony. Our findings for the combined set of reinforcement measures fortify the inferences we drew from Table 5 and Table 6 regarding the relevance of the content reinforcement measures to analyst output.

6 Visual Measures and Firm Outcomes

Textual readability has been shown to be significantly associated with firm outcomes such as cost-of-equity (Rjiba et al., 2021) and changes in bond ratings (Bonsall and Miller, 2017). In this section, we explore the relationship between *visual readability* and these (as well as other) firm outcomes. Additionally, our findings relating visual readability to better information assimilation beg the question of the association with firm performance, which may further inform us regarding the informational role of visuals.

6.1 Total Risk, Systematic Risk, and Cost-of-Equity

To test whether visual content included in a fiscal year t annual report predicts fiscal year $t+1$'s risk measures, we focus on three dependent variables (*DEP*); the first is the standard deviation of returns (*SdRet*) over fiscal year t+1, the second is the firm's market beta (*MktBeta*) estimated using daily returns during fiscal year t+1; and the third is the firm's cost-of-equity (*Cost-of-Equity*) in fiscal year t+1, estimated as in Frank and Shen (2016) (see Table C.1 for details). The regression specification takes the following form:

$$DEP_{j,t+1} = \alpha + \beta \cdot VIS_{j,t} + \sum_{k=1}^{K} \gamma_k \cdot X_{k,j,t} + f_j + y_{t+1} + \epsilon_{j,t+1}, \tag{5}$$

where *VIS* is the visual metric of interest in the annual report of firm j in fiscal year t; k indicates the explanatory variables; t denotes the fiscal year, and j denotes the firm. The control variables are similar to those defined in Table 5, and are estimated as of the end of fiscal year t. See Table C.1 for more details. We include firm and year fixed effects (f_j) and report firm (f_j) and year (y_t) fixed effects.

Table 10 reports the results for *AVC*, *IMGC*, and *RFC*. Specifications 1-3, 4-6, and 7-9 report results for *SdRet*, *MktBeta*, and *Cost-of-Equity*, respectively. Across all specifications, we find a negative association between each of *AVC*, *IMGC*, and *RFC* and the subsequent year's total risk. For example, a one standard deviation increase in *AVC* is associated with a reduction of 1.5% in total risk (in standard deviation units). We find similar results for *MktBeta* and *Cost-of-Equity*, where a one standard deviation increase in *AVC* (*RFC*) results in a reduction of about 1.8% (1.2%) for both *MktBeta* and *Cost-of-Equity* in standard deviation units, albeit the coefficients for *RFC* are not statistically significant.

[Table 10]

The absolute drop in beta of about 0.01 (coefficient (0.018) $\times$ standard deviation (0.38)) is statistically and economically significant. The results for the cost-of equity are also economically significant; the absolute drop in cost-of-equity is 4.5 basis points (coefficient (0.018) $\times$ standard deviation (0.025)).

6.2 Changes in Credit Ratings

To measure the relationship between visuals and the cost-of-debt, we focus on changes in subsequent credit ratings. We identify the set of bonds that were active during our sample period using the TRACE database. We retrieve the bond ratings for each identified issuer after merging the TRACE data by issuer (firm) to the Mergent FISD and CRSP databases.[22] We combine S&P 500 and Moody's ratings, convert letter-rating grades into numbers, and multiply the reverse numerical scale by -1 (such that positive changes reflect bond upgrades). We then construct a daily firm-level index that tracks credit rating agencies' ratings across all bonds in the sample. Finally, we calculate changes in the index level from the end of fiscal year t to the end of fiscal year $t+1$. The regression specification takes the following form:

$$ChngRate_{j,t+1} = \alpha + \beta \cdot VIS_{j,t} + \sum_{k=1}^{K} \gamma_k \cdot X_{k,j,t} + f_j + y_{t+1} + \epsilon_{j,t+1}. \tag{6}$$

[22]The Mergent matching process reduces the sample from 15,518 to 6.572 firm-year observations.

We augment our set of control variables by including: the firm's leverage (*D/E*) at the end of fiscal year t to capture credit risk, the level of the rating index at the end of fiscal year t (*AvgRate*), and the lagged dependent rating change variable, *ChngRate*, at the end of fiscal year t. Since we expect firm-specific information to be reacted to mainly in the high-yield bond market (Hotchkiss and Ronen, 2002; Ronen and Zhou, 2013), we are especially interested in the reaction to visuals in firms whose average bond rating is below investment grade.

[Table 11]

Table 11 reports the findings for *AVC*, and results for *IMGC* and *RFC* are reported in Table C.6 for parsimony. Panel A indicates a positive relationship between the use of images and changes in ratings. As expected, the relationship is economically stronger for high-yield bonds, where the effect is 2 to 3 times larger than that for investment-grade bonds. In Panels B and C, we separately consider downgrades and upgrades. Bonds with no credit rating changes appear in both sub-samples. A comparison of the results in Panels B and C suggests that our results are largely driven by the bond downgrade subsample. That is, the use of visuals in annual reports appears to reduce the likelihood of observing a downgrade. The results for *IMGC* are qualitatively similar. As for *RFC*, the results are not significant.

Overall, our results are consistent with an information story, where an increase in the use of images is associated with higher ratings by credit rating agencies.

6.3 Visual Measures and Firm Performance

Our results relating visual readability to information assimilation lead us to inquire whether visuals are related to future firm performance. While we do not have a clear prediction, the empirical results may be helpful in furthering our understanding of the informational role of visuals, in particular, of images and their content reinforcement to the textual narrative.

Thus, for completeness, in Table C.7, we examine the association between year t visual measures and the firm ROA at the end of fiscal year $t+1$ and the firm's cumulative stock returns ($ANNRET$) in fiscal year $t+1$. The results demonstrate a positive and marginally significant (at the 10% level) relationship between visual prevalence (AVC) and subsequent year ROA. Notably, the effect is not large. The coefficients of *IMGC* and *RFC* are not significant, but share similar economic magnitude. We also document a positive (small) but insignificant association between the visual measures and subsequent year *ANNRET*.

While the above effects are marginal, they point against a non-fundamental story in which firms would use visuals merely as a marketing tool, or where images are employed only in an opportunistic way, when performance is poor. Rather, these results, albeit weak, are supportive of our information-based story.

7 Identification: Brokerage Firm Closures and Visual Prevalence

Analysts play an important information production role in the markets through their firm data synthesis and dissemination efforts. Notably, the decision to cover certain stocks is an endogenous decision for brokerage firms.

As an identification strategy, we take advantage of Kelly and Ljungqvist (2012)'s setting and focus on terminations of sell-side analyst coverage as a result of brokerage firm closures: between 2000-2008, 43 brokerage firms closed their research departments due to adverse changes in the economics of sell-side research, leading to 4,429 coverage terminations. Importantly, these closures were 1. well publicized and 2. plausibly exogenous at the level of the affected stocks, as they were unrelated to individual firms' future prospects. We conjecture that when firms lose coverage, they are incentivized to increase their use of visuals (images) to substitute for the loss of information production.

We match the Kelly and Ljungqvist (2012) list of brokerage firms with our data, and identify 23 (out of their 25) brokerage closure events which overlap (2002 to 2007) with our sample period. To correct for a potential bias in staggered difference-in-difference analyses (Baker, Larcker, and Wang, 2022), we follow Gormley and Matsa (2011) and use stacked difference-in-difference regressions with cohort-firm and cohort-year fixed effects. For each cohort (stack) we include first-time-treated firms, but not past-treated firms. As control firms we use non-prior-treated ones. "Pre" is the year of the brokerage firms' closures and "post" is post-closure year. Using propensity scores, we match on: *Pages*, *InstHold*, *LnNews*, *ROA*, *AnnRet*, *LnAssets*, *LnBM*, *SdRet*, *Turnover*, *LnSize*, as well as on lagged *IMGC*.

We run the following model:

$$DEP_{i,j,t} = \alpha + \beta \cdot DID_{i,j,t} + \gamma_{i,j} + \omega_{i,t} + \epsilon_{i,j,t}, \tag{7}$$

where i is the cohort, j is the firm and t is the year. *DEP* is either the change in brokerage coverage in year t, or the image use in the annual report of firm j in fiscal year t. *DID* is the $Treated \times Post$. All specifications include cohort-firm ($\gamma_{i,j}$) and cohort-year ($\omega_{i,t}$) fixed effects. Standard errors are clustered by firm.

[Table 12]

Panel A of Table 12 reports the results. The outcome variable in the first two columns (without and with controls, respectively) is the change in coverage ($\Delta AnalystCoverage$), and the second output variable in the third and fourth columns (without and with controls, respectively) is *IMGC*. Post-brokerage-firm closure, treatment firms experienced a significant drop of 0.56 analysts on average (coefficient= -0.563; t-stat= -2.95). Correspondingly, the number of image-pages per annual report increased significantly, by on average 1.3 pages (coefficient= 1.344; t-stat= 2.58); This increase is economically significant given the average number of image-pages per annual report (5.14 for the full sample; 6.85 for firms with any visual pages).

To check for pre- and post trends, we run difference-in-difference regressions substituting "t+1" and "t+2" ("t-1" and "t-2") for the event year. Panel B presents the results. None of the brokerage coverage drop effects in the years $t-1$ and $t-2$ are statistically or economically significant, confirming a parallel trend in the outcome variable during the prior two years. The $t+1$ and $t+2$ effects are also insignificant, suggesting the persistence of the average treatment effect over the two years following the event year. Figure 6 plots the difference-in-difference coefficient estimates together with their 95% confidence intervals.

Our combined results support the idea that firms increase their use of images when they face an exogenous drop in analyst coverage.

8 Conclusion

Over the last couple of decades, firms have increased their use of images, graphics, and other visual elements in their financial reporting. While studies have extensively explored the effect of *textual* readability of financial reports on the firm's information environment, little is known about the determinants, and effect of "*visual* readability" on important financial outcomes.

To our knowledge, this paper is the first to explore the use of visual content, including images, charts, infographics, maps, and team/management photos, such as to enhance "visual readability" in annual reports. We coin the term "visual readability" to investigate how images can improve the way readers assimilate the information in annual reports. Most importantly, we create a novel measure of content reinforcement, representing the information content investors can extract from images, complementing and reinforcing particulars contained in the textual narrative.

We use machine-learning methods to innovate by teasing out important characteristics of (and categorizing) the visual content we examine. We conjecture that images provide information content that reinforces the textual narrative in the annual report, and serve as an important source of firm information dissemination.

In support of an information-based story explaining our results, we find that a higher use of image-pages and image content reinforcement is associated with higher (lower) analyst forecast accuracy (dispersion). The economic significance of visual readability is comparable to that of well-known measures of textual readability. The visual measures we employ provide consistent results across a broad set of firm outcomes. They are intuitive and relatively straightforward and demonstrate the utility of imagery in providing information that is relevant to financial decision-making and results.

As machine learning algorithms become more advanced, we expect future research to further explore the various aspects of visual content on the information environment and financial outcomes.

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Figure 1: American Science and Engineering, Inc.

This figure presents four report pages from one annual report of American Science and Engineering, Inc.

Source: Report pages from the 2008 American Science and Engineering, Inc. Annual Report.

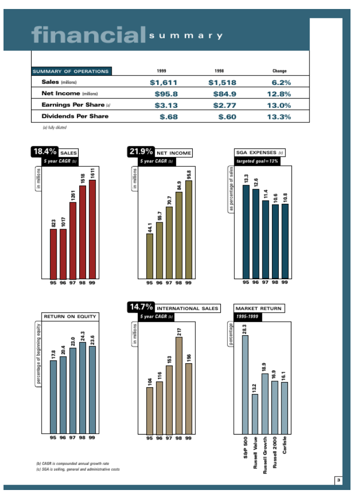
Figure 2: Classification of Visual Elements

This Figure illustrates our five visual categories. Each report page below is identified as dominantly one of the following: images (*IMG*), team/management photos (*T*), charts (*CHAR*), maps (*MAPS*), or infographics (*INFO*).

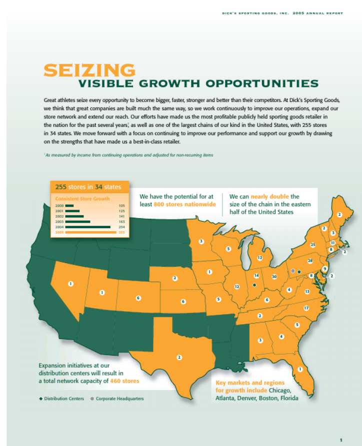
Panel A: Images

Panel B: Teams

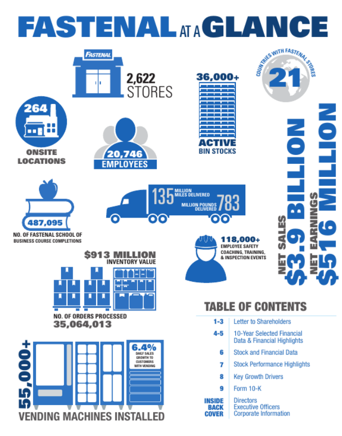
Panel C: Charts



Panel D: Maps



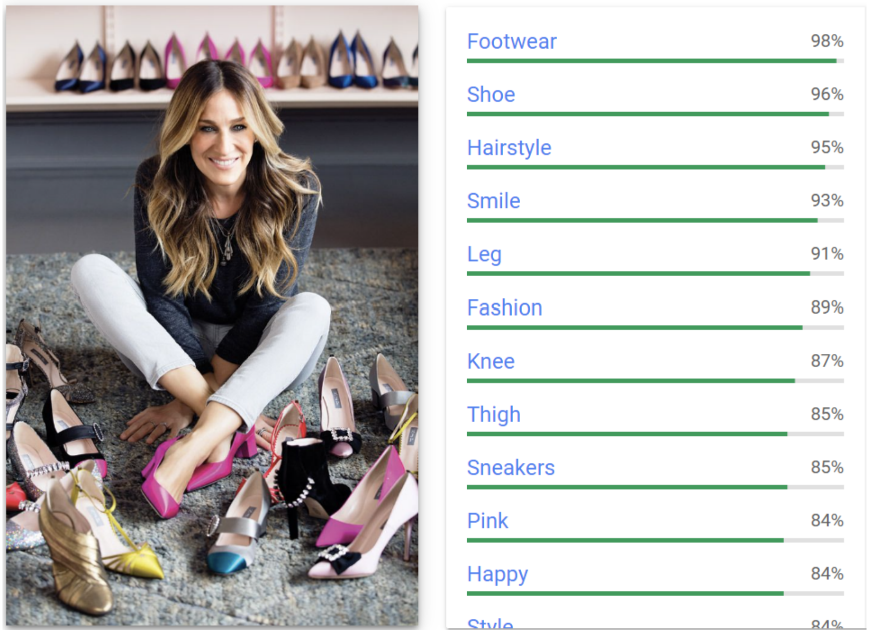
Panel E: Infographics



Source: (Top Left) Report page from the 2008 Coach (Now Tapestry) Annual Report; (Top Right) Report page from the 2016 Clairvest Group Inc Annual Report; (Bottom Left) Report page from the 1999 Carlisle Companies, Inc Annual Report; (Bottom Center) Report page from the 2005 DICK'S Sporting Goods Inc Annual Report; (Bottom Right) Report page from the 2015 Fastenal Co Annual Report.

Figure 3: Image-Pages and Google Vision Labels

This figure provides an example Google Vision's API Label output. The image of the woman with shoes is processed through Google Vision, and the labels are produced along with their corresponding probabilities.



Source: https://dontmesswithtaxes.typepad.com/.a/6a00d8345157c669e20263e9633c41200b-pi.

Figure 4: Reinforcing Annual Report Image Pages

This figure provides examples of reinforcing image-pages (to the annual report textual narrative) from four annual reports in our sample. The Google Vision labels that match the text for each image-page are: For PACCAR (top left): "vehicle", "motor vehicle"; for Ethan Allen Interiors (top right): "furniture"; for Teleflex (bottom left): "health care provider; for Toll Brothers (bottom right): "property".

Source: (Top Left) Report page from the 2010 PACCAR Inc Annual Report; (Top Right) Report page from the 2007 Ethan Allen Interiors Inc Annual Report; (Bottom Left) Report page from the 2006 Teleflex Inc Annual Report; (Bottom Right) Report page from the 2013 Toll Brothers Inc Annual Report.

Figure 5: Reinforcing Image-Pages: Reinforcement to Other Textual Narrative

This figure provides examples of reinforcing image-pages. The three image-pages in Panel A are from three different annual reports in our sample. All three reinforce the textual narrative of the annual reports in which they appear, as well as both the Business (BUS) and MD&A sections of the 10-K. Panel B reports the Google Vision labels and corresponding confidence levels, along with a breakdown of which narrative text each label matches (annual report, business description, and/or the MD&A section of the firm's 10K filing).

Panel A: Reinforcing Image-pages

Source: (Top Left) Report page from the 2005 Texas Roadhouse Inc. Annual Report; (Top Center) Report page from the 2005 Mattel Inc. Annual Report; (Top Right) Report page from the 2013 Sprouts Farmers Market Inc Annual Report.

Panel B: Reinforcement Matches to Textual Narrative by Document Type

Texas Roadhouse (TXRH, NASDAQ)				
Label	Prob.	AR	BUS	MDA
dish	99%	1	0	0
food	99%	1	1	1
cuisine	99%	1	1	0
meal	95%	1	1	1
ingredient	92%	1	1	0
meat	90%	1	1	0
produce	78%	1	1	0
garnish	77%	0	0	0
carne asada	71%	0	0	0
steak	71%	1	1	0

Mattel (MAT, NASDAQ)				
Label	Prob.	AR	BUS	MDA
child	93%	1	1	1
play	83%	1	1	1
photography	78%	0	0	0
toddler	78%	0	0	0
fun	70%	1	1	0
doll	69%	1	1	1
toy	67%	1	1	1
photomontage	63%	0	0	0
collage	54%	0	0	0
child model	53%	0	0	0

Sprouts Farmers Market (SFM, NASDAQ)				
Label	Prob.	AR	BUS	MDA
ingredient	96%	1	1	0
local food	96%	1	1	0
produce	95%	1	1	1
box	94%	1	1	0
whole food	94%	0	0	0
natural foods	93%	1	1	0
marketplace	92%	1	1	0
trade	90%	1	1	1
fruit	88%	1	1	0
carton	85%	0	0	0

Figure 6: Difference-in-Difference by Period

This figure plots the difference-in-difference regression coefficients reported in Panel B of Table 12.

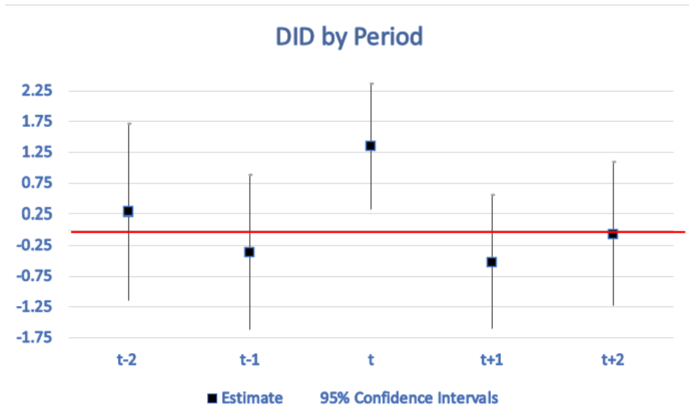


Table 1: Summary Statistics of Annual Report Pages and Visual Measures

This table reports summary statistics of annual report pages and their visual content. Panel A reports the average, standard deviation, and percentile statistics of visual prevalence measures by visual element-pages categories and of the reinforcement content measures. Panel B restricts the sample to reports that include visual elements. Panel C reports statistics for the full sample by GICS sectors. The full sample includes 15,477 firm-year observations from 1,363 unique firms and spans the years from 2002 to 2019. See Table A.1 for the data collection process and Table C.1 for variable definitions.

Panel A: Statistics of Annual Report Pages and Visual Measures - Full Sample

	Mean	Std. Dev.	5%	10%	25%	Median	75%	90%	95%
# Report Pages	117.936	61.008	34.000	57.000	84.000	112.000	142.000	178.000	212.000
IMGC	5.135	7.953	0.000	0.000	0.000	3.000	7.000	12.000	16.000
TC	0.945	1.739	0.000	0.000	0.000	0.000	1.000	3.000	4.000
CMIC	0.124	0.428	0.000	0.000	0.000	0.000	0.000	1.000	1.000
AVC	6.204	8.940	0.000	0.000	0.000	4.000	9.000	15.000	20.000
RFC	4.378	6.486	0.000	0.000	0.000	1.000	7.000	13.000	18.000
RFC_{BUS}	2.856	4.670	0.000	0.000	0.000	0.000	4.000	9.000	13.000
RFC_{MDA}	1.805	3.286	0.000	0.000	0.000	0.000	2.000	6.000	9.000
RFC_{BUSMDA}	3.271	5.100	0.000	0.000	0.000	1.000	5.000	10.000	14.000
$RFC_{BUSMDA+}$	3.589	5.793	0.000	0.000	0.000	0.000	5.000	11.000	16.000
RFC_{BUSMDA_IFBOTH}	1.138	2.178	0.000	0.000	0.000	0.000	1.000	4.000	6.000
# of Firm-year Obs.	15,477								

Panel B: Statistics of Annual Report Pages and Visual Measures - Restricted Sample

	Mean	Std. Dev.	5%	10%	25%	Median	75%	90%	95%
# Report Pages	112.204	54.511	28.000	50.000	80.000	108.000	139.000	172.000	201.000
$IMGC$	6.847	8.522	1.000	1.000	2.000	5.000	9.000	14.000	18.000
TC	1.260	1.907	0.000	0.000	0.000	1.000	2.000	4.000	5.000
$CMIC$	0.166	0.488	0.000	0.000	0.000	0.000	0.000	1.000	1.000
AVC	8.273	9.458	1.000	1.000	3.000	6.000	11.000	17.000	22.000
RFC	5.837	6.898	0.000	0.000	0.000	4.000	9.000	15.000	20.000
RFC_{BUS}	3.809	5.045	0.000	0.000	0.000	2.000	6.000	11.000	14.000
RFC_{MDA}	2.407	3.598	0.000	0.000	0.000	1.000	4.000	7.000	10.000
RFC_{BUSMDA}	4.361	5.471	0.000	0.000	0.000	2.000	7.000	12.000	16.000
$RFC_{BUSMDA+}$	4.786	6.247	0.000	0.000	0.000	2.000	7.000	13.000	18.000
RFC_{BUSMDA_IFBOTH}	1.517	2.398	0.000	0.000	0.000	0.000	2.000	5.000	6.000
# of Firm-year Obs.	11,607								

Panel C: Statistics of Annual Report Pages and Visual Measures by GICS Sectors - Full Sample

Sector GICS code	Energy 10	Mat. 15	Ind. 20	Con. Disc. 25	Con. St. 30	Health 35	Fin. 40	Inf. Tech. 45	Com. Ser. 50	Util 55	Real Est. 60
# Report Pages(Mean)	133.54	114.65	102.41	108.92	98.90	113.00	141.21	116.61	130.10	154.85	122.16
# Report Pages(Std.Dev)	71.32	45.63	48.19	49.60	44.78	52.96	73.78	50.87	53.95	112.44	64.08
AVC(Mean)	6.25	7.61	6.62	5.93	8.89	4.91	6.90	4.40	4.17	8.16	6.20
AVC(SD)	6.53	8.65	8.07	8.25	11.04	7.66	10.55	9.45	8.60	7.12	9.01
$IMGC$(Mean)	5.28	6.40	5.53	5.13	7.57	3.91	5.18	3.75	3.55	6.69	5.24
$IMGC$(Std.Dev)	5.54	7.82	7.26	7.31	9.90	6.81	9.10	8.68	7.69	6.16	8.11
TC(Mean)	0.83	0.99	0.96	0.69	1.15	0.92	1.58	0.56	0.56	1.32	0.83
TC(Std.Dev)	1.55	1.38	1.54	1.40	1.83	1.68	2.48	1.41	1.43	1.78	1.72
$CMIC$(Mean)	0.13	0.21	0.14	0.11	0.17	0.08	0.14	0.09	0.06	0.14	0.12
$CMIC$(Std.Dev)	0.39	0.54	0.43	0.41	0.52	0.32	0.53	0.34	0.26	0.43	0.41
RFC(Mean)	4.52	5.11	5.73	5.70	8.04	2.95	3.04	2.28	2.68	5.57	3.54
RFC(Std.Dev)	6.31	6.52	7.39	7.89	9.49	4.97	4.43	3.80	4.68	6.13	5.35
RFC_{BUS}(Mean)	2.90	3.15	3.76	4.24	5.25	2.16	1.54	1.55	1.68	3.16	2.02
RFC_{BUS}(Std.Dev)	4.70	4.75	5.47	6.13	6.41	3.80	2.33	2.79	3.15	3.93	3.43
RFC_{MDA}(Mean)	1.87	1.86	2.36	2.56	3.26	1.17	1.16	0.82	1.30	2.12	1.79
RFC_{MDA}(Std.Dev)	3.21	3.41	4.00	3.90	4.80	2.39	2.09	1.77	2.59	3.13	2.99
$RFC_{BUSMDA+}$(Mean)	3.71	3.81	4.78	5.22	5.94	2.60	2.19	1.94	2.27	4.29	2.73
$RFC_{BUSMDA+}$(Std.Dev)	5.79	5.85	6.89	7.51	7.73	4.52	3.27	3.47	4.33	5.31	4.49
RFC_{BUSMDA_IFBOTH}(Mean)	1.16	1.15	1.52	1.72	1.97	0.76	0.68	0.56	0.81	1.27	0.95
RFC_{BUSMDA_IFBOTH}(Std.Dev)	2.13	2.31	2.70	2.76	3.07	1.58	1.19	1.23	1.79	1.95	1.72
# of Firm-year Obs.	656	890	2561	2346	909	1664	2148	2161	381	609	1152

Table 2: Number of Annual Reports with Visuals by Year

This table reports statistics of the number of annual reports that include visual report pages. *AR(V)* denotes reports that have pages with any visual content. *AR(I)* denotes the number of annual reports with at least one image-page, *AR(T)* denotes the number of annual reports with at least one team photos-page, *AR(CMI)* denotes the number of annual reports with at least one CMI page. The bottom row reports the time-series averages of the columns. See Table C.1 and Table 1 for variable and sample definitions.

FYEAR	Reports	AR(V)	%	AR(I)	%	AR(T)	%	AR(CMI)	%
2002	361	297	82.3%	289	80.1%	187	51.8%	52	14.4%
2003	534	446	83.5%	439	82.2%	275	51.5%	60	11.2%
2004	622	534	85.9%	526	84.6%	332	53.4%	81	13.0%
2005	694	584	84.1%	574	82.7%	380	54.8%	77	11.1%
2006	750	633	84.4%	615	82.0%	397	52.9%	113	15.1%
2007	804	636	79.1%	623	77.5%	385	47.9%	112	13.9%
2008	842	634	75.3%	614	72.9%	347	41.2%	90	10.7%
2009	828	619	74.8%	604	72.9%	337	40.7%	77	9.3%
2010	856	638	74.5%	623	72.8%	351	41.0%	113	13.2%
2011	864	631	73.0%	621	71.9%	301	34.8%	91	10.5%
2012	910	656	72.1%	641	70.4%	351	38.6%	103	11.3%
2013	925	651	70.4%	635	68.6%	353	38.2%	101	10.9%
2014	1003	686	68.4%	660	65.8%	379	37.8%	107	10.7%
2015	1016	697	68.6%	680	66.9%	366	36.0%	95	9.4%
2016	1129	776	68.7%	754	66.8%	381	33.7%	114	10.1%
2017	1129	776	68.7%	753	66.7%	381	33.7%	97	8.6%
2018	1164	827	71.0%	806	69.2%	366	31.4%	39	3.4%
ALL	14431	10721	74.3%	10457	72.5%	5869	40.7%	1522	10.5%

Table 3: Summary Statistics of Firm Characteristics and Correlations

This table reports summary statistics and correlations. Panel A reports the cross-sectional statistics of time series averages of the firm characteristics. Panels B and C report the correlations of our visual classifications metrics, the *FOG* textual-based readability measure, and firm controls. All variables are demeaned by firm to capture within-firm correlations. All visual metrics are winzorised at the 99th percentile of their sample distributions. See Table C.1 and Table 1 for variable and sample definitions.

Panel A: Cross-Sectional Statistics

	Mean	Std. Dev.	10%	25%	Median	75%	90%
SizeInMil	11656.316	31862.225	614.562	1117.974	2671.120	8455.463	24240.240
AssetsInMil	15648.578	41756.746	460.572	1118.229	3120.500	10122.333	34012.025
BookToMarket	0.544	0.338	0.185	0.306	0.498	0.717	0.936
SdRet	0.022	0.007	0.014	0.017	0.021	0.026	0.032
Turnover	0.010	0.006	0.005	0.006	0.008	0.012	0.016
MktBeta	1.112	0.318	0.686	0.904	1.120	1.321	1.505
AnnRet	0.167	0.168	0.022	0.092	0.148	0.219	0.327
InstHold	0.675	0.161	0.454	0.579	0.700	0.792	0.853
Δ*InstHold*	-0.001	0.045	-0.041	-0.022	-0.002	0.016	0.042
#News	129.512	123.309	49.500	66.286	94.300	144.625	237.167
ROA	0.123	0.082	0.024	0.066	0.119	0.170	0.224
Cost-of-Equity	0.114	0.025	0.082	0.098	0.115	0.130	0.145
Cost-of-Debt	0.053	0.021	0.031	0.041	0.052	0.063	0.077
D/E	0.923	1.477	0.034	0.233	0.616	1.187	2.106
AdvExpToSale	0.012	0.032	0.000	0.000	0.000	0.011	0.036
AnalystsCoverage	9.985	6.743	2.909	4.796	8.042	13.964	19.817
# of firms	1,363						

Panel B: Correlations of Visual Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) *AVC*	1.00										
(2) *IMGC*	0.97	1.00									
(3) *TC*	0.55	0.34	1.00								
(4) *CMIC*	0.22	0.14	0.11	1.00							
(5) *RFC*	0.58	0.57	0.30	0.10	1.00						
(6) RFC_{BUS}	0.48	0.47	0.25	0.10	0.80	1.00					
(7) RFC_{MDA}	0.40	0.39	0.21	0.08	0.71	0.72	1.00				
(8) RFC_{BUSMDA}	0.51	0.50	0.26	0.10	0.85	0.96	0.82	1.00			
(9) $RFC_{BUSMDA+}$	0.48	0.48	0.25	0.10	0.80	0.94	0.85	0.94	1.00		
(10) RFC_{BUSMDA_IFBOTH}	0.37	0.36	0.19	0.07	0.66	0.79	0.90	0.78	0.91	1.00	
(11) *FOG*	-0.02	-0.02	-0.01	-0.02	0.00	-0.00	-0.00	-0.00	-0.01	-0.00	1.00

Panel C: Correlations of Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LnNews	1.00									
AnnRet	0.01	1.00								
ROA	0.07	0.10	1.00							
AdvExpToSale	0.02	-0.03	-0.05	1.00						
LnSize	0.25	0.16	0.25	0.02	1.00					
LnBM	0.00	-0.33	-0.34	0.00	-0.47	1.00				
SdRet	0.07	0.06	-0.16	-0.01	-0.47	0.27	1.00			
Tunover	0.15	0.01	0.00	0.03	-0.09	0.05	0.42	1.00		
LnAssets	0.28	-0.10	-0.08	0.02	0.73	0.07	-0.24	-0.00	1.00	
D/E	-0.02	-0.01	-0.06	-0.00	-0.06	-0.35	0.09	0.07	0.07	1.00

Table 4: The Determinants of *IMGC*

This table reports results from panel regressions of *IMGC* from the firm's annual report of year t on various explanatory variables. For completeness, Table C.2 reports results for *AVC* and *RFC* (dependent variables). *LDEP* is the lagged dependent variable. See Table C.1 and Table 1 for variable and sample definitions. All explanatory variables are measured as of end of fiscal year t. The regressions include firm and year fixed effects. Standard errors are clustered by firm and year and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. All visual metrics are winzorised at the 99th percentile of their sample distributions. (Z) stands for a Z-Score adjustment (a mean of zero and a standard deviation of one).

	IMGC(Z)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LDEP (Z)	0.432***	0.431***	0.432***	0.432***	0.429***	0.428***	0.426***
	(10.59)	(10.51)	(10.49)	(10.49)	(10.40)	(10.37)	(10.33)
Pages (Z)	-0.016	-0.015	-0.015	-0.015	-0.018	-0.016	-0.013
	(-0.88)	(-0.82)	(-0.80)	(-0.80)	(-0.98)	(-0.88)	(-0.71)
LnNews (Z)	0.037**	0.034**	0.035**	0.035**	0.019	0.016	0.030*
	(2.79)	(2.50)	(2.51)	(2.52)	(1.29)	(1.06)	(1.98)
701_801_DISCLOSURE (Z)	0.021*	0.021*	0.021*	0.021*	0.020*	0.020*	0.022*
	(1.78)	(1.82)	(1.86)	(1.85)	(1.77)	(1.77)	(1.93)
AnnRet (Z)		0.017**	0.017**	0.017**	0.020***	0.014**	0.020***
		(2.73)	(2.74)	(2.74)	(3.15)	(2.35)	(3.14)
ROA (Z)		0.041***	0.040***	0.040***	0.044***	0.034**	0.028*
		(3.06)	(2.92)	(2.91)	(3.16)	(2.45)	(2.00)
InstHold (Z)			0.002	0.002	-0.003	-0.005	-0.002
			(0.17)	(0.16)	(-0.27)	(-0.40)	(-0.18)
AdvExpToSale (Z)			-0.016	-0.016	-0.016	-0.016	-0.015
			(-0.92)	(-0.93)	(-0.87)	(-0.89)	(-0.86)
FOG(Z)				-0.004	-0.008	-0.007	-0.008
				(-0.33)	(-0.71)	(-0.70)	(-0.74)
LnAssets (Z)					0.140***	0.151***	0.132***
					(3.66)	(3.68)	(3.10)
LnBM (Z)						-0.035**	-0.030*
						(-2.27)	(-1.86)
SdRet (Z)							-0.034***
							(-2.98)
Turnover (Z)							-0.043***
							(-3.26)
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	13,579	13,557	13,452	13,452	13,452	13,452	13,451
R^2	0.597	0.598	0.597	0.597	0.598	0.598	0.600

Table 5: Visual Prevalence, Image Content Reinforcement, and Subsequent-Year Analyst Forecast Accuracy

This table reports results from panel regressions of analyst quarterly forecast errors of quarters q1–q4 in fiscal year t+1 on fiscal year t visual metrics and other explanatory variables. Panel A - C report results based on *AVC*, *IMGC*, and *RFC*, respectively. For inclusion in our analysis, we require that at least two stocks be followed by each analyst i in quarter q. We use a within-analyst quarterly forecast accuracy measure, $WAFE_{i,j,q}$. The measure is calculated as $(AFE_{i,j,q} - \overline{AFE_{j,q}})$ / $\overline{AFE_{j,q}}$, and is the absolute scaled forecast error for analyst i's forecast of firm j's earnings in quarter q of fiscal year t+1, minus the mean absolute scaled forecast error for analyst i across all the stocks the analyst follows during quarter q, divided by the mean absolute scaled forecast error of the analyst, across all stocks the analyst follows in quarter t. We average the quarterly forecast errors over fiscal year t+1. See Table C.1 and Table 1 for variable and sample definitions. All explanatory variables are measured as of end of fiscal year t. The regressions include firm and analyst × year fixed effects. Standard errors are clustered by analyst and year. t-statistics are reported in parentheses. Panel B also includes *TC* and *CMIC* as fixed effects (i.e., dummy indicators). *TC* and *CMIC* coefficient estimates are reported in Table C.3. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. All visual metrics are winzorised at the 99th percentile of their sample distributions. (Z) stands for a Z-Score adjustment.

Panel A: Analyst Accuracy and *AVC*

	(1)	(2)	(3)	(4)	(5)
AVC (Z)	-0.041***	-0.042***	-0.042***	-0.024***	-0.025***
	(-4.99)	(-5.10)	(-5.09)	(-3.12)	(-3.19)
Pages	0.001***	0.001***	0.001***	0.000	0.000
	(3.20)	(3.16)	(3.14)	(1.26)	(1.23)
DaysToEarnAnn	0.001***	0.001***	0.001***	0.001***	0.001***
	(5.96)	(5.97)	(5.97)	(5.31)	(5.58)
LnNews	0.048**	0.048**	0.047**	0.080***	0.079***
	(2.18)	(2.17)	(2.14)	(2.99)	(3.04)
AnnRet	-0.185***	-0.185***	-0.185***	-0.036***	-0.032***
	(-3.37)	(-3.35)	(-3.37)	(-3.03)	(-2.70)
ROA	-2.708***	-2.690***	-2.683***	-0.316	-0.355*
	(-13.20)	(-13.03)	(-13.04)	(-1.59)	(-1.80)
InstHold	-0.248***	-0.251***	-0.252***	-0.154***	-0.156***
	(-6.98)	(-7.26)	(-7.16)	(-5.07)	(-5.20)
LnAssets	-0.034	-0.034	-0.038	0.527***	0.495***
	(-1.16)	(-1.19)	(-1.32)	(16.01)	(14.14)
AdvExpToSale		1.459**	1.494**	1.518***	2.258***
		(2.33)	(2.38)	(3.37)	(2.92)
FOG(Z)			0.032***	0.022**	0.021**
			(3.63)	(2.35)	(2.29)
LnBM				-0.071***	-0.061***
				(-4.05)	(-3.65)
SdRet				6.067***	5.595***
				(3.55)	(3.44)
Turnover				-0.565	-1.053
				(-0.38)	(-0.74)
LnSize				-0.714***	-0.710***
				(-21.96)	(-21.69)
Analyst Disp					0.937***
					(4.13)
Firm FE	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES
Observations	141,867	141,831	141,831	141,829	141,759
R^2	0.490	0.490	0.490	0.520	0.524

Panel B: Analyst Accuracy and *IMGC*

	(1)	(2)	(3)	(4)	(5)
IMGC(Z)	-0.033***	-0.034***	-0.034***	-0.024***	-0.025***
	(-3.80)	(-3.86)	(-3.85)	(-2.94)	(-3.08)
Firm Controls	YES	YES	YES	YES	YES
TC and *CMIC* FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES
Observations	141,867	141,831	141,831	141,829	141,759
R^2	0.490	0.490	0.490	0.520	0.524

Panel C: Analyst Accuracy and *RFC*

	(1)	(2)	(3)	(4)	(5)
RFC(Z)	-0.027***	-0.027***	-0.028***	-0.012	-0.012*
	(-3.57)	(-3.63)	(-3.67)	(-1.60)	(-1.72)
Firm FE	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES
Observations	141,867	141,831	141,831	141,829	141,759
R^2	0.490	0.490	0.490	0.520	0.524

Table 6: Image Content Reinforcement with Other Pertinent Textual Narrative

This table extends the results for *RFC* reported in Table 5. We replace *RFC* with additional information reinforcement measures that reinforce the narrative of the business and MD&A sections in the 10-K filings. Within each panel of this table, each row represents a distinct regression set. For parsimony, we do not report the full set of control variables below. Panel A reports results based for RFC_{BUS} and RFC_{MDA}, as well as for three variations of *RFC*; RFC_{BUSMDA}, in which we consider reinforcement to the combined text of the business and MD&A sections; $RFC_{BUSMDA+}$, in which a label that matches a word appearing in the textual narrative of both sections is counted once for each section, and RFC_{BUSMDA_IFBOTH}, which considers only label-to-text matches that appear in *both* sections. Panel B presents the results for *RFC-IP*, a variant of *RFC*, in which label-to-text matching reflects the incidence of labels per image-page (per report). We report results for $RFC\text{-}IP_{BUSMDA}$, $RFC\text{-}IP_{BUSMDA+}$ and $RFC\text{-}IP_{BUSMDA\_IFBOTH}$. In Panel C, we present results for reinforcement measures that capture label-to-text matches to (10) "Important Sentences," derived using NLP summarization tools. We report results for $RFC_{BUS\_MDA\_IS}$, $RFC_{BUSMDA+(IS)}$ and $RFC_{BUSMDA\_IFBOTH(IS)}$. Panel D presents the results for the *RFC-IP* measures based on Important Sentences ($RFC\text{-}IP_{BUSMDA(IS)}$, $RFC\text{-}IP_{BUSMDA+(IS)}$ and $RFC\text{-}IP_{BUSMDA\_IFBOTH(IS)}$). See Table C.1 and Table 1 for variable and sample definitions. All explanatory variables are measured as of end of fiscal year t. The regressions include firm and analyst × year fixed effects. For parsimony, controls are not reported. Standard errors are clustered by analyst and year. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. All visual metrics are winzorised at the 99th percentile of their sample distributions. (Z) stands for a Z-Score adjustment.

Panel A: *RFC* Reinforcement with Business and MD&A Sections

	(1)	(2)	(3)	(4)	(5)
$RFC_{BUS}(Z)$	-0.031***	-0.031***	-0.031***	-0.018**	-0.018**
	(-3.17)	(-3.21)	(-3.22)	(-2.17)	(-2.15)
$RFC_{MDA}(Z)$	-0.028***	-0.028***	-0.028***	-0.019**	-0.019**
	(-2.99)	(-3.02)	(-3.02)	(-2.33)	(-2.36)
$RFC_{BUSMDA}(Z)$	-0.031***	-0.031***	-0.031***	-0.018**	-0.018**
	(-3.16)	(-3.21)	(-3.21)	(-2.13)	(-2.15)
$RFC_{BUSMDA+}(Z)$	-0.030***	-0.031***	-0.031***	-0.017*	-0.017*
	(-2.96)	(-3.00)	(-3.01)	(-1.95)	(-1.97)
$RFC_{BUSMDA\_IFBOTH}(Z)$	-0.029***	-0.030***	-0.030***	-0.019**	-0.019**
	(-3.02)	(-3.04)	(-3.06)	(-2.29)	(-2.30)

Panel B: *RFC-IP* Reinforcement with Business and MD&A Sections

	(1)	(2)	(3)	(4)	(5)
$RFC\text{-}IP_{BUSMDA}(Z)$	-0.030***	-0.031***	-0.031***	-0.020**	-0.020**
	(-2.79)	(-2.83)	(-2.80)	(-2.07)	(-2.07)
$RFC\text{-}IP_{BUSMDA+}(Z)$	-0.032***	-0.033***	-0.033***	-0.022**	-0.022**
	(-2.99)	(-3.02)	(-2.99)	(-2.29)	(-2.27)
$RFC\text{-}IP_{BUSMDA\_IFBOTH}(Z)$	-0.029***	-0.030***	-0.030***	-0.021**	-0.020**
	(-3.00)	(-3.03)	(-3.01)	(-2.42)	(-2.37)

Panel C: *RFC* Reinforcement with Business and MD&A Sections - Important Sentences

	(1)	(2)	(3)	(4)	(5)
$RFC_{BUS\_MDA\_IS}(Z)$	-0.027***	-0.028***	-0.028***	-0.015***	-0.015***
	(-3.70)	(-3.75)	(-3.74)	(-2.77)	(-2.76)
$RFC_{BUSMDA+(IS)}(Z)$	-0.025***	-0.026***	-0.025***	-0.014**	-0.014**
	(-3.14)	(-3.17)	(-3.15)	(-2.34)	(-2.29)
$RFC_{BUSMDA\_IFBOTH(IS)}(Z)$	-0.010	-0.010	-0.010	-0.006	-0.005
	(-1.39)	(-1.39)	(-1.36)	(-1.09)	(-0.89)
Observations	141,867	141,831	141,831	141,829	141,759
R^2	0.490	0.490	0.490	0.520	0.524

Panel D: *RFC-IP* Reinforcement with Business and MD&A Sections - Important Sentences

	(1)	(2)	(3)	(4)	(5)
$RFC\text{-}IP_{BUSMDA(IS)}(Z)$	-0.028***	-0.028***	-0.028***	-0.017**	-0.017**
	(-3.52)	(-3.59)	(-3.59)	(-2.56)	(-2.58)
$RFC\text{-}IP_{BUSMDA+(IS)}(Z)$	-0.027***	-0.027***	-0.027***	-0.017**	-0.016**
	(-3.19)	(-3.24)	(-3.22)	(-2.41)	(-2.38)
$RFC\text{-}IP_{BUSMDA\_IFBOTH(IS)}(Z)$	-0.013*	-0.013*	-0.013	-0.009	-0.008
	(-1.68)	(-1.67)	(-1.63)	(-1.45)	(-1.27)

Table 7: Visual Measures and Analyst Cognitive Constraints

This table extends the analysis conducted in Table 5. Results are reported for *AVC* and *RFC* based on three sub-samples: the number of stocks an analyst follows (stock coverage) (Panel A), industry concentration (Panel B), and textual readability (Panel C). Table C.4 reports results using *IMGC*. For each sub-sample in each panel, the three columns correspond to columns 1, 3, and 5 of Table 5. In Panel A the “High COV” (“Low COV”) sub-sample is comprised of the top (bottom) analyst tercile in terms of stock coverage. Panel B presents results for analysts in the “High COV” tercile, ranked by their industry concentration. For each analyst, we calculate the max fraction of stocks in any industry they cover. “Low Industry Concentration” (“High Industry Concentration”) indicates that the analyst is in the bottom (top) tercile of industry concentration. In Panel C, the “High FOG” (“Low FOG”) sub-sample is comprised of stocks that appear in the top (bottom) tercile of stock textual readability. The regressions include firm and analyst × year fixed effects. For parsimony, controls are not reported. Standard errors are clustered by analyst and year. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. (Z) stands for a Z-Score adjustment. All visual metrics are winzorised at the 99th percentile of their sample distributions.

Panel A: Analyst Accuracy and Stock Coverage

	High COV			Low COV		
	(1)	(2)	(3)	(4)	(5)	(6)
AVC (Z)	-0.042***	-0.042***	-0.024**	-0.012	-0.012	0.000
	(-4.28)	(-4.26)	(-2.65)	(-0.64)	(-0.62)	(0.01)
Firm Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES	YES
Observations	71,495	71,495	71,493	15,409	15,409	15,409
R^2	0.507	0.508	0.538	0.542	0.542	0.565

	High COV			Low COV		
	(1)	(2)	(3)	(4)	(5)	(6)
RFC(Z)	-0.031***	-0.032***	-0.017**	0.005	0.005	0.019
	(-3.89)	(-3.95)	(-2.18)	(0.29)	(0.30)	(1.16)
Firm Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES	YES
Observations	71,495	71,495	71,493	15,409	15,409	15,409
R^2	0.507	0.507	0.538	0.542	0.542	0.565

Panel B: Analyst Accuracy and Industry Concentration

	Low Industry Concentration			High Industry Concentration		
	(1)	(2)	(3)	(4)	(5)	(6)
AVC (Z)	-0.069***	-0.068***	-0.054***	-0.026	-0.025	-0.017
	(-4.44)	(-4.44)	(-4.17)	(-1.43)	(-1.38)	(-1.00)
Firm Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES	YES
Observations	16,925	16,925	16,925	13,588	13,588	13,588
R^2	0.526	0.527	0.550	0.532	0.533	0.558

	Low Industry Concentration			High Industry Concentration		
	(1)	(2)	(3)	(4)	(5)	(6)
RFC(Z)	-0.054***	-0.054***	-0.042***	-0.042**	-0.044**	-0.035*
	(-4.18)	(-4.17)	(-3.26)	(-2.16)	(-2.26)	(-1.81)
Firm Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES	YES
Observations	16,925	16,925	16,925	13,588	13,588	13,588
R^2	0.526	0.526	0.550	0.533	0.533	0.558

Panel C: Analyst Accuracy and Textual Readability - Across Stocks

	High FOG			Low FOG		
	(1)	(2)	(3)	(4)	(5)	(6)
AVC (Z)	-0.069***	-0.069***	-0.055***	-0.019	-0.019	-0.014
	(-3.76)	(-3.77)	(-2.77)	(-1.25)	(-1.29)	(-1.03)
Firm Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES	YES
Observations	26,163	26,163	26,163	25,968	25,968	25,968
R^2	0.621	0.622	0.646	0.613	0.613	0.634

	High FOG			Low FOG		
	(1)	(2)	(3)	(4)	(5)	(6)
RFC(Z)	-0.070***	-0.072***	-0.040**	0.025	0.025	0.032*
	(-2.97)	(-3.00)	(-2.11)	(1.51)	(1.52)	(1.94)
Firm Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES	YES
Observations	26,163	26,163	26,163	25,968	25,968	25,968
R^2	0.621	0.622	0.646	0.613	0.613	0.634

Table 8: Visual Prevalence, Image Content Reinforcement, and Subsequent-Year Analyst Forecast Accuracy – Other Firm Information Dissemination Efforts

This table extends the analysis conducted in Table 5 by controlling for additional information dissemination efforts made by the firm. Panel A (B) reports results for *AVC*(*RFC*). In each panel, the first column reports the results from Column 5 of Table 5 for reference. In all panels, *701_801_DISCLOSURE* is the log of the number of 7.01 and 8.01 items disclosed in 8K during the fiscal year. *CORPORATE EVENTS* is the log of the number of corporate events that include relevant information to investors (such as investor conferences, corporate access events, and analyst marketing events) during the fiscal year. *PRESS RELEASES* is the log of the number of firm press releases during the fiscal year. Other variables are based on earnings calls transcripts. We use Loughran and McDonald's textual measures and focus on both the management and Q&A parts. The measures include the tone (*SENT*), uncertainty (*UNC*) and strong modal (*SMODAL*) of the text. The regressions include firm and analyst × year fixed effects. For parsimony, controls are not reported. Standard errors are clustered by analyst and year. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. (Z) stands for a Z-Score adjustment. All visual metrics are winzorised at the 99th percentile of their sample distributions.

Panel A: Analyst Accuracy and *AVC*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AVC (Z)	-0.025***	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***	-0.024***
	(-3.19)	(-3.11)	(-3.11)	(-3.12)	(-3.09)	(-3.07)	(-3.08)
701_801_DISCLOSURE (Z)		-0.048***	-0.048***	-0.048***	-0.047***	-0.048***	-0.047***
		(-3.93)	(-3.91)	(-3.91)	(-3.79)	(-3.89)	(-3.78)
CORPORATE EVENTS (Z)			-0.026**	-0.026**	-0.026**	-0.025**	-0.025**
			(-2.51)	(-2.53)	(-2.46)	(-2.35)	(-2.36)
PRESS RELEASES (Z)				-0.002	-0.002	-0.000	-0.002
				(-0.19)	(-0.24)	(-0.04)	(-0.17)
MGMT SENT (Z)					-0.044***		-0.040***
					(-5.24)		(-4.16)
MGMT UNC (Z)					0.006		0.006
					(0.80)		(0.80)
MGMT SMODAL (Z)					0.014*		0.013*
					(1.87)		(1.88)
QA SENT (Z)						-0.026***	-0.013
						(-3.42)	(-1.55)
QA UNC (Z)						-0.004	-0.006
						(-0.34)	(-0.47)
QA SMODAL (Z)						0.003	0.003
						(0.36)	(0.36)
Firm FE	YES	YES	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	141,759	141,759	141,759	141,759	141,759	141,759	141,759
R^2	0.524	0.524	0.524	0.524	0.525	0.525	0.525

Panel B: Analyst Accuracy and *RFC*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RFC(Z)	-0.012*	-0.012*	-0.012*	-0.012*	-0.012	-0.012*	-0.012
	(-1.72)	(-1.75)	(-1.73)	(-1.73)	(-1.64)	(-1.75)	(-1.65)
701_801_DISCLOSURE (Z)		-0.049***	-0.049***	-0.048***	-0.048***	-0.049***	-0.048***
		(-3.93)	(-3.91)	(-3.91)	(-3.79)	(-3.89)	(-3.78)
CORPORATE EVENTS (Z)			-0.026**	-0.026**	-0.026**	-0.025**	-0.025**
			(-2.51)	(-2.53)	(-2.47)	(-2.36)	(-2.36)
PRESS RELEASES (Z)				-0.002	-0.003	-0.000	-0.002
				(-0.19)	(-0.24)	(-0.04)	(-0.17)
MGMT SENT (Z)					-0.044***		-0.039***
					(-5.22)		(-4.14)
MGMT UNC (Z)					0.006		0.006
					(0.85)		(0.84)
MGMT SMODAL (Z)					0.014*		0.014*
					(1.89)		(1.91)
QA SENT (Z)						-0.026***	-0.014
						(-3.45)	(-1.57)
QA UNC (Z)						-0.003	-0.005
						(-0.29)	(-0.42)
QA SMODAL (Z)						0.003	0.003
						(0.29)	(0.28)
Firm FE	YES	YES	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES	YES	YES
Firm and Year Cluster	YES	YES	YES	YES	YES	YES	YES
Observations	141,759	141,759	141,759	141,759	141,759	141,759	141,759
R^2	0.524	0.524	0.524	0.524	0.525	0.525	0.525

Table 9: Visual Prevalence, Image Content Reinforcement, and Subsequent-Year Analyst Forecast Dispersion

This table reports results from panel regressions of firm dispersion of analyst earnings forecasts of quarters q1–q4 in fiscal year t+1 on fiscal year t visual metrics and other explanatory variables. $AnalystDISP_{i,j}$ is the standard deviation across the most recent analyst earnings forecasts preceding the earnings announcement date for firm i and a given quarter j, normalized the absolute value of the mean across the most recent analyst earnings forecasts. $AnalystDISP_{i,j}$ values are based on the average of the $AnalystDISP_{i,j}$ in quarters 1 to 4. The table reports results for *AVC*, *IMGC*, and *RFC*. See Table C.1 and Table 1 for variable and sample definitions. All explanatory variables are measured as of end of fiscal year t. The regressions include firm and year fixed effects. Standard errors are clustered by firm and year, and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. All visual metrics are winzorised at the 99th percentile of their sample distributions. (Z) stands for a Z-Score adjustment.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AVC (Z)	-0.025***	-0.025***	-0.014*						
	(-2.99)	(-2.97)	(-1.84)						
IMGC(Z)				-0.024***	-0.023***	-0.015*			
				(-2.97)	(-2.95)	(-1.99)			
RFC(Z)							-0.020***	-0.020***	-0.012*
							(-2.97)	(-3.01)	(-1.86)
LagDEP	0.143***	0.140***	0.106***	0.143***	0.141***	0.106***	0.142***	0.140***	0.106***
	(4.42)	(4.39)	(3.42)	(4.43)	(4.40)	(3.43)	(4.43)	(4.40)	(3.41)
Pages	0.000**	0.000**	0.000	0.000**	0.000**	0.000	0.000**	0.000**	0.000*
	(2.38)	(2.44)	(1.57)	(2.38)	(2.44)	(1.56)	(2.54)	(2.60)	(1.68)
LnNews	0.059***	0.059***	0.066***	0.059***	0.059***	0.066***	0.058***	0.058***	0.065***
	(2.81)	(2.80)	(3.16)	(2.80)	(2.80)	(3.16)	(2.75)	(2.75)	(3.11)
AnnRet	-0.141***	-0.142***	-0.086***	-0.141***	-0.143***	-0.086***	-0.141***	-0.143***	-0.086***
	(-5.23)	(-5.27)	(-3.54)	(-5.22)	(-5.26)	(-3.55)	(-5.22)	(-5.26)	(-3.54)
ROA	-1.895***	-1.904***	-1.166***	-1.893***	-1.902***	-1.163***	-1.905***	-1.914***	-1.168***
	(-11.73)	(-11.67)	(-7.02)	(-11.69)	(-11.64)	(-6.99)	(-11.90)	(-11.86)	(-7.06)
insthold	-0.171**	-0.174**	-0.111	-0.171**	-0.174**	-0.111	-0.171**	-0.174**	-0.110
	(-2.07)	(-2.12)	(-1.36)	(-2.07)	(-2.12)	(-1.36)	(-2.06)	(-2.11)	(-1.36)
LnAssets	-0.025	-0.030	0.145***	-0.024	-0.030	0.146***	-0.025	-0.031	0.146***
	(-0.85)	(-1.04)	(3.74)	(-0.83)	(-1.03)	(3.75)	(-0.86)	(-1.06)	(3.76)
AdvExpToSale		0.271	0.333		0.261	0.325		0.248	0.320
		(0.44)	(0.59)		(0.43)	(0.58)		(0.41)	(0.57)
FOG(Z)		0.021*	0.020*		0.022*	0.020*		0.022**	0.020*
		(1.98)	(1.89)		(1.99)	(1.91)		(2.00)	(1.91)
LnBM			-0.010			-0.010			-0.010
			(-0.38)			(-0.39)			(-0.39)
SdRet			6.880***			6.891***			6.902***
			(4.31)			(4.32)			(4.33)
Turnover			2.918			2.872			2.948*
			(1.66)			(1.63)			(1.68)
LnSize			-0.214***			-0.214***			-0.215***
			(-4.63)			(-4.62)			(-4.66)
701_801_DISCLOSURE (Z)			-0.039**			-0.039**			-0.039**
			(-2.59)			(-2.59)			(-2.59)
CORPORATE EVENTS (Z)			0.004			0.004			0.004
			(0.26)			(0.27)			(0.26)
PRESS RELEASES (Z)			-0.023**			-0.023**			-0.023**
			(-2.05)			(-2.06)			(-2.03)
TC and *CMIC* FE	NO	NO	NO	YES	YES	YES	NO	NO	NO
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm and Year Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	13,084	13,077	13,077	13,084	13,077	13,077	13,084	13,077	13,077
R^2	0.452	0.452	0.467	0.452	0.453	0.467	0.451	0.452	0.467

Table 10: Visual Measures and Subsequent-Year Stock Volatility, Beta and Cost-of-Equity

This table reports results from panel regressions of the firm's daily standard deviation of stock returns (*SdRet*), stock beta (*MktBeta*), and cost-of-equity capital (*Cost-of-Equity*) on fiscal year t+1 on fiscal year t visual metrics and other explanatory variables. We report results for *AVC*, *IMGC*, and *RFC*. As in Table 5, columns 4-6 include *TC* and *CMIC* fixed effects. See Table C.1 and Table 1 for variable and sample definitions. All explanatory variables are measured as of end of fiscal year t. The regressions include firm and year fixed effects. Standard errors are clustered by firm and year and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. All visual metrics are winzorised at the 99th percentile of their sample distributions. (Z) stands for a Z-Score adjustment.

	SdRet (Z)			*MktBeta (Z)*			*Cost-of-Equity (Z)*		
	(1) *t+1*	(2) *t+1*	(3) *t+1*	(4) *t+1*	(5) *t+1*	(6) *t+1*	(7) *t+1*	(8) *t+1*	(9) *t+1*
AVC (Z)	-0.015** (-2.80)			-0.018** (-2.65)			-0.018** (-2.67)		
IMGC(Z)		-0.015** (-2.26)			-0.013* (-1.98)			-0.013* (-2.01)	
RFC(Z)			-0.014** (-2.71)			-0.012 (-1.07)			-0.011 (-1.04)
LDEP	0.236*** (3.25)	0.236*** (3.25)	0.236*** (3.25)	0.225*** (5.30)	0.226*** (5.30)	0.225*** (5.30)	0.212*** (4.72)	0.212*** (4.72)	0.212*** (4.72)
Pages	0.000 (0.68)	0.000 (0.68)	0.000 (0.84)	-0.000 (-1.19)	-0.000 (-1.17)	-0.000 (-1.07)	-0.000 (-0.63)	-0.000 (-0.62)	-0.000 (-0.52)
LnNews	0.022 (1.00)	0.021 (1.00)	0.021 (0.98)	0.070 (1.33)	0.070 (1.33)	0.069 (1.32)	0.083 (1.53)	0.083 (1.52)	0.082 (1.52)
AnnRet	-0.039 (-1.01)	-0.039 (-1.01)	-0.039 (-1.02)	0.071 (1.47)	0.071 (1.47)	0.071 (1.46)	0.074 (1.52)	0.074 (1.52)	0.074 (1.52)
ROA	-0.139 (-0.78)	-0.137 (-0.77)	-0.141 (-0.79)	-0.097 (-0.40)	-0.097 (-0.40)	-0.101 (-0.42)	-0.049 (-0.21)	-0.049 (-0.21)	-0.053 (-0.23)
insthold	-0.100** (-2.88)	-0.100** (-2.87)	-0.100** (-2.89)	0.194** (2.51)	0.194** (2.51)	0.193** (2.51)	0.194** (2.54)	0.194** (2.55)	0.194** (2.54)
AdvExpToSale	-0.144 (-0.26)	-0.146 (-0.27)	-0.159 (-0.29)	0.911 (1.52)	0.913 (1.52)	0.898 (1.49)	0.897 (1.45)	0.899 (1.45)	0.885 (1.43)
LnAssets	0.238*** (3.27)	0.238*** (3.27)	0.238*** (3.27)	0.161** (2.39)	0.161** (2.39)	0.161** (2.40)	0.151** (2.38)	0.151** (2.37)	0.151** (2.39)
FOG(Z)	-0.016** (-2.19)	-0.016** (-2.19)	-0.016** (-2.18)	-0.001 (-0.12)	-0.002 (-0.13)	-0.001 (-0.11)	-0.004 (-0.36)	-0.004 (-0.38)	-0.004 (-0.35)
LnBM	-0.112*** (-4.21)	-0.112*** (-4.18)	-0.112*** (-4.19)	-0.080* (-2.04)	-0.080* (-2.04)	-0.080* (-2.04)	-0.071* (-1.94)	-0.071* (-1.94)	-0.071* (-1.93)
SdRet				16.539** (2.25)	16.544** (2.25)	16.567** (2.25)	16.106* (2.01)	16.116* (2.01)	16.136* (2.01)
Turnover	4.007* (1.81)	3.994* (1.81)	4.034* (1.83)	-0.768 (-0.29)	-0.750 (-0.28)	-0.714 (-0.27)	-0.670 (-0.25)	-0.650 (-0.24)	-0.612 (-0.23)
LnSize	-0.347*** (-5.46)	-0.347*** (-5.45)	-0.348*** (-5.46)	-0.127** (-2.36)	-0.127** (-2.37)	-0.128** (-2.38)	-0.132** (-2.44)	-0.132** (-2.45)	-0.132** (-2.46)
TDUM (Z)		-0.001 (-0.12)			-0.005 (-0.64)			-0.005 (-0.61)	
CMIDUM (Z)		-0.004 (-0.71)			-0.001 (-0.18)			-0.002 (-0.35)	
TC and *CMIC* FE	NO	NO	NO	YES	YES	YES	NO	NO	NO
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm and Year Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	15,030	15,030	15,030	13,705	13,705	13,705	13,705	13,705	13,705
R^2	0.724	0.724	0.724	0.592	0.592	0.592	0.616	0.616	0.616

Table 11: Visual Measures and Subsequent-Year Bond Ratings

This table reports results from panel regressions of changes in corporate bonds ratings (*ChngRate*) in fiscal year t+1 on fiscal year t *AVC* and other explanatory variables. Table C.6 report results for *IMGC* and *RFC*. We use Mergent-FISD to track all changes in credit ratings of all corporate bonds for a given issuer in our sample. We construct a firm-level average bond rating index, which is calculated as the equally-weighted average of the ratings of the firm's outstanding bonds. *AvgRate* is the firm's average bond rating at the end of fiscal year t. *ChngRate* is the change in *AvgRate* during fiscal year t+1. "ALL" refers to all available corporate bonds. "High Yield" refers to high-yield bonds, where the firm's average bond rating is below investment grade. Panel A includes all changes in ratings (i.e., negative, zero, and positive changes). Panel B includes negative and zero changes (the "downgrade sample"). Panel C includes positive and zero changes (the "upgrade sample"). See Table C.1 and Table 1 for variable and sample definitions. All explanatory variables are measured as of end of fiscal year t. The regressions include firm and year fixed effects. Standard errors are clustered by firm and year and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. All visual metrics are winzorised at the 99th percentile of their sample distributions. (Z) stands for a Z-Score adjustment.

Panel A: Full Sample

	ALL				High-Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	t+1	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*
AVC (Z)	0.056***	0.056***	0.034**	0.034**	0.107**	0.107**	0.080	0.079
	(3.96)	(3.95)	(2.35)	(2.32)	(2.35)	(2.37)	(1.70)	(1.68)
LDEP	0.137***	0.137***	0.085***	0.084**	0.144**	0.144**	0.114**	0.116**
	(3.69)	(3.72)	(3.03)	(2.57)	(2.58)	(2.62)	(2.25)	(2.25)
AvgRate	0.279***	0.280***	0.326***	0.327***	0.336***	0.341***	0.389***	0.389***
	(9.92)	(9.97)	(11.03)	(11.24)	(9.97)	(10.37)	(10.60)	(10.68)
Pages	-0.000	-0.000	0.000	0.000	0.001	0.001	0.001	0.001
	(-0.40)	(-0.40)	(0.47)	(0.47)	(0.98)	(0.90)	(1.39)	(1.42)
LnNews	-0.018	-0.017	-0.013	-0.015	-0.094	-0.093	-0.127	-0.130
	(-0.29)	(-0.26)	(-0.27)	(-0.30)	(-0.98)	(-0.97)	(-1.51)	(-1.54)
AnnRet	0.239**	0.239**	0.119**	0.119**	0.163**	0.166**	0.054	0.053
	(2.72)	(2.72)	(2.67)	(2.80)	(2.55)	(2.59)	(1.65)	(1.68)
ROA	3.701***	3.696***	1.996***	2.043***	3.649***	3.622***	2.132***	2.100***
	(6.74)	(6.73)	(3.84)	(3.97)	(5.58)	(5.59)	(3.42)	(3.40)
InstHold	0.154	0.157	0.079	0.073	0.252	0.262	0.184	0.178
	(1.54)	(1.58)	(0.76)	(0.71)	(1.31)	(1.37)	(1.01)	(0.98)
AdvExpToSale	-0.968	-1.012	-0.884	-0.912	-0.793	-1.030	-1.143	-1.107
	(-0.98)	(-1.02)	(-0.84)	(-0.85)	(-0.45)	(-0.61)	(-0.61)	(-0.59)
LnAssets	0.307***	0.310***	-0.043	0.017	0.339***	0.355***	0.025	0.130
	(5.01)	(5.03)	(-0.55)	(0.21)	(3.87)	(4.00)	(0.24)	(1.02)
FOG(Z)		-0.007	-0.003	-0.002		-0.051	-0.032	-0.034
		(-0.50)	(-0.17)	(-0.11)		(-1.51)	(-0.96)	(-0.99)
SdRet			-7.880	-7.763			2.073	1.792
			(-1.05)	(-1.03)			(0.28)	(0.24)
Turnover			-9.760**	-9.526**			-9.883*	-9.801
			(-2.20)	(-2.15)			(-1.74)	(-1.73)
LnSize			0.485***	0.422***			0.521***	0.432***
			(6.11)	(4.60)			(5.67)	(3.82)
LnBM				-0.070				-0.115
				(-1.17)				(-1.11)
D/E				-0.030				-0.032
				(-1.56)				(-1.11)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm and Year Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,557	6,557	6,557	6,557	2,715	2,715	2,715	2,715
R^2	0.291	0.291	0.324	0.325	0.339	0.341	0.366	0.367

Panel B: Downgrade Sample

	ALL				High-Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	t+1	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*
AVC (Z)	0.046^{***}	0.046^{***}	0.029^{**}	0.029^{**}	0.128^{***}	0.128^{***}	0.104^{**}	0.102^{**}
	(3.56)	(3.55)	(2.27)	(2.20)	(2.96)	(2.99)	(2.65)	(2.59)
Firm Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm and Year Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,072	5,072	5,072	5,072	1,825	1,825	1,825	1,825
R^2	0.298	0.298	0.334	0.334	0.411	0.411	0.434	0.435

Panel C: Upgrade Sample

	ALL				High-Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	t+1	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*
AVC (Z)	0.007	0.007	0.004	0.004	0.020	0.021	0.020	0.020
	(0.88)	(0.87)	(0.46)	(0.46)	(0.54)	(0.57)	(0.53)	(0.53)
Firm Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm and Year Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,429	5,429	5,429	5,429	2,272	2,272	2,272	2,272
R^2	0.263	0.264	0.269	0.270	0.284	0.286	0.293	0.293

Table 12: Brokerage Mergers and Closures, Analyst Coverage, and Visual Prevalence

This table reports results from an identification strategy based on Kelly and Ljungqvist (2012)'s list of brokerage firm closures. We follow Gormley and Matsa (2011) and use stacked difference-in-difference regressions with cohort-firm and cohort-year fixed effects. For each cohort (stack) we include first-time-treated firms but not past-treated firms. As control firms we use non-prior-treated ones. "Pre" is the year of the brokerage firms' closures and "post" is post-closure year. Using propensity scores, we match on: *Pages*, *InstHold*, *LnNews*, *ROA*, *AnnRet*, *LnAssets*, *LnBM*, *SdRet*, *Turnover*, *LnSize*, and on lagged year *IMGC*. All specifications include $cohort \times firm$ and $cohort \times year$ fixed effects, and standard errors are clustered by firm. *DID* refers to $Treated \times \ Post$. In Panel A, the first two columns (without and with controls, respectively) is the change in coverage ($\Delta AnalystCoverage$) and the second output variable in the third and fourth columns (without and with controls, respectively) is *IMGC*. To check for prior and posterior trends in Panel B we run difference-in-difference regressions substituting "t+1" and "t+2" ("t-1" and "t-2") for the event year. Panel B shows the results.

Panel A: Drop in Analyst Coverage and Increase in Image-Pages

	$\Delta AnalystCoverage$		*IMGC*	
	(1)	(2)	(3)	(4)
DID	-0.563***	-0.522***	1.344**	1.279**
	(-2.95)	(-2.75)	(2.58)	(2.47)
Cohort X Firm FE	YES	YES	YES	YES
Cohort X Year FE	YES	YES	YES	YES
Firm Controls	NO	YES	NO	YES
Observations	1,256	1,256	1,256	1,256
R^2	0.556	0.561	0.801	0.830

Panel B: Pre and Post Event Analysis

	t-2	t-1	t	t+1	t+2
	(1)	(2)	(3)	(4)	(5)
DID	0.281	-0.373	1.344**	-0.525	-0.070
	(0.38)	(-0.59)	(2.58)	(-0.95)	(-0.12)
Cohort X Firm FE	YES	YES	YES	YES	YES
Cohort X Year FE	YES	YES	YES	YES	YES
Observations	504	764	1,256	1,066	812
R^2	0.829	0.786	0.801	0.802	0.828

Appendix A: Data Collection Process

In this Appendix, we describe the data collection process (Panel A) and provide time series statistics (Panel B) for our annual report data.

Table A.1: Data Collection Process

This table describes the annual report data construction process. We downloaded and analyzed all digitally available reports for S&P 1500 firms trading in the United States (with a matched PERMNO) between 1989 and 2019. We applied filters to ensure data integrity and availability in arriving at the final sample reported in Table 1 as outlined below (Panel A). Panel B reports the time series statistics of firms' annual reports containing visual elements (AV) starting from 1993 to 2019. *# REPORTS* is the number of firms with annual reports. *# AV REPORTS* is the number of annual reports with visual elements. *# PAGES* is the total number of annual report pages across all reports in a given year. See Table C.1 for variable definitions. Any Visual (AV) pages are those for which any visual elements can be detected on the report page, where visual elements have an image size of at least 100K or vividness of at least 100.

Panel A: Data Filtering Process

Procedure Description	Sample
Firm annual reports collected for S&P 1500 firms between 1989 and 2019	19,656
Less reports from 1989 to 1992	28
Less reports that broken and cannot be opened	165
Less reports that are duplicated	588
Less reports with >= 500 or <= 5 pages	134
Less reports with no fiscal year identified	512
Final sample 1993-2019 before additional filters	18,229
Keeping the sample between 2002 and 2019	16,861
Keeping firms with media coverage	15,477

Panel B: Time-Series Statistics before Additional Restrictions

FYEAR	*# REPORTS*	*#* AV	%	*# Report Pages*
1993	21	7	33.3%	2,651
1994	32	14	43.8%	3,142
1995	44	19	43.2%	4,545
1996	65	31	47.7%	7,351
1997	104	59	56.7%	8,571
1998	157	100	63.7%	10,944
1999	252	188	74.6%	15,514
2000	338	272	80.5%	21,913
2001	402	325	80.8%	26,106
2002	482	402	83.4%	37,173
2003	578	485	83.9%	46,377
2004	663	569	85.8%	58,879
2005	741	624	84.2%	67,822
2006	802	675	84.2%	78,498
2007	857	682	79.6%	90,241
2008	902	681	75.5%	102,974
2009	889	671	75.5%	101,743
2010	924	687	74.4%	110,377
2011	942	694	73.7%	113,142
2012	997	715	71.7%	124,834
2013	1,025	722	70.4%	131,987
2014	1,072	731	68.2%	139,259
2015	1,122	772	68.8%	146,080
2016	1,221	837	68.6%	161,373
2017	1,218	840	69.0%	160,807
2018	1,250	891	71.3%	169,465
2019	1,129	760	67.3%	155,007
ALL	18,229	12,438	68.2%	2,096,775

Appendix B: Visual Classification Methodology

In this Appendix, we describe how we classify annual report pages based on their visual content into the categories depicted in Figure 2 (sub-section B.1), as well as the additional steps to construct the *RFC* measures (sub-section B.2).

B.1. Classification of Visual Pages using Machine Learning Tools

To identify which report pages contain visual elements and which do not, we first construct a training sample of report pages with visual elements (AV "any visual") and those without. Based on this sample we trained a TensorFlow classification mode (based on Google Brain open-source machine learning and AI software library for training and inference of deep neural networks) to do binary classification on all report pages. To construct a representative training sample, we combined human judgement with color composition and page size. Specifically, for each report page, we extracted the 16 basic HTML colors (such as black, white, grey, red, yellow, etc.) and calculated the color composition/distribution. If the main colors (over 90% of pixels) are black, white, and grey, the page is not classified as a visual page; if more colors are contained in the page, the page is classified as visual. To calculate page size, we first convert each report page into image format and then calculate its physical file size. Visual pages contain colors, different shapes, styles, etc, and are thus more likely to be larger in file size. We combined the objective information obtained from color and file size with subjective judgment processes to obtain our initial validation sample, which yielded a 96% accuracy rate.

For those pages classified as AV we combined artificial intelligence and a rule-based system to classify visual annual report pages in our sample pages into our 5 five distinct predefined hierarchical categories: image-pages, team-pages; charts-pages; maps-pages; and infographics-pages. In lieu of manually selecting training samples for each visual element category, we rely on the following simple process: First, we process the pages through the Google Vision API and identify which labels typify each of the 5 visual categories. We then classify each page into the corresponding categories using these labels. For example, if a page yields the label "map", this page is assigned to the MAPS group.

This initial classification process yields a pool of page candidates for each category. Based on these candidate pools, we construct a representative training sample to train a classification model. If a page contains visual content of more than one category, we categorize it by the dominant visual category that best described its visual content. Figure 2 provides an example of visual pages that have been classified into the five categories. When there are mixed visuals on a page, classification is based on the dominant category. Finally, we train TensorFlow to classify as above.

Image-pages (*IMG*) were categorized with an accuracy rate of about 97%. The remaining four visual categories were classified with an accuracy rate of roughly 71%. To increase the accuracy rate, we augmented our algorithms using Google Vision and heuristic rules to increase the accuracy of the other categories. For example, if one of the top three Google Vision labels for a visual page contain the word "map" or "maps", then this page is classified as a maps-page. This combined approach improved classification accuracy rates of map-pages, charts-pages, and teams-pages to approximately 86%, and of infographics-pages to roughly 78%.

Infographics-pages typically contain a broad mix of text, fonts, colors, numbers, icons, small graphs, shapes, and/or photos. They are therefore difficult to identify using machine learning methods and are hence often subject to misclassification error. We therefore rely on Google Tesseract Optical Character Recognition to capture the location, size and style of textual elements. Combining the information from these last two steps, we then apply a rule set to reclassify those misclassified infographics, increasing infographic classification accuracy from 78% to 85%, which is comparable to the accuracy rate of the other visual categories.

After validating these procedures, we applied them to the remaining visual pages in our sample. Finally, we removed pages that could not be classified in one of the five visual categories with a certain threshold (50% by default). The majority of these were textual pages that were printed on a non-white page (for example, a blue background with text written in black).

B.2. Construction of the *RFC* Measure

To construct *RFC*, our measure of reinforcement of image content to narrative text, we follow a two-step procedure, as in Ronen et al. (2023). We process each of the image-pages through Google Vision and analyze the algorithm-generated image labels that associate visual items with confidence levels. We first filter out images that are uninformative such as not to obfuscate the analysis with spurious word matches as follows: 1. we derive stop labels by training Google

Vision on a sub-sample of images to identify a bag of words that consistently capture uninformative labels, which are: “adaptation,” “aqua,” “atmosphere,” “atmospheric phenomenon,” “azure,” “background,” “beige,” “black,” “black-and-white,” “blue,” “brown,” “circle,” “cobalt blue,” “colorfulness,” “daytime,” “design,” “diagram,” “document,” “drawing,” “ecoregion,” “electric blue,” “floor plan,” “font,” “fractal art,” “graphic,” “graphic design,” “graphics,” “gray,” “green,” “grey,” “illustration,” “leaf,” “light,” “line,” “line art,” “liquid,” “logo,” “magenta,” “map,” “maroon,” “material property,” “music,” “orange,” “organism,” “paper,” “paper product,” “parallel,” “pattern,” “pie chart,” “pink,” “plan,” “plot,” “poster,” “purple,” “rectangle,” “red,” “schematic,” “screenshot,” “sky,” “slope,” “space,” “square,” “teal,” “technical drawing,” “text,” “triangle,” “turquoise,” “violet,” “water,” “watermark,” “wave,” “white,” “world,” and “yellow”; 2. if any of the top three labels for an image correspond to a stop label, the image is filtered out as “uninformative.” Figure B.3 presents examples of representative uninformative image-pages from four different annual reports. The top three labels produced by Google Vision are listed in descending order of confidence. In each of these examples, all three of the top labels are stop-labels.

Finally, we process all labels for informative image-pages and calculating the number of informative image labels per image-page that match the annual report’s text. For each report, we then construct (RFC) by summing the matches from all image-pages in the report. RFC is calculated without double-counting labels-to-text matches, whereas RFC-IP sums label-to-text matches across all image-pages in a report. Other variants considered in the paper examine the reinforcement of the labels to alternative narrative text sources, such as the business description and MD&A sections of 10-K filings, for RFC_{BUS} and RFC_{MDA}, respectively.

Table B.1 provides a list of the 100 most prevalent informative labels in our sample and Figure 4 presents examples of reinforcing image-pages along with their reinforcing labels.

In contrast, Figure B.3 provides examples of informative image pages that are not reinforcing (no label-to-text matches exist). In the top right image, for example, the labels generated for the 2004 Hanmi Financial Corporation Annual Report are “bowed string instrument”, “cellist”, “cello”, “classical music”, “musical instrument”, “musician”, “recital”, “string instrument”, and “violin family.” None of these match any of the words in the textual narrative of the 2004 Annual Report. and the image-page is thereby classified as non-reinforcing.

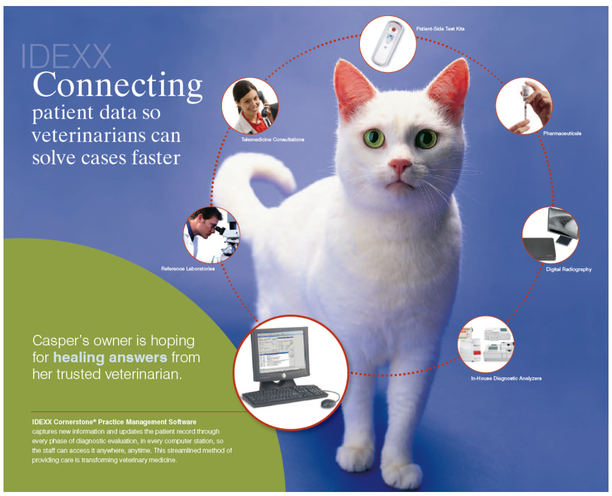
Table B.1: Reinforcing Labels – Examples

This table provides a list of the 100 most prevalent informative labels (top three for each image-page), ranked by the number of years they appear in our sample. "AnnualReport" reports the top 100 labels that match the annual report, "BUS" reports the top 100 labels that match the business description section of the firm's 10-K filing, and "MD&A" reports the top 100 labels that match the MD&A section for the firm's 10-K filing.

Rank	AnnualReport	BUS	MD&A	Rank	AnnualReport	BUS	MD&A
1	aircraft	aircraft	building	51	cuisine	dish	book
2	engineering	engineering	advertising	52	dish	floor	cap
3	advertising	advertising	brand	53	pipe	pipe	community
4	architecture	architecture	car	54	skin	skin	locomotive
5	brand	brand	city	55	website	website	metal
6	brochure	brochure	engineering	56	airline	airline	produce
7	building	building	event	57	art	denim	research
8	car	car	food	58	boat	gas	clothing
9	city	city	infrastructure	59	denim	shoe	company
10	clothing	clothing	nature	60	gas	soil	field
11	event	event	number	61	jeans	art	road
12	food	food	property	62	sharing	beauty	boat
13	hand	hand	service	63	shoe	boat	bottle
14	human	human	table	64	soil	bottle	construction equipment
15	infrastructure	infrastructure	transport	65	arm	company	electricity
16	metal	metal	vehicle	66	beauty	dress	history
17	motor vehicle	motor vehicle	aircraft	67	book	footwear	meal
18	nature	nature	furniture	68	bottle	jeans	pipe
19	number	number	hand	69	cap	style	recipe
20	plant	plant	plant	70	company	construction equipment	sharing
21	property	property	fashion	71	dress	electricity	soil
22	publication	publication	human	72	electricity	farm	steel
23	recipe	room	industry	73	field	field	denim
24	room	service	joint	74	footwear	fruit	home
25	service	tire	machine	75	head	head	shelf
26	table	transport	retail	76	history	home	shoe
27	tire	vehicle	room	77	home	interior design	winter
28	transport	wheel	website	78	metropolitan area	meal	agriculture
29	vehicle	wood	airline	79	style	metropolitan area	alcohol
30	wheel	customer	architecture	80	air travel	road	asphalt
31	wood	drink	aviation	81	construction equipment	sharing	bridge
32	aviation	electronics	construction	82	farm	trade	flooring
33	customer	face	customer	83	fruit	arm	hospital
34	drink	fashion	face	84	interior design	asphalt	metropolitan area
35	electronics	furniture	people	85	meal	cabinetry	motor vehicle
36	face	industry	airplane	86	research	cap	motorcycle
37	fashion	ingredient	brochure	87	road	locomotive	mountain
38	floor	joint	footwear	88	shelf	research	railway
39	furniture	machine	ingredient	89	trade	crane	restaurant
40	industry	people	publication	90	asphalt	flooring	trade
41	ingredient	produce	tire	91	cabinetry	heat	travel
42	joint	recipe	air travel	92	crane	history	beer
43	machine	retail	child	93	lip	hospital	collection
44	people	table	dish	94	locomotive	lawn	cuisine
45	produce	airplane	drink	95	media	media	dog
46	retail	aviation	electronics	96	railway	motorcycle	drilling rig
47	airplane	child	farm	97	travel	shelf	lawn
48	child	community	floor	98	winter	steel	ship
49	community	construction	gas	99	agriculture	truck	tractor
50	construction	cuisine	wood	100	bridge	chair	watch

Figure B.1: Page Level Analysis versus Individual Element Analysis

This figure illustrates the importance of conducting analysis at the whole-page level as opposed to at the level of the individual elements contained on the page. While both images convey similar messages- a main object and small items of interest surrounding them, they are technically composed differently, the one of the left as one image and the one on the right as many. Focusing on the latter would assign equal weights to each image element, whereas focusing on the former assigns differential weights, depending on the dimensionality and salience of the distinct elements.



Source: (Left) Report page from the 2005 IDEXX Laboratories, Inc. Annual Report;(Right) https://dontmesswithtaxes.typepad.com/.a/6a00d8345157c669e20263e9633c41200b-pi.

Figure B.2: Uninformative Annual Report Image Pages

This figure presents four representative uninformative image-pages in our sample. The top three Google Vision labels generated for each page are, in decreasing order of confidence, and from left to right: For LogMeIn (top left):"text," "font," and "electric blue"; for Dycom (top right): 'logo," "graphic design," and "graphics"; For Genworth Financial (bottom left):"text," "logo," and "font"; for ProAssurance Corporation (bottom right): "green," "colorfulness," and "text"; For a full list of stop labels used to identify uninformative labels, see section B.2.3 of this Appendix.

Source: (Top Left) Report page from the 2012 LogMeIn Inc Annual Report; (Top Right) Report page from the 2014 Dycom Industries, Inc Annual Report; (Bottom Left) Report page from the 2008 Genworth Financial Annual Report; (Bottom Right) Report page from the 2016 ProAssurance Corporation Annual Report.

Figure B.3: Non-Reinforcing Image-Pages

This figure provides examples of informative but non-reinforcing image-pages from four annual reports in our sample. The Google Vision labels generated for each page are, from left to right: For Cheesecake Factory (top left): "amber", "art", "artifact", "carving", "craft", "creative arts", "molding", "relief", "symmetry", and "visual arts"; for Hanmi Financial Corporation (top right): "bowed string instrument", "cellist", "cello", "classical music", "musical instrument", "musician", "recital", "string instrument", and "violin family"; for Alexion Pharmaceuticals Inc (bottom left): "fun", "happy", "interaction", "jeans", "leisure", "people in nature", "photo caption", "photography", and "smile"; for Tyler Technologies Inc (bottom right): "boardsport", "ocean", "sea", "skimboarding", "surface water sports", "surfing", "tide", and "wind wave". None of these labels match any words in the annual report textual narratives, and the pages are therefore deemed not to be reinforcing ($RFC = 0$).

Source: (Top Left) Report page from the 2003 Cheesecake Factory Inc Annual Report; (Top Right) Report page from the 2004 Hanmi Financial Corp Annual Report; (Bottom Left) Report page from the 2010 Alexion Pharmaceuticals Inc Annual Report; (Bottom Right) Report page from the 2014 Tyler Technologies Inc Annual Report.

Appendix C - Variable Definitions and Additional Analysis

This Appendix includes a description of the key variables used in the paper and provides additional analysis that supports our findings.

– Table C.1 provides the variable definitions.

– Table C.2 reports results for the analysis conducted in Table 4 (visual determinants) using *AVC* and *RFC* as the visual measures.

– Table C.3 repeats the analysis conducted in Panel B of Table 5 but reports coefficients for *TC* and *CMIC* Indicators.

–Table C.4 reports results for the analysis conducted in Table 7 (sub-samples analysis) using *IMGC* as the visual prevalence measure.

–Table C.5 reports the results for the analysis conducted in Table 9 (analyst dispersion) using additional reinforcement measures.

–Table C.6 reports results for the analysis conducted in Table 11 (changes in bond ratings) using *AVC* and *RFC* as the visual measures.

–Table C.7 reports results of the firm's ROA and annual cumulative returns on *AVC*, *IMGC*, and *RFC*.

Table C.1: Variable Definitions

Variable	Definition
Visual Prevalence and Content Reinforcement Measures	
AVC	For each firm, fiscal year and report, AVC is the number of pages with any visual element (AV), excluding pages with only text, within an annual report. AV includes pages with images (IMG), team/management photos (T), charts ($CHAR$), maps (MAP) and infographics ($INFO$).
$IMGC$	For each firm, fiscal year and report, $IMGC$ is the number of image-pages (IMG) within an annual report.
TC	For each firm, fiscal year and report, TC is the number of team/management photos-pages (T) within an annual report.
$CMIC$	For each firm, fiscal year and report, $CMIC$ is the union of the numbers of charts-pages ($CHAR$), maps-pages (MAP), and infographics-pages ($INFO$) within an annual report.
RFC	For each firm, fiscal year and report, RFC is the number of informative labels that match words discussed in the textual narrative of the annual report.
RFC_{BUS}	For each firm, fiscal year and report, RFC_{BUS} is the number of informative labels that match words discussed in the business section of the firm 10-K report.
RFC_{MDA}	For each firm, fiscal year and report, RFC_{MDA} is the number of informative labels that match words discussed in the MD&A section of the firm 10-K report.
RFC_{BUSMDA}	For each firm, fiscal year and report, RFC_{BUSMDA} is the number of informative labels that match words discussed in the union of the business and MD&A sections of the firm 10-K report.
$RFC_{BUSMDA+}$	For each firm, fiscal year and report, $RFC_{BUSMDA+}$ is the number of informative labels that match words discussed in the business and MD&A sections of the firm 10-K report. That is, a label that appears in both sections is counted twice.
RFC_{BUSMDA_IFBOTH}	For each firm, fiscal year and report, RFC_{BUSMDA_IFBOTH} is the number of informative labels that match words discussed in *both* the business and MD&A sections of the firm 10-K report.
Textual Readability	
FOG	Gunning Fog Index (*FOG*), incorporates the number of words per sentence and the number of complex words in a document to derive a measure of the readability or syntactic complexity of firms' 10-K filings. The measure is obtained from WRDS's SEC Analytics Suite.
FILESIZE	Loughran and McDonald (2014)'s 10-K file size measure (*FILESIZE*), which is the file size (in megabytes) listed for the "complete submission text file" on EDGAR for the 10-K filing. The measure is obtained from WRDS's SEC Analytics Suite.

Variable	Definition
Firm Control Variables	
Pages	The number of pages in a given annual report.
LnNews	The natural logarithm of the total number of news articles covering the firm j in fiscal year t.
AnnRet	The 12-month cumulative stock return of firm j in fiscal year t.
ROA	The return on assets of firm j in fiscal year t.
InstHold	Aggregate institutional investor holdings based on the most recent quarter up to the end of fiscal year t. The institutional holdings data is obtained from Thomson Reuters S34 file.
Δ*InstHold*	The annual change in % institutional holdings of firm j during fiscal year t, calculated as the difference between % institutional holdings at the end of fiscal year t and the end of fiscal year t-1.
AdvExpToSale	Annual advertising expenses normalized by annual sales as in Da, Engelberg, and Gao (2011) and Lou (2014).
LnAssets	The natural logarithm of the firm's assets calculated at the end of fiscal year t.
LnSize	The natural logarithm of the firm's market capitalization calculated at the end of fiscal year t.
LnBM	The natural logarithm of the firm's book-to-market, calculated as in Fama and French (1992).
SdRet	The daily standard deviation of stock returns during fiscal year t.
Turnover	The average of the firm's daily stock turnover during fiscal year t.
D/E	The firm's debt-to-equity ratio at the end of fiscal year t.
MktBeta	Firm beta calculated using daily returns over fiscal year t.
Cost-of-Equity	The cost of equity capital (*Cost-of-Equity*) is calculated following Frank and Shen (2016). First, firm beta is calculated using daily returns over the fiscal year. Then, using the CAPM relation, the cost of equity for fiscal year t is calculated as $\textit{Cost-of-Equity} = r_f + \beta E(r_M - r_f)$. The risk-free rate, r_f, is the ten-year annualized Treasury yield from Federal Reserve economic Data (FRED). $E(r_M - r_f)$ is the historical mean of the Fama and French market excess return; that is, fiscal year t equity premium is the average of the Fama and French annualized market excess return from July 1926 to the end of fiscal year t.

Variable	Definition
Firm Control Variables (cont'd)	
AnalystsCoverage	The average number of analysts following firm j during fiscal year t.
Δ*AnalystCoverage*	The difference between the average number of analysts following firm j during fiscal year t and fiscal year *t-1*.
AvgRate	We use Mergent-FISD to track all changes in credit ratings of all corporate bonds for a given issuer in our sample. We construct a firm-level average bond rating index, which is calculated as the equally-weighted average of the ratings of the firm's outstanding bonds. *AvgRate* is the firm's average bond rating at the end of fiscal year t.
ChngRate	The change in *AvgRate* during fiscal year t.
HY Dummy	1 if the firm's average bond rating is below investment grade, and zero otherwise.
Analyst Earnings Forecast Measures	
AnalystDisp	The standard deviation across the most recent analyst earnings forecasts preceding the earnings announcement date for firm i and a given quarter j, normalized the absolute value of the mean across the most recent analyst earnings forecasts (obtained from IBES).
WAFE	Within-analyst quarterly forecast accuracy measure, calculated as $(AFE_{i,j,q} - \overline{AFE_{i,q}})$ / $\overline{AFE_{i,q}}$, where $WAFE_{i,j,q}$ is the absolute forecast error for analyst i's forecast of firm j's earnings in quarter q of fiscal year t+1, minus the mean absolute forecast error for analyst i across all the stocks she follows during quarter q, divided by the mean absolute forecast error of the analyst, across all stocks she follows in quarter t.
DaysToEarnAnn	The number of days from the forecast date to the earnings announcement date, computed for each analyst forecast in any given quarter.
Other Measures	
701_801_DISCLOSURE	The log of item types 7.01 and 8.01 of 8-Ks filed during the fiscal year.
CORPORATE EVENTS	We use Bloomberg's Corporate Events Calendar (the EVTS function) to obtain information about scheduled corporate events such as investor conference events, corporate access events, and analyst marketing events. *CORPORATE EVENTS* is the log of the number of corporate events during the fiscal year. The data are available from 2010.
PRESS RELEASES	The log of the number of firm press releases during the fiscal year. The data are obtained from RavenPack's press-release file.

Table C.2: The Determinants of *AVC* and *RFC*

This table repeats the analysis conducted in Table 4 and reports results from panel regressions of *AVC* (Panel A) and *RFC* (Panel B) from the firm's annual report of year t, on various explanatory variables. The sample period is from 2002 to 2019. See Table C.1 and Table 1 for variable and sample definitions. All explanatory variables are measured as of end of fiscal year t. The regressions include firm and year fixed effects. Standard errors are clustered by firm and year and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. All visual metrics are winzorised at the 99th percentile of their sample distributions.(Z) stands for a Z-Score adjustment.

Panel A: The Determinants of *AVC (Z)*

	AVC (Z)						
	(1) *t+1*	(2) *t+1*	(3) *t+1*	(4) *t+1*	(5) *t+1*	(6) *t+1*	(7) *t+1*
LDEP (Z)	0.464***	0.463***	0.463***	0.463***	0.460***	0.459***	0.457***
	(12.12)	(12.04)	(12.02)	(12.02)	(11.91)	(11.87)	(11.81)
Pages (Z)	-0.021	-0.019	-0.019	-0.019	-0.023	-0.021	-0.018
	(-1.10)	(-1.03)	(-1.03)	(-1.03)	(-1.20)	(-1.10)	(-0.93)
LnNews (Z)	0.041***	0.038***	0.038***	0.039***	0.023*	0.020	0.033**
	(3.49)	(3.18)	(3.16)	(3.19)	(1.75)	(1.47)	(2.47)
701_801_DISCLOSURE (Z)	0.018	0.018	0.018	0.018	0.017	0.017	0.019
	(1.60)	(1.63)	(1.65)	(1.65)	(1.55)	(1.55)	(1.71)
AnnRet (Z)		0.017***	0.017***	0.017***	0.020***	0.014**	0.021***
		(2.91)	(2.94)	(2.94)	(3.35)	(2.47)	(3.31)
ROA (Z)		0.041***	0.040***	0.040***	0.044***	0.033**	0.026*
		(3.18)	(3.08)	(3.06)	(3.30)	(2.49)	(1.95)
InstHold (Z)			0.000	0.000	-0.005	-0.006	-0.005
			(0.01)	(0.02)	(-0.44)	(-0.59)	(-0.49)
AdvExpToSale (Z)			-0.016	-0.016	-0.016	-0.016	-0.015
			(-0.91)	(-0.91)	(-0.84)	(-0.87)	(-0.85)
FOG(Z)				-0.004	-0.008	-0.008	-0.008
				(-0.42)	(-0.83)	(-0.81)	(-0.88)
LnAssets (Z)					0.139***	0.150***	0.130***
					(4.01)	(4.07)	(3.39)
LnBM (Z)						-0.037**	-0.030*
						(-2.53)	(-2.05)
SdRet (Z)							-0.042***
							(-3.19)
Turnover (Z)							-0.034**
							(-2.81)
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	13,579	13,557	13,452	13,452	13,452	13,452	13,451
R^2	0.632	0.633	0.632	0.632	0.633	0.634	0.635

Panel B: The Determinants of *RFC(Z)*

	RFC(Z)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	t+1	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*
LDEP (Z)	0.399***	0.399***	0.398***	0.398***	0.393***	0.392***	0.391***
	(14.94)	(14.76)	(14.77)	(14.79)	(14.63)	(14.62)	(14.50)
Pages (Z)	0.038**	0.040***	0.041***	0.041***	0.036**	0.037**	0.040**
	(2.74)	(2.88)	(2.91)	(2.91)	(2.55)	(2.67)	(2.87)
LnNews (Z)	0.047***	0.043**	0.043**	0.043**	0.021	0.020	0.030*
	(2.99)	(2.82)	(2.72)	(2.75)	(1.18)	(1.11)	(1.84)
701_801_DISCLOSURE (Z)	0.011	0.012	0.011	0.011	0.010	0.010	0.011
	(1.04)	(1.08)	(1.03)	(1.03)	(0.90)	(0.93)	(1.07)
AnnRet (Z)		0.004	0.004	0.004	0.008	0.006	0.012**
		(0.91)	(0.85)	(0.86)	(1.69)	(1.34)	(2.31)
ROA (Z)		0.043***	0.041***	0.041***	0.046***	0.044***	0.037***
		(3.59)	(3.45)	(3.43)	(3.76)	(3.52)	(2.97)
InstHold (Z)			0.002	0.002	-0.006	-0.007	-0.007
			(0.18)	(0.19)	(-0.68)	(-0.81)	(-0.86)
AdvExpToSale (Z)			-0.034*	-0.034*	-0.033	-0.034*	-0.033*
			(-1.86)	(-1.86)	(-1.73)	(-1.76)	(-1.81)
FOG(Z)				-0.004	-0.010	-0.009	-0.010
				(-0.36)	(-0.85)	(-0.82)	(-0.87)
LnAssets (Z)					0.206***	0.198***	0.180***
					(6.39)	(5.98)	(5.57)
LnBM (Z)						-0.011	-0.005
						(-0.96)	(-0.43)
SdRet (Z)							-0.041**
							(-2.70)
Turnover (Z)							-0.018*
							(-1.91)
Firm FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Firm and Year Cluster	YES	YES	YES	YES	YES	YES	YES
Observations	13,579	13,557	13,452	13,452	13,452	13,452	13,451
R^2	0.643	0.644	0.644	0.644	0.645	0.646	0.647

Table C.3: Table 5 Panel B, Coefficients for *TC* and *CMIC* Indicators Reported

This table repeats the analysis conducted in Panel B of Table 5 but reports coefficients for *TC* and *CMIC* Indicators (*TDUM* and *CMIDUM*). See Table C.1 and Table 1 for variable and sample definitions. All explanatory variables are measured as of end of fiscal year t. The regressions include firm and analyst $\times$ year fixed effects. Standard errors are clustered by analyst and year. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.All visual metrics are winzorised at the 99th percentile of their sample distributions. (Z) stands for a Z-Score adjustment.

	(1)	(2)	(3)	(4)	(5)
IMGC(Z)	-0.033***	-0.034***	-0.034***	-0.024***	-0.025***
	(-3.80)	(-3.86)	(-3.85)	(-2.94)	(-3.08)
TDUM (Z)	-0.012	-0.012	-0.012	-0.004	-0.003
	(-1.50)	(-1.52)	(-1.45)	(-0.52)	(-0.43)
CMIDUM (Z)	0.000	0.000	0.000	0.009	0.010
	(0.02)	(0.02)	(0.03)	(1.16)	(1.27)
Firm Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES
Observations	141,867	141,831	141,831	141,829	141,759
R^2	0.490	0.490	0.490	0.520	0.524

Table C.4: Regression of Subsequent-Year Analyst Quarterly Earnings Forecast Errors by Sub-Samples—*IMGC* and *RFC*

This table extends the analysis conducted in Table 7 replacing *AVC* and *RFC* with *IMGC*, where we partition the sample into analyst coverage (Panel A), industry concentration (Panel B) and textual readability (Panel C). The regressions include firm, analyst, and year fixed effects. Standard errors are clustered by analyst and year. *t*-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. (Z) stands for a Z-Score adjustment. All visual metrics are winzorised at the 99th percentile of their sample distributions.

Panel A: Analyst Coverage

	High COV			Low COV		
	(1)	(2)	(3)	(4)	(5)	(6)
IMGC(Z)	-0.033***	-0.033***	-0.024**	-0.011	-0.011	-0.002
	(-2.99)	(-3.01)	(-2.36)	(-0.58)	(-0.58)	(-0.11)
Firm Controls	YES	YES	YES	YES	YES	YES
TC and *CMIC* FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES	YES
Observations	71,495	71,495	71,493	15,409	15,409	15,409
R^2	0.507	0.508	0.538	0.542	0.542	0.565

Panel B: Industry Concentration

	Low Industry Concentration			High Industry Concentration		
	(1)	(2)	(3)	(4)	(5)	(6)
IMGC(Z)	-0.066***	-0.066***	-0.056***	-0.022	-0.021	-0.021
	(-4.49)	(-4.49)	(-4.53)	(-1.11)	(-1.09)	(-1.15)
Firm Controls	YES	YES	YES	YES	YES	YES
TC and *CMIC* FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES	YES
Observations	16,925	16,925	16,925	13,588	13,588	13,588
R^2	0.526	0.527	0.551	0.533	0.533	0.558

Panel C: Textual Readability

	High FOG			Low FOG		
	(1)	(2)	(3)	(4)	(5)	(6)
IMGC(Z)	-0.051**	-0.051**	-0.055***	-0.013	-0.013	-0.014
	(-2.45)	(-2.47)	(-2.68)	(-0.81)	(-0.83)	(-1.11)
Firm Controls	YES	YES	YES	YES	YES	YES
TC and *CMIC* FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Analyst X Year FE	YES	YES	YES	YES	YES	YES
Observations	26,163	26,163	26,163	25,968	25,968	25,968
R^2	0.621	0.622	0.646	0.613	0.613	0.634

Table C.5: Visual Prevalence, Image Content Reinforcement, and Subsequent-Year Analyst Forecast Dispersion - Other Reinforcement Measures

This table extends the analysis conducted in Table 9 replacing RFC with the business and MD&A content reinforcing measures (RFC_{BUSMDA}, $RFC_{BUSMDA+}$, and RFC_{BUSMDA_IFBOTH}). See Table C.1 and Table 1 for variable and sample definitions. All explanatory variables are measured as of end of fiscal year t. The regressions include firm and year fixed effects. Standard errors are clustered by firm and year, and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. All visual metrics are winzorised at the 99th percentile of their sample distributions. (Z) stands for a Z-Score adjustment.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$RFC_{BUSMDA}(Z)$	-0.026***	-0.025***	-0.019**						
	(-3.05)	(-3.09)	(-2.41)						
$RFC_{BUSMDA+}(Z)$				-0.025***	-0.024***	-0.018**			
				(-2.97)	(-3.00)	(-2.28)			
$RFC_{BUSMDA\_IFBOTH}(Z)$							-0.019**	-0.019**	-0.012*
							(-2.46)	(-2.47)	(-1.75)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm and Year Cluster	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	13,084	13,077	13,077	13,084	13,077	13,077	13,084	13,077	13,077
R^2	0.452	0.452	0.467	0.452	0.452	0.467	0.451	0.452	0.467

Table C.6: Regression of Subsequent-Year Firm Changes in Bond Ratings — *IMGC* and *RFC*

This table repeats the analysis conducted in Table 11 using *IMGC* and *RFC* instead of *IMGC*. The specifications match Table 11 where controls are excluded for brevity. See Table C.1 and Table 1 for variable and sample definitions. All explanatory variables are measured as of end of fiscal year t. The regressions include firm and year fixed effects. Standard errors are clustered by firm and year and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. All visual metrics are winzorised at the 99th percentile of their sample distributions. (Z) stands for a Z-Score adjustment.

Panel A: *IMGC*- Downgrade Sample

	ALL				High-Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMGC(Z)	0.033^{***}	0.033^{***}	0.019	0.018	0.106^{**}	0.106^{**}	0.085^{**}	0.084^{**}
	(3.12)	(3.11)	(1.61)	(1.51)	(2.73)	(2.76)	(2.41)	(2.34)
Firm Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,072	5,072	5,072	5,072	1,825	1,825	1,825	1,825
R^2	0.297	0.297	0.333	0.334	0.409	0.410	0.433	0.434

Panel B: *IMGC*- Upgrade Sample

	ALL				High-Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMGC(Z)	0.005	0.005	0.002	0.002	0.019	0.020	0.019	0.019
	(0.67)	(0.65)	(0.29)	(0.29)	(0.56)	(0.58)	(0.54)	(0.54)
Firm Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,429	5,429	5,429	5,429	2,272	2,272	2,272	2,272
R^2	0.263	0.264	0.269	0.270	0.284	0.286	0.293	0.293

Panel C: *RFC*- Downgrade Sample

	ALL				High-Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	t+1	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*
RFC(Z)	0.024^{*}	0.024^{*}	0.010	0.008	0.002	0.002	-0.007	-0.007
	(1.82)	(1.83)	(0.65)	(0.53)	(0.07)	(0.06)	(-0.22)	(-0.21)
Firm Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm and Year Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,072	5,072	5,072	5,072	1,825	1,825	1,825	1,825
R^2	0.297	0.297	0.333	0.334	0.405	0.406	0.431	0.431

Panel D: *RFC*- Upgrade Sample

	ALL				High-Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	t+1	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*	*t+1*
RFC(Z)	0.028^{*}	0.028^{*}	0.012	0.011	0.013	0.014	0.004	0.005
	(1.92)	(1.95)	(0.76)	(0.70)	(0.44)	(0.49)	(0.12)	(0.14)
Firm Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm and Year Cluster	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,557	6,557	6,557	6,557	2,715	2,715	2,715	2,715
R^2	0.289	0.290	0.323	0.324	0.336	0.338	0.364	0.365

Table C.7: Regression of Subsequent-Year Firm ROA and Annual Cumulative Returns on Visual Measures

This table reports results from panel regressions of the firm's ROA (Columns 1–3 and annual cumulative returns (Columns 4–6) in fiscal year t+1 on fiscal year t visual metrics and other explanatory variables. We report results for *AVC*, *IMGC*, and *RFC*. See Table C.1 and Table 1 for variable and sample definitions. All explanatory variables are measured as of end of fiscal year t. The regressions include firm and year fixed effects. Standard errors are clustered by firm and year and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. All visual metrics are winzorised at the 99th percentile of their sample distributions. (Z) stands for a Z-Score adjustment.

	ROA			ANNRET		
	(1) *t+1*	(2) *t+1*	(3) *t+1*	(4) *t+1*	(5) *t+1*	(6) *t+1*
AVC (Z)	0.008* (1.74)			0.014 (1.56)		
IMGC(Z)		0.006 (1.25)			0.012 (1.28)	
RFC(Z)			0.008 (1.63)			0.002 (0.23)
LDEP	0.510*** (15.04)	0.510*** (15.02)	0.510*** (15.07)	-0.049 (-1.68)	-0.049 (-1.68)	-0.049 (-1.68)
Pages	0.000 (0.05)	0.000 (0.07)	-0.000 (-0.06)	0.000 (0.17)	0.000 (0.18)	0.000 (0.13)
LnNews	0.002 (0.20)	0.002 (0.20)	0.003 (0.22)	0.027 (1.23)	0.027 (1.24)	0.028 (1.24)
AnnRet	0.069*** (3.20)	0.069*** (3.20)	0.069*** (3.20)			
ROA				1.004** (2.70)	1.001** (2.68)	1.007** (2.71)
insthold	0.008 (0.19)	0.008 (0.19)	0.008 (0.19)	-0.122 (-1.45)	-0.122 (-1.45)	-0.122 (-1.45)
AdvExpToSale	0.742 (1.15)	0.744 (1.15)	0.750 (1.16)	0.188 (0.12)	0.195 (0.13)	0.191 (0.12)
LnAssets	-0.249*** (-7.36)	-0.249*** (-7.35)	-0.249*** (-7.41)	0.251*** (2.91)	0.251*** (2.91)	0.252*** (2.91)
FOG(Z)	0.004 (0.38)	0.003 (0.38)	0.003 (0.37)	-0.007 (-0.55)	-0.007 (-0.57)	-0.007 (-0.56)
LnBM	-0.143*** (-6.31)	-0.143*** (-6.29)	-0.143*** (-6.33)	-0.064 (-1.55)	-0.064 (-1.55)	-0.064 (-1.55)
SdRet	2.443** (2.31)	2.438** (2.31)	2.434** (2.30)	13.954*** (3.39)	13.947*** (3.39)	13.925*** (3.39)
Turnover	-6.216** (-2.37)	-6.211** (-2.37)	-6.229** (-2.38)	-13.858*** (-3.22)	-13.841*** (-3.22)	-13.922*** (-3.22)
LnSize	0.140*** (4.75)	0.140*** (4.73)	0.140*** (4.74)	-0.672*** (-7.45)	-0.672*** (-7.46)	-0.671*** (-7.49)
TC and *CMIC* FE	NO	YES	NO	NO	YES	NO
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm and Year Cluster	YES	YES	YES	YES	YES	YES
Observations	15,050	15,050	15,050	15,098	15,098	15,098
R^2	0.825	0.825	0.825	0.304	0.304	0.304