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 use novel machine-learning algorithms to construct visual-readability metrics. We innovate by creating 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 image convey reinforcing information are 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 capital, 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, information dissemination, information 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 of graphs/charts (e.g., Beattie and Jones, 2000; Christensen, Fronk, Lee, and Nelson, 2020), they have not examined images' readability and impact, likely due to the obscurity of how images' information content is perceived. This paper partially addresses this literature gap by examining whether images 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.[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.[3]

One challenge facing researchers is the systematic identification of images as distinct from

[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 their investor relation section of their website. 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).

other visual elements (graphs/charts, infographics, team photos, and maps). We overcome this challenge by combining machine learning algorithms and heuristic rules to objectively identify distinct visual elements. We identify visual content at the annual report page level. Page-level visual representation best captures the natural focal point of readers. Using our algorithms, we split annual report pages into those containing text, and those containing visual elements. We classify the latter into five categories: pages with visual elements that are predominantly images (henceforth image-pages), team/management photos-pages, charts-pages, maps-pages, and infographics-pages. This categorization enables focusing on the unique role of image pages, while probing whether other visual elements add value.

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 investors' ability to consume and process visual information content. We posit that visual readability is affected by three potentially overlapping channels. The first, (*visual attention enhancement*), directs attention to specific content (excluding general brand-related material) the firm views as important. The second (*visual engagement enhancing*) engenders heightened cognitive engagement in the narrative. The third, (*content reinforcement*), reinforces the concepts inherent in the narrative.

We develop measures that correspond to these channels. The first measure, *AVC*, is the count of the number of pages with any visual element (excluding pages with only text). We decompose *AVC* into submeasures: *IMGC* is the number of image-pages; *TC* is the number of team/management photos-pages); and *CMIC* is the union of the numbers of charts-pages, maps-pages, and infographics-pages. *AVC* along with its submeasures, which we refer to collectively as "visual prevalence measures", proxy for the intensity of attention-enhancing and engagement-evoking visual information in a report.

Our second measure, content reinforcement (*RFC*), captures the content reinforcement-channel. Following Ronen, Ronen, Zhou, and Gans (2022), we process the image pages using Google Vision and ascertain the degree to which labels corresponding to concrete objects match the report text.[4] *RFC* is then constructed as the total number of informative image labels that match words within the report's narrative. Higher values of *RFC* represent stronger reinforcement (mapping between

[4]See Section 3.1.2, Section 3.1.3, and Appendix C for details on visual page classification and the filters required to construct a meaningful reinforcement measure.

the image information content and the textual narrative information content).

Focusing on annual reports of the S&P 1500 firms from 2002 to 2019, we first identify visual usage. Around 70% of our sample firms include visual elements, with on average, 6.2 pages of visuals (AVC) per annual report. The majority of visual pages (on average 5.14 per report) are classified as image pages ($IMGC$). On average, charts, maps, and infographics account for 0.124 pages per report ($CMIC$) and Team/Management photos (TC) account for 0.95 pages per report. Consistent with images being the bulk of visuals, the correlation between AVC and $IMGC$ is 0.97.

We begin by examining the relation between visual readability and analyst earnings forecast accuracy. Sell-side analysts are a major source of information production and considered to be a sophisticated set of investors. Lehavy et al. (2011) finds that lower textual readability (measured by FOG) results in lower analyst forecast accuracy. To compare the effects of *visual* readability and *textual* readability, we capture, along the lines of Clement (1999), the accuracy of the earnings forecasts for a given stock relative to the average accuracy across the sample stocks that the analyst covers. We include analyst fixed effects, which ensure a "within analyst" comparison and control for individual analyst characteristics.

We find that high visual use (AVC) in the annual report of year t is associated with lower forecast errors (i.e., higher accuracy) in subsequent quarters. That is, analysts exhibit higher accuracy for stock A relative to stock B, if the former is associated with more visuals. We also confirm Lehavy et al. (2011)'s findings as applied to visuals using FOG. Importantly, we find that the effect of visual readability is comparable to that of textual readability. Exploring the interaction between textual readability and visual readability, we find that the effect of visual readability is stronger when textual readability is low. This points to a substitution effect: when the 10-K text is obscure, analysts resort to the annual reports that contain images.

We examine the effects of both visual prevalence and content reinforcement on forecast accuracy. We find that, only the number of image-pages ($IMGC$) results in a negative and significant relation with forecast errors. This demonstrates the importance of our classification and the relevance of images to analyst information production. Zooming in on the content reinforcement of images, we find that RFC also gives rise to higher accuracy. In other words, the larger the number of matches between informative image labels and the text, the higher the accuracy.

We further explore the impacts on analyst forecast dispersion. We find that AVC and $IMGC$

(but not TC or $CMIC$) in the annual report of year t results in lower earnings forecast dispersion (lower disagreement) in subsequent quarters. Moreover our content reinforcement measure (RFC) is also associated with lower dispersion with economic significance that is comparable to the results found using $IMGC$.

Given these results, it is fair to conclude that firms use visuals to better disseminate information to investors. 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 the use of visuals (images) to substitute for the loss of information production. Our results confirm that firms indeed increase the 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.

We further explore whether visuals affect outcomes related to the firm's information environment (standard deviation of returns, market beta, and cost-of-equity capital). 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 capital over the subsequent year.

We also capture the information environment of the firm's debt by exploiting changes in credit ratings. Splitting the sample between bond upgrades and downgrades, we find that the effect of visuals is concentrated in the sample of bond downgrades, and in particular in high-yield bonds, where information is more valuable (Hotchkiss and Ronen, 2002). Specifically, an increase in the use of images (IMG) in year t is 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.

Finally, we explore the impetus for firms to use image-pages in their annual reports. We find that more news coverage over the fiscal year is associated with a larger number of image-pages in the subsequent annual report. Firms also tend to increase their use of visual content when they experience growth in total assets over the year, seemingly to highlight expansion with visual aids. However, we detect no relation between the firm's annual advertising expenses and image-pages, suggesting firms do not view visuals as merely a marketing tool.

While visuals appear to enhance the readability of a firm's financial report in support of an information-based motivation, one can also surmise a non-information-based (non-fundamental-based) rationale. For example, firms may use visuals as a marketing tool to boost their image or engender positive sentiment (hype).[5] However, our finding that the use of visuals results in higher analyst accuracy—presumably the sophisticated set of investors—as opposed to retail investors, is more consistent with an information-based story than a sentiment or retail attention-based story (Barber and Odean, 2008). To confirm that the use of visual information does not lead to short-term overreaction, we explore the relation between visuals and subsequent year annual returns and do not detect a reversal pattern.

Our overall set of results is consistent with an information story, where visuals facilitate the assimilation of information by readers. Our identification strategy supports the use of visuals as a substitute for lost analyst coverage. Nonetheless, we acknowledge that in the absence of an exogenous shock related to the use of images, we cannot rule out the possibility that alternative $information - based$ stories are also at play. One possibility is that within-firm changes in the use of visuals are correlated with changes in the overall quality of the firm's information dissemination, or the overall effort to convey information to investors. For example, the use of visuals can also be correlated with the overall quality of the narrative. Although this is possible, the fact that we control for a large set of characteristics that are associated with performance and quality, including textual readability, should mitigate this concern. Notably, the correlation between our visual metrics and standard text-based readability measures (FOG) is very low, suggesting that our visual content metrics capture distinct features of readability. Still, if the use of images is associated with unobservable changes in the quality of information, at a minimum our visual measures appear to capture such changes and can be used by researchers to study or control for information quality.

The second information-based alternative explanation is that firms tend to use more visual content when their prospects are good, suggesting that the visuals signal positive private information, giving rise to a reduction in risk. Having controlled for news, asset growth, past returns, and returns on assets, which potentially control for future growth, we alleviate this concern. It is also possible that image use is increased when things are bad to offset the impact of a negative shock, such as a bond downgrade. However, were this to be the case, future reversals in fortune would likely occur; we fail to observe such reversals. Despite the above considerations, if image use is correlated with

[5] For example, Obaid and Pukthuanthong (2021) construct a daily sentiment index using photos from the Wall Street Journal Online Archive and show that it can predict market return reversals.

firm private information about future prospects (not captured by observables), then one can argue that images are an important source of intelligence.

Our paper contributes to the established literature on readability. Existing studies examine *textual* readability. You and Zhang (2009), for example, find lower incorporation of information (underreaction) when 10-Ks are more textually complex. Lee (1994) finds that less readable reports are associated with more analyst dispersion. In this study, however, we focus on *visual* readability. Our visual readability measures are distinct from the text-based readability measures used in the literature. We show that through the content–reinforcement channel, 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 existing literature that explores the use of visual information in other contexts, such as marketing, peer lending, crowdfunding, and financial outcomes. To the best of our knowledge, we are the first to explore the impact of images contained in financial reports on staekholders.[6] 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. While other papers explored the effect of visual attention on stock prices (e.g., Nekrasov, Teoh, and Wu, 2021; Obaid and Pukthuanthong, 2021), our findings support an information-based explanation. 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.

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

[6] 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.

is displayed. 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.[7] 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 with high values of intangible assets were more likely to employ visual and stylistic elements in their financial reporting.

A few studies explore the relationship between the aesthetics of images and investor decisions. For example, in an experimental study, Townsend and Shu (2010) show 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. Pope and Sydnor (2011) 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; Malik,

[7]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).

Vir Singh, Lee, and Srinivasan (2017) find that MBA student profile photos on a professional website command a (subjective) beauty premium; and Hu and Ma (2020) find that more positive startup pitch videos (i.e., happy, warm, passionate) increases funding probability. Other studies show how a photo can affect outcomes in firm market valuation and CEO compensation (Graham, Harvey, and Puri, 2016; Blankespoor, Hendricks, and Miller, 2017; Halford and Hsu, 2020).

A few other contemporaneous studies examine whether and how imagery affects stock price reactions. Nekrasov et al. (2021) show that visuals in firm earnings announcements in Tweets increase investor attention to the earnings news, which can result in a lower drift, but also in price reversals. Obaid and Pukthuanthong (2021) construct a daily market level sentiment index using news photos and find that photo pessimism predicts return reversals.

This study focuses on the information 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. Thus, for example, while Nekrasov et al. (2021) and Obaid and Pukthuanthong (2021) document price reversals associated with investor attention and sentiment, our study shows that the 'visual attention' captured by our measures is not associated with reversals; it is associated with fundamentals such as lower risk, higher analyst accuracy, and lower analyst dispersion.

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 Annual-Reports.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 details this data construction process.[8] 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.[9] 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

To overcome the challenge of systematically identifying images as distinct from other visual elements, we combine machine learning algorithms and heuristic rules to classify visual elements into 5 distinct categories: graphs/charts ($CHAR$); team or management photos (T); images, excluding team photos (IMG); infographics ($INFO$); and maps (MAP). Figure 2 illustrates the classification.

Since a page is a natural focal point for readers, our investigation is at the *page* level (not the individual visual element level), even though many of the annual report pages in our sample contain mixed visual elements.[11] Figure 3 presents a report page (from the 2019 Annual Report of the Lancaster Colony Corporation) with mixed visual elements: images, a graph, and text.

[8] 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.

[9] Since we conduct our analysis at the report page level, we convert each page into an "image" in terms of file format to ensure that converted pages can be used in image- related processing.

[10] 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] Indeed, most firms that provide design services for annual reports create templates, designs, and 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

We assume that readers process all information, and synthesize the various elements holistically, simultaneously considering not only each individual element on a page, but other factors such as the size, layout, and position of the visual elements.

Using our algorithms, we split the 2,096,775 annual report pages contained in our sample into those containing only text, and those containing visual elements (137,453 pages). We classify the latter into five categories: pages with visual elements that are predominantly: images (henceforth image-pages), team/management photos-pages, charts-pages, maps-pages, and infographics-pages.[12]

3.1.3 Visual Measures

We construct two broad sets of visual measures. The first captures visual prevalence and the second captures content reinforcement. The visual prevalence set includes as measures: *AVC*, the number of pages with any visual element (excluding pages with only text), *IMGC* (the number of image-pages); *TC* (the number of team/management photos-pages); and *CMIC* (the union of the numbers of charts-pages, maps-pages, and infographics-pages).[13]

The other measure, *RFC*, captures the content-reinforcement channel (where visual content is used to reinforce textual information). To construct *RFC*, we follow a two-step procedure, as in Ronen et al. (2022). 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. Labels that correspond to concrete objects are classified as informative and the remainder are classified as uninformative (Figure 4 provides an example).[14] In Panel A, the labels generated by the image capture clear objects. Conversely, the labels in Panel B are uninformative, and comprise words such as "font," "graphics," "logo," etc.

Finally, we construct (*RFC*) by calculating the number of informative image labels that match

[12]For example, we classify a page that mainly contains charts but also has a less dominant background image as charts-pages. Appendix C.1 describes the machine learning tools used to classify the pages into various categories. Visual pages that do not fall into any of these five categories are classified as "colorful elements" (comprising pages with a single color or with a few colorful lines). We exclude these non-informative pages from the analysis.

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

[14]To correctly classify images, we train GV 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.

the annual report's text. Higher values of *RFC* represent stronger reinforcement (mapping between the image information content and the textual narrative information content). Figure 5 shows a report page from the 2015 J&J Snack Foods Corporation annual report. Two of the five labels generated by GV are "Pretzel" and "Snack," both of which appear in the annual report narrative ("largest manufacturer of soft *pretzels* in the United States, Mexico, and Canada. Other *snack* food products include.."), resulting in two reinforcing labels that are counted in the *RFC* measure of J&J in year 2015.

Our classification is essential for distinguishing among investor reactions to different types of information and isolating the impact of imagery. Notably, this classification scheme does not involve subjective identification, nor does it attempt to evaluate the relevance or meaning of the informative content and thus potentially mitigates concerns of confounding, concurrently released information.

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

Table 1 reports the summary statistics of our visual measures and classifications. To be included in the sample, a firm needs to be part of the S&P 1500 Index, and have media coverage of at least one news article in a given year. The final sample consists of 15,477 firm-year observations from 1,363 unique firms for the period January 2002 to December 2019.

Panel A of Table 1 reports the mean and standard deviation of the visual prevalence measures (*AVC*, *IMGC*, *TC*, and *CMIC*) and of *RFC*, along with percentile statistics. We also report the ratios of each of these measures to the total number of report pages per firm-year annual report. For example, *IMGR* is *IMGC* divided by the number of report pages.

[Table 1]

The mean number of pages per report is 117.94. The means (standard deviations) per report are 6.20 (8.94%) for *AVC*, 5.14 (7.95%) for *IMGC*, 0.95 (1.73%) for *TC*, and 0.12 (0.43%) for *CMIC*. The *AVC* and *IMGC* ratios (8.4% and 6.9% respectively) suggest that firms regard images as the most important element when designing pages with visual elements. Notably, all the other visual element categories (team/management photos-pages, charts-pages, maps-pages, and infographic-pages) account for a far lesser combined ratio (1.5%) of report pages. The mean number of *RFC* (text-reinforcing image labels) per report is 7.42, with a standard deviation of 9.06.

Panel B of Table 1 reports similar statistics for annual reports that contain pages with visual elements (11,607 firm-year observations). Focusing on this sample expectedly increases the means and the corresponding ratios. Thus, similar to Panel A, the increase in the ratios of *AVC* (*IMGC*) from 8.94% to 11.2% (from 6.9% to 9.2%) far outstrips the increase in the combined ratios of *TC* and *CMIC* (from 1.5% to 2%).

Visuals are not concentrated in specific (GICS) sectors. Panel C shows dispersed use of visuals. Expectedly and intuitively, relative to other sectors, Consumer Staples (GICS code 30) exhibits more extensive use of visual elements overall (importantly, including image-pages), while the Financial Sector (GICS code 40) includes pages with team photos more frequently than other sectors.

[Table 2]

Table 2 reveals that number of annual reports (reports including visual elements) increased monotonically (with two exceptions) over our sample years from 361 in 2002 to a maximum of 1,164 in 2018 (from 297 in 2002 to a maximum of 827 in 2018). In 2018, 71.0% of reports include visual elements. Importantly, 69.2% include images-pages. In contrast, only 31.4% of reports include team/management photo-pages and 3.4% include pages with charts, infographics, or maps. 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 classifications metrics and $textual-based$ readability measures. All measures are demeaned to capture within-firm correlations. The 0.97 correlation between *AVC* and *IMGC* confirms the salience 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 0.55 with *IMGC*, consistent with firms possibly using images such as to reinforce textual information. The low correlation between our metrics and the *FOG* readability measure (-0.02) 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 Analysts' Earnings Forecast and Visual Readability

Proceeding from a maintained hypothesis that analysts resort to reviewing annual reports in addition to 10-Ks – especially since 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. Our examination parallels Lehavy et al. (2011)'s usage of the *FOG* index to study the relation between textual readability and analyst forecasts. Our focus on visual readability both complements Lehavy et al. (2011)'s study and deepens our understanding of how users of annual reports assimilate financial information.

We focus on how visual readability is related to both analysts' earnings forecast accuracy and dispersion (disagreement). Our predictor variables include *AVC*, which captures the broadest aspects of visual readability, and its components. We separately zoom in on our content reinforcement measure, *RFC*. In all tests, we contrast the economic significance of *visual* readability with that of the *FOG* measure of *textual* readability.

4.1 The Accuracy of Analysts' Earnings Forecasts

We first explore the relation between visual readability and analyst forecast errors. We conduct our analysis within analyst, across the stocks that each analyst covers. For inclusion in our analysis, we require that at least two stocks be followed by each analyst i in quarter q. Similar to Clement (1999) and Jame, Johnston, Markov, and Wolfe (2016) we construct our within-analyst quarterly forecast accuracy measure (*WAFE*) as:

$$WAFE_{i,j,q} = \frac{(AFE_{i,j,q} - \overline{AFE_{i,q}})}{\overline{AFE_{i,q}}}, \tag{1}$$

where $AFE_{i,j,q}$ is the absolute analyst i's forecast error ($|forecast - actual|$) of firm j's earnings in quarter q of fiscal year $t+1$. $\overline{AFE_{i,q}}$ is the mean absolute earnings forecast error of analyst i across all stocks covered during quarter q. The regression specification takes the following form:

$$WAFE_{i,j,t+1,q} = \alpha + \beta \cdot VIS_{j,t} + \sum_{k=1}^{K} \gamma_k \cdot X_{k,j,t} + A_i + f_j + y_{t+1,q} + \epsilon_{i,j,t+1,q}, \tag{2}$$

where *VIS* is the selected visual measure, A_i is the analyst fixed effect, f_j is the firm fixed effect, and $y_{t+1,q}$ is the year-quarter fixed effect. 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 control for the degree of analyst dispersion (*Analyst Disp*). We include the *FOG* index so as to contrast the partial effects and economic significance of visual and textual readbility. The set of firm control 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 cumulative stock returns over fiscal year t (*AnnRet*), the return on assets for 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*).

In Table 4, the coefficients reported in columns 1-3 (4-6) are based on the averages of quarterly analyst forecast errors of quarters 1 and 2 (quarters 3 and 4). Panel A presents results for *AVC* and displays all the control variables. To obtain a meaningful economic significance measure we Z-Score adjust the dependent variable as well as *AVC* and *FOG*. 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 4]

Specification 1 of Panel A indicates that *AVC* has a negative and statistically significant coefficient. A larger number of visual pages is associated with greater accuracy of earnings forecasts. The effect is economically significant. One standard deviation increase in *AVC* is associated with about 2.5% in accuracy in terms of the standard deviation of WAFE.

The coefficient of *DaysToEarnAnn* loads positively as expected: the earlier the forecast, the less accurate it is. *Analyst Disp* also loads positively, suggesting that stocks with higher forecast dispersion are associated with larger forecast errors. Institutional holdings load negatively, consistent with better governance. News and growth in assets both loads positively, consistent with accuracy loss, potentially due to expanded operations making earnings harder to predict. Finally, 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.

Panel B shows the results for the components of *AVC*: *IMGC*, *TC* and *CMIC*. For brevity, we do not report the control variables. The findings reveal that images, not the infrequent (and apparently not relevant to analysts) team/management photos, or charts/maps/infographics drive the predictive power of *AVC*.

In Panel C of Table 4 we see that *RFC* has a negative and statistically significant coefficient. Heightened content reinforcement is associated with more accurate earnings forecasts. Recall that unlike the mere count of images, *RFC* is the number of informative labels that match words discussed in the textual narrative of the annual report. *RFC* thus proxies for the images' *information content*. This finding corroborates the "information channel" of image use by firms.

[Table 5]

Motivated by the economic significance of our visual measures, we explore the interaction between visual readability and textual readability. Table 5 reports the results. The coefficient on the interaction term, *IMGC* and *FOG* is negative and significant in all specifications. For example, the coefficient estimates of *IMGC*, *FOG* and *IMGC* $\times$ *FOG*, during the first half year (Column 3), are -0.020, 0.029 and -0.013, respectively. This suggests that a one standard deviation increase in *FOG* increases the effect of *IMGC* on accuracy by about 65% (from -0.020 to -0.033). The fact that the effect of visual readability is stronger when textual readability is low points to a substitution effect. That is, when the 10-K text is obscure, analysts resort to the annual report images for insights. On a broader level, this result highlights the importance of imagery usage, especially when words fall short of conveying pertinent information.

4.2 Dispersion of Analyst Earnings Forecasts

We explore the relation between our visual measures and analysts' disagreement as captured in the dispersion in their quarterly earnings forecasts, normalized by the absolute value of the quarterly earnings forecasts mean. The regression specification takes the following form::

$$AnalystDisp_{j,t+1,q} = \alpha + \beta \cdot VIS_{j,t} + \sum_{k=1}^{K} \gamma_k \cdot X_{k,j,t} + f_j + y_{t+1,q} + \epsilon_{j,t+1,q}. \tag{3}$$

where *VIS* is the selected visual measure, f_j is the firm fixed effect, and $y_{t+1,q}$ is the year-quarter fixed effect. We control for the dispersion of analyst forecasts in the corresponding quarter of fiscal year t. Control variables are as in Equation 2. As in Table 4, Table 6 reports the results by semi-annual fiscal period. The coefficients reported in columns 1-3 (4-6) are based on the averages of analysts' dispersion in quarterly earnings forecasts of quarters 1 and 2 (quarters 3 and 4).

Panel A reports the results for *AVC*. We find a negative relation between *AVC* and the dispersion of analysts forecasts, suggesting that the use of visuals lessens disagreement across analysts. The results are attenuated once other firm controls are included (Columns 3 and 6). When *AVC* is broken down into its components in Panel B, *IMGC* emerges as the main driver of these results. Finally, in Panel C, *RFC* continues to load negatively and significantly.

4.3 Drop in Analyst Coverage and Firm Use of Visuals

Analysts are important information producers and inform market participants by synthesizing firm data. As such, it is plausible that in order to compensate for a drop in analyst coverage, firms increase their information dissemination efforts. Thence, we hypothesize that a drop in analyst coverage will result in greater efforts to inform by use of imagery content.

Notably, analyst coverage is an endogenous decision. As identification strategy, we take advantage of Kelly and Ljungqvist (2012)'s setting and focus on terminations of analyst coverage as a result of brokerage firm closures. Using their list of brokerage firms closures, we are able to match and use 23 events (of their 25 events) during 2002 to 2007 which overlap with our sample. Table 7 reports the effect of these events on analyst coverage and firms' use of images.

[Table 7]

Panel A reports the first stage, second stage and reduced form estimation. We construct a dummy variable (*Brokerage_Event_Dummy*) that equals one if the firm was covered by one of the brokerage firms in the year of the event, and zero otherwise. The first stage regression explores the drop in analyst coverage due to the event by using the change in average analyst coverage ($\Delta AnalystCoverage$) between the year of the event and the subsequent year. The affected firms in our sample experienced a drop of on average, 0.40 analysts after the brokerage firm closure. In our second stage, we use the predicted coverage change as an IV to estimate the effect of a drop in coverage on that year's annual report. We find a negative and statistically significant coefficient, which indicates that a drop in coverage results in an increase in the number of images used in the annual report. To facilitate economic interpretation, we also report the reduced form estimation by replacing the IV with the brokerage event dummy variable. We find that affected firms exhibited an increase of image-pages by an average of 0.73 per report. This is economically significant given that the average number of image-pages in an annual report is 5.14 (6.85) for all firms (firms that use visuals in their annual reports). To mitigate effects of unobservables, we conduct pre- and post-event tests wherein we shift the event year t by two years from $t-2$ to $t+2$. As Panel B shows, none of the effects of the drop in brokerage coverage on the number of image - pages during the years $t-1$ and $t-2$ is statistically or economically significant, confirming a parallel trend in the outcome variable during the prior two years.

5 Predicting Firm Outcomes Using Visual Information

In this section, we explore the association between visual content and the subsequent fiscal year firm-specific measures: firm-specific risk measures and cost-of-equity capital. We also examine the extent to which visual content is associated with corporate bond ratings.

5.1 Total Risk, Systematic Risk, and Cost-of-Equity Capital

We 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 (denoted *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 $t+1$; the third is the firm's cost-of-equity capital (*Cost-of-Equity Capital*) in fiscal year t+1, estimated as in Frank and Shen (2016) (see Table B.1 for details). The regression specification takes the following form:

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

where *VIS* is the visual metric of interest in the annual report of 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 Equation 2, and are estimated up to the end of fiscal year t. See Table B.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 8 reports the results with Z-scored dependent and explanatory variables of interest. Specifications 1-3, 4-6, and 7-9 report results for *SdRet*, *MktBeta*, and *Cost-of-Equity Capital*, respectively. Across all specifications, we find a negative association between *AVC* and the subsequent year's total risk. A one standard deviation increase in *AVC* is associated with a reduction of 1.5% – 2.3% in total risk (in standard deviation units). We find similar results for *MktBeta* and *Cost-of-Equity Capital*, where a one standard deviation increase in *AVC* results in a reduction of about 1.8% – 2.9% for both *MktBeta* and *Cost-of-Equity Capital* in standard deviation units.

[Table 8]

The absolute drop in beta is 0.011 (coefficient (0.029) × standard deviation (0.38)) is statistically significant and comparable to or exceeds changes reported in other studies. For example, Chen, Singal, and Whitelaw (2016) find that after 2000, the increase in beta during the first year after including a firm in the S&P 500 Index is not significant. The absolute drop in cost-of-equity capital is 7.3 basis points (coefficient (0.029) $\times$ standard deviation (0.025)).

We also estimate the effects of the *AVC* components (Panel B). In addition to images (*IMGC*), team photos (*TC*) also load negatively when predicting beta and cost-of-equity capital, suggesting pictorial representations, such as images or team photos are predictive of risk measures, but not *CMIC* which consists of non-pictorial graphic representations. Furthermore, note importantly, that *RFC* loads negatively when predicting all outcome variables (*SdRet*, *MktBeta*, and *Cost-of-Equity Capital*; see Panel C). This result confirms the important role that the content reinforcement measure, *RFC* plays.

5.2 Changes in Credit Ratings

Similar to equity risk measures, visuals contributing to a more transparent information environment should also be associated with improved credit ratings. We focus on changes in credit ratings during fiscal year $t+1$. To capture rating changes, we first match available corporate bonds on TRACE by company with an identified issuer on Mergent FISD, convert letter rating grades into numbers, and multiply the reverse numerical scale by -1 (such that positive changes reflect bond upgrades).[15] We then construct a daily firm-level index that tracks credit rating agencies' ratings across all available bonds. 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:

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

Beyond the firm controls employed in the regressions, we also control for leverage (D/E) at the end of fiscal year t to capture credit risk. We also control for the level of the rating index at the end of fiscal year t (*AvgRate*), and the lagged dependent variable. 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 9]

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

Table 9 reports the findings for our main variable, *IMGC*. Panel A indicates a positive relation between the use of images and changes in ratings. As expected, the relation is economically stronger for high-yield bonds, where the effect is 2 - 3 times larger. In Panels B and C we consider downgrades and upgrades separately. We include bonds with zero changes in both samples. The results in Panel A appear to be driven by bond downgrades. Specifically, the use of images in annual reports reduces the likelihood of observing a downgrade – we do not detect an effect in the sample of bond upgrades. 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.

5.3 Is There Evidence of a Non-Fundamental Story?

While the evidence is consistent with an information-based story, firms may also use visuals as a marketing tool, which can lead to positive sentiment and a short-term non-fundamental boost in the stock price (hype). Such a non-fundamental boost should lead to a subsequent price reversal. To test this, we explore whether the use of visuals is associated with price reversals. We run our main specification at the annual level to examine the association between visuals and cumulative stock returns during fiscal year $t+1$:

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

Table 10 reports the results. The coefficient estimates of *AVC*, *IMGC* and *RFC* do not show signs of return reversals. In fact, controlling for size and book-to-market, the coefficients are positive, albeit statistically insignificant. This suggests the use of visuals does not lead to overreaction.

6 Determinants of the Use of Visual Information

In this section, we explore the relation between the use of visuals and a set of explanatory variables. The regression specification takes the following form:

$$VIS_{j,t} = \alpha + \beta \cdot VIS_{j,t-1} + \sum_{k=1}^{K} \gamma_k \cdot X_{k,j,t} + f_j + y_t + \epsilon_{j,t}, \tag{7}$$

where *VIS* is our visual measure of interest. $VIS_{j,t-1}$ is *VIS* of the previous fiscal year; k denotes the specific explanatory variable; t denotes the fiscal year; and j denotes the firm. The set of explanatory variables is similar to the variables used in our previous analysis. To facilitate economic interpretation, we Z-Score adjust both the dependent variable and our variables of interest.[16]

Table 11 reports the results for the use of images (*IMGC*). Results using *AVC* or *RFC* lead to similar conclusions. In all specifications, we control for the *IMGC* in the previous year, as well as the number of report pages. We find a positive association between the number of news articles about the firm over the fiscal year and the use of images, suggesting that the increased media coverage pertains to the year's fundamental events that are reflected in both 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, which translates to an increase of ($3\% \times 1.55 =$) 4.65% in *IMGC* relative to its average.

We also find that annual returns (*AnnRet*) are positively correlated with the use of images; a one standard deviation increase in *AnnRet* results in an increase of 2% in the use of images. Since positive returns are associated with growth, this result is in line with what we might expect – higher growth would lead to an increased need and/or desire for firms to highlight improved operations or prospects. Similarly, a one standard deviation increase in *ROA* is associated with an increase of about 3% in *IMGC*.

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 relation between the firm's advertising expenses and the use of images. Our results indicate that images are uncorrelated with adverting expenses, suggesting that *IMGC* 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.

In the last three specifications of Table 11 (columns 5-7), we include other firm characteristics, most notably firm assets that reflect growth in firm activity. Strikingly, we find that an increase in total assets is associated with an increase in *IMGC*, and that the effect appears to be economically significant. A one standard deviation increase in assets results in an increase of 13.2% in *IMGC*. *LnBM* is negatively associated with *IMGC* suggesting that higher growth (low *LnBM*) leads to higher use of visuals. Finally, *SdRet* and *Turnover* are negatively associated with *IMGC*.

Overall, these results indicate that firms increase their use of images in annual reports as a

[16] 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.

result of greater news coverage and growth in assets, consistent with an information-based story, wherein firms strive to convey relevant information by using imagery.

7 Conclusion

In response to the SEC's quest for improved readability of 10-Ks, 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 create novel machine learning methods to tease out important characteristics of the visual content we examine. We conjecture that images provide information content that reinforces the textual narrative in the annual report, and serves as an important source of firm information dissemination.

Over the last couple of decades, firms have increased the 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 effects of "*visual* readability" on important financial outcomes. We find that increased news coverage and asset growth are determinants of increased visual content. The majority of the visual content – widely used across sectors – is concentrated in the use of pages dominated by images, rather than by team photos, charts, maps, or infographics.

In support of an information story explaining these findings, we find that a higher use of image-pages is associated with higher (lower) analyst forecast accuracy (dispersion). The economic significance of visual use is comparable to that of well-known measures of textual readability. Utilizing an identification strategy, we show that firms increase the use of visuals when facing an exogenous drop in analyst coverage. The use of visual content is associated with the firm's overall information environment: visual content is associated with lower risk, lower market betas, and higher bond ratings during the following year. In contrast, the use of visuals is not associated with short-term overreaction.

The visual measures that we employ provide consistent results across a broad set of firm outcomes. They are intuitive and relatively straightforward. Most notably, the novel measure of content reinforcement we use is strongly associated with future financial outcomes of interest. This association demonstrates 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 firm outcomes.

Future research hopefully will explore more granular characteristics of images and how these characteristics can differentially be related to financial and other outcomes.

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Figure 1: American Science and Engineering, Inc.

This figure provides examples of the use of images in the annual reports of American Science and Engineering, Inc.

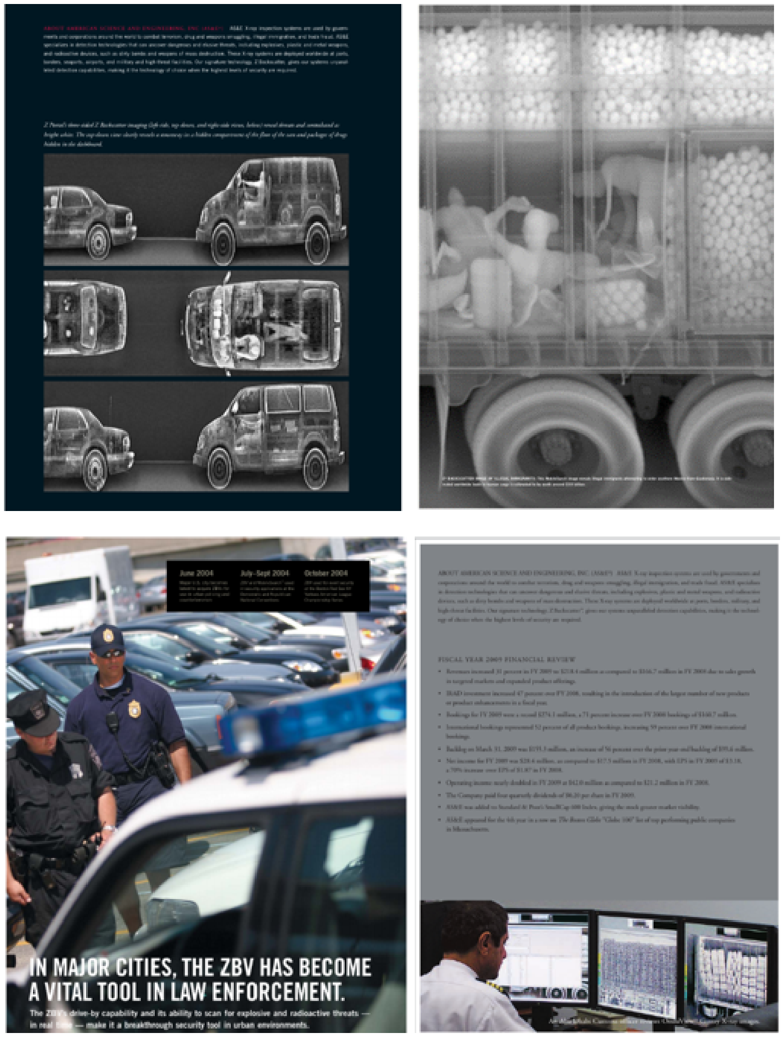


Figure 2: Classification of Visual Elements

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

Figure 3: Page Level Analysis

As shown by the below 2019 annual report page of the Lancaster Colony Corporation, report pages can combine mixed visual elements, including images, graphs, text and other visual elements. This figure illustrates the importance of analyzing visual content at the page level.

INNOVATION

In June 2019, Lancaster Colony Corporation opened a new state-of-the-art Innovation Center near our company headquarters in central Ohio. This 45,000 square foot facility brings together the best in culinary arts, food science and technology.
The Innovation Center also enables greater collaboration and innovation among our Foodservice and Retail teams to develop relevant, consumer-centric, on-trend products that serve to strengthen our existing customer relationships and build new ones.

Marzetti Culinary Team Featured on the Cover
(From left to right): Culinary Specialists **Chris Domanik**, **Jack Cory** and **Joe Ciaciura**; and Director of Strategic Product Development, **Sandy Bichsel**.

FINANCIAL HIGHLIGHTS

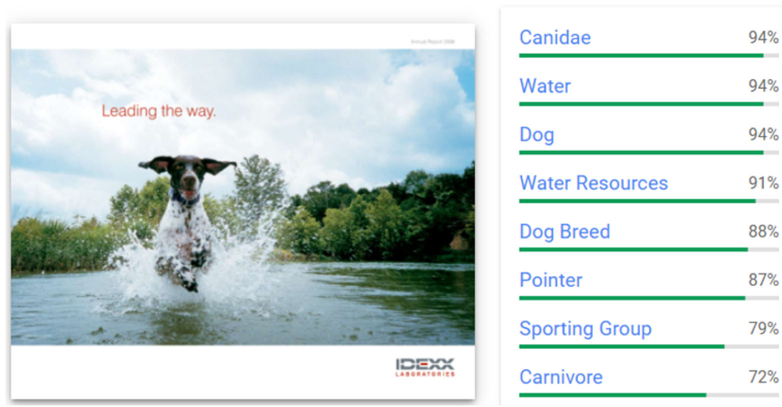
	Years Ended June 30			
(In Thousands, Except Per Share Figures)	2019		2018	
Net Sales	$	1,307,787	$	1,222,925
Gross Profit	$	326,198	$	303,506
Income Before Income Taxes	$	195,542	$	174,203
Taxes Based on Income	$	44,993	$	38,889
Net Income	$	150,549	$	135,314
Per Common Share:				
Net Income – Diluted	$	5.46	$	4.92
Cash Dividends	$	2.55	$	2.35
Shareholders' Equity	$	26.44	$	23.73
Total Assets	$	905,399	$	804,491
Shareholders' Equity	$	726,873	$	652,282
Weighted Average Common Shares Outstanding – Diluted		27,537		27,459

Note: Financial results for the fiscal year ended June 30, 2019 include the favorable impact on Income Before Income Taxes of a $17.1 million non-cash, pre-tax reduction to the fair value of the acquisition-related contingent consideration for Angelic Bakehouse, Inc. Please refer to the company's Form 10-K filing for additional details.

Figure 4: Determining Whether an Image is Informative

This figure illustrates the classification of images into informative and uninformative. Based on the GV-generated labels placed to the right of the images, the image in Panel A (2006 IDEXX Laboratories) is classified as informative, whereas the image in Panel B is classified as uninformative.

Panel A: Informative Labels



Panel B: Uninformative Labels

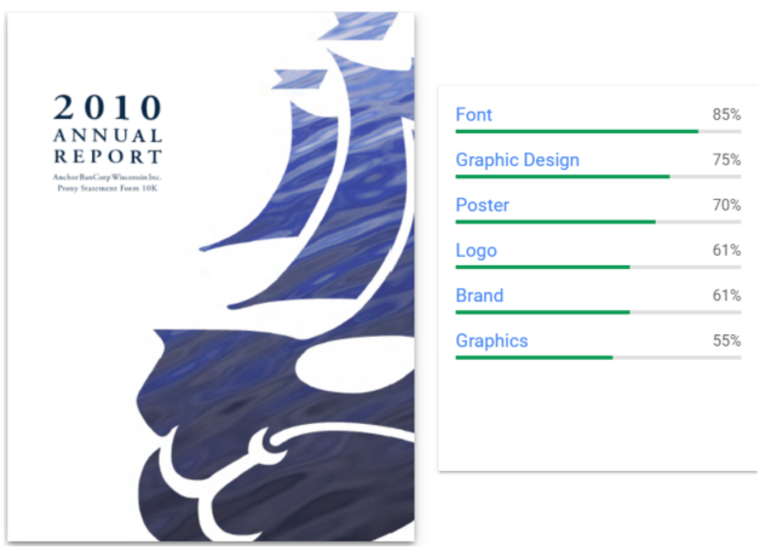


Figure 5: Determining whether Informative Images are Reinforcing

This figure illustrates the derivation of the reinforcement (RFC) measure. For each informative image, we calculate the number of image-label to text matches. For example, two of the GV-generated labels for the 2015 J&J Snack Foods Corporation annual report cover page shown below match the report narrative: “J&J believes it is the largest manufacturer of soft pretzels in the United States, Mexico and Canada. Other snack food products include funnel cake...”.

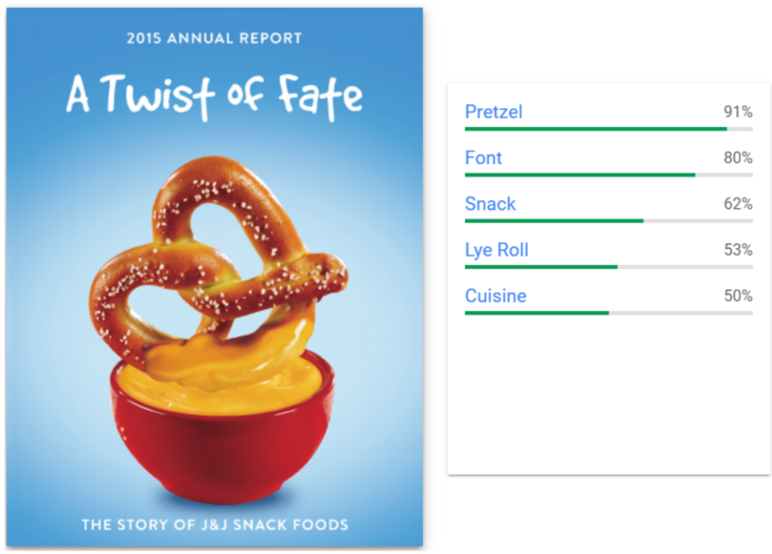


Figure 6: Page Level Analysis versus Individual Element Analysis

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. Specifically, focusing on the latter may assign equal weights to all elements, whereas focusing on the former would assign differential weights, depending on the dimensionality and salience of the distinct elements (IDEXX Laboratories, Inc. 2005). See Appendix C.2 for more detail.

Panel A: Full Page Image

Panel B: Other Parsed Images

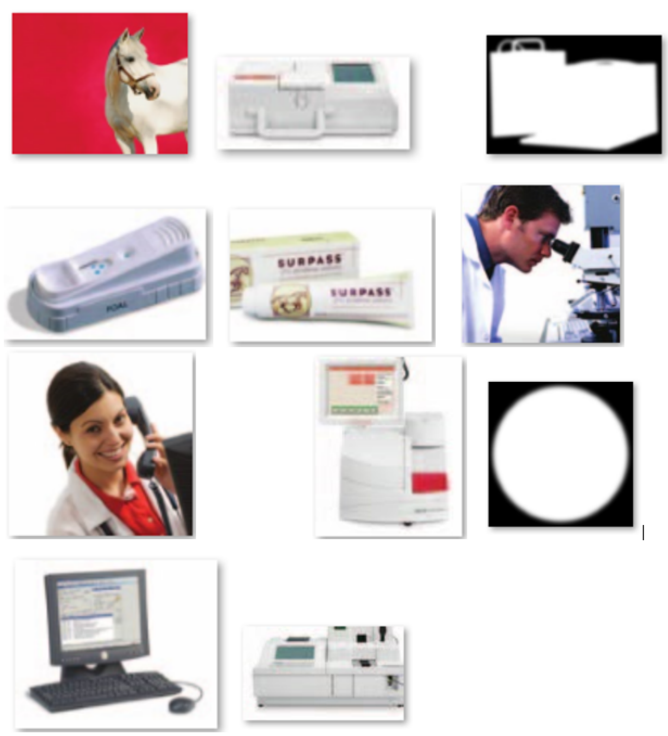


Table 1: Summary Statistics of Report Pages with Visual Elements

This table reports summary statistics of visual content at the annual report page level. To be included in the sample, a firm needs to be part of the S&P 1500 Index. We also require firms to have media coverage of at least one news article in a given year. The sample ranges from 2002 to 2019, and includes 15,477 firm-year observations, over 1,363 unique firms. See Table A.1 for the data collection process. See Table B.1 for variable definitions. We split annual report pages into those containing text, and those containing visual elements (AV). We classify AV into five categories: pages with visual elements that are predominantly images (IMG), team/management photos-pages (T), charts-pages ($CHAR$), maps-pages (MAP), and infographics-pages ($INFO$), where we aggregate $CHAR$, MAP and $INFO$ into one category (CMI). Panel A reports the average, standard deviation, and percentile statistics by visual element category. For all visual elements, the suffix "C" refers to the count of visual pages. For example, $IMGC$ is the number of pages with images in an annual report. In a similar manner, the suffix "R" refers the ratio of the number of visual pages to the number of annual report pages. For example, $IMGR$ is the ratio of $IMGC$ to the number of pages in the annual report. RFC is the reinforcement variable, calculated as the number of informative labels that match words discussed in the textual narrative of the annual report. Panel B restricts the statistics to reports that includes visual elements (11,607 firm-year observations). Panel C reports statistics broken down by GICS sectors across the 15,477 year-firm observations.

Panel A: Pooled Statistics

	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
AVC	6.204	8.940	0.000	0.000	0.000	4.000	9.000	15.000	20.000
$IMGC$	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
AVR	0.084	0.147	0.000	0.000	0.000	0.033	0.090	0.212	0.397
$IMGR$	0.069	0.125	0.000	0.000	0.000	0.026	0.073	0.173	0.316
TR	0.013	0.034	0.000	0.000	0.000	0.000	0.012	0.035	0.063
$CMIR$	0.002	0.008	0.000	0.000	0.000	0.000	0.000	0.003	0.010
RFC	7.417	9.059	0.000	0.000	0.000	4.000	12.000	20.000	26.000
# of Firm-year Obs.	15,477								

Panel B: Pooled Statistics - Reports with Visual Pages

	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
AVC	8.273	9.458	1.000	1.000	3.000	6.000	11.000	17.000	22.000
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
AVR	0.112	0.161	0.007	0.010	0.023	0.056	0.119	0.276	0.500
IMGR	0.092	0.137	0.005	0.008	0.019	0.045	0.097	0.227	0.393
TR	0.018	0.039	0.000	0.000	0.000	0.006	0.018	0.045	0.080
CMIR	0.002	0.009	0.000	0.000	0.000	0.000	0.000	0.008	0.013
RFC	9.890	9.217	0.000	0.000	3.000	8.000	15.000	23.000	28.000
# of Firm-year Obs.	11,607								

Panel C: Pooled Statistics - GICS Sectors

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)	7.33	8.34	8.87	8.68	11.35	5.69	6.68	3.85	5.19	10.03	7.76
RFC(Std.Dev)	8.94	9.05	9.71	10.10	11.81	7.86	7.92	5.56	10.26	9.09	8.29
# of Firm-year Obs.	656	890	2561	2346	909	1664	2148	2161	381	609	1152

Table 2: Time Series Statistics of Report Pages with Visual Elements

This table reports time-series statistics averages of the number of annual reports per year, together with the number of reports containing visual elements by visual element category (# AV, # IMG, # T, and # CMI). We report statistics for 2002-2018 for which we have full information. See Table B.1 and Table 1 for variable and sample definitions.

FYEAR	reports	# AV	%	# IMG	%	# T	%	# CMI	%
ALL	14431	10721	74.3%	10457	72.5%	5869	40.7%	1522	10.5%
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%

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, textual-based readability measures, and firm controls. All variables are demeaned by firm to capture within firm correlations. The sample period is from 2002 to 2019. All visuals metrics are winzorised at the 99% of their sample distribution. The sample ranges from 2002 to 2019 and includes 15,477 firm-year observations and 1,363 unique firms. See Table B.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 Capital	0.114	0.025	0.082	0.098	0.115	0.130	0.145
Cost-of-Debt Capital	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)
(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*	0.62	0.55	0.54	0.13	1.00	
(6) *FOG*	-0.02	-0.02	-0.01	-0.02	-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: Regression of Subsequent-Year within-Analyst Earnings Forecast Errors on Firm Visual Metrics

This table reports results from panel regressions of within-analyst forecast errors of quarters q1–q4 in fiscal year t+1 on fiscal year t visual metrics and other explanatory variables. For inclusion in our analysis, we require that at least two stocks be followed by each analyst i in quarter q. The within-analyst quarterly forecast accuracy measure, $WAFE_{i,j,q}$, is calculated as $(AFE_{i,j,q} - \overline{AFE_{i,q}})$ / $\overline{AFE_{i,q}}$, and 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. We report results based on semi-annual fiscal periods, where the first (second) period's $WAFE_{i,j}$ values are based on the average of the $WAFE_{i,j,q}$ in quarters 1 and 2 (quarters 3 and 4). Panel A report results for *AVC* including the full set of control variables. Panels B and C report results for *AVC* components (*IMGC*, *TC* and *CMIC*) and *RFC*, respectively, where controls are excluded for brevity. See Table B.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, analyst, and year-quarter fixed effects. Standard errors are clustered by analyst and year-quarter. t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.All visuals metrics are winzorised at the 99% of their sample distribution. (Z) stands for a Z-Score adjustment.

Panel A: *AVC*

	WAFE (avg. of q1(t+1) and q2(t+1))			*WAFE* (avg. of q3(t+1) and q4(t+1))		
	(1)	(2)	(3)	(4)	(5)	(6)
AVC (Z)	-0.025***	-0.025***	-0.023***	-0.017*	-0.017*	-0.014
	(-3.73)	(-3.69)	(-3.39)	(-1.82)	(-1.81)	(-1.52)
Pages	0.000	0.000	0.000	0.000	0.000	0.000
	(0.47)	(0.43)	(0.31)	(0.60)	(0.59)	(0.42)
DaysToEarnAnn	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(6.09)	(6.08)	(6.14)	(6.78)	(6.78)	(6.52)
Analyst Disp	0.636***	0.635***	0.621***	1.275***	1.274***	1.261***
	(4.34)	(4.34)	(4.35)	(7.70)	(7.69)	(7.78)
LnNews	0.056**	0.055**	0.054**	0.039**	0.039**	0.041**
	(2.46)	(2.44)	(2.21)	(2.14)	(2.12)	(2.15)
AnnRet	0.010	0.010	0.005	-0.015	-0.015	-0.009
	(0.75)	(0.74)	(0.33)	(-0.81)	(-0.82)	(-0.51)
ROA	-0.180	-0.174	-0.067	-0.065	-0.063	0.076
	(-1.42)	(-1.38)	(-0.52)	(-0.49)	(-0.47)	(0.57)
insthold	-0.115*	-0.116*	-0.093	-0.219***	-0.220***	-0.185***
	(-1.88)	(-1.91)	(-1.48)	(-3.87)	(-3.85)	(-3.15)
AdvExpToSale	2.111***	2.126***	2.177***	1.845*	1.854*	1.939**
	(3.90)	(3.91)	(4.07)	(1.85)	(1.86)	(2.02)
LnAssets	0.217***	0.214***	0.297***	0.209***	0.208***	0.283***
	(9.72)	(9.57)	(8.86)	(8.23)	(8.08)	(7.03)
FOG(Z)		0.025***	0.024***		0.008	0.007
		(3.07)	(2.93)		(0.90)	(0.83)
LnBM			-0.076***			-0.049**
			(-4.15)			(-2.32)
SdRet			2.953***			3.327**
			(2.81)			(2.44)
Turnover			-1.818			-4.463***
			(-1.48)			(-2.79)
LnSize			-0.076***			-0.076**
			(-3.08)			(-2.01)
Firm FE	YES	YES	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Firm and Year-Quarter Cluster	YES	YES	YES	YES	YES	YES
Observations	125,984	125,984	125,983	102,984	102,984	102,984
R^2	0.389	0.389	0.390	0.372	0.372	0.373

Panel B: *IMGC* vs. *CMIC* and *TC*

	$WAFE$ (avg. of q1(t+1) and q2(t+1))			$WAFE$ (avg. of q3(t+1) and q4(t+1))		
	(1)	(2)	(3)	(4)	(5)	(6)
IMGC(Z)	-0.021**	-0.021**	-0.020**	-0.019**	-0.019**	-0.018**
	(-2.31)	(-2.28)	(-2.14)	(-2.25)	(-2.25)	(-2.10)
TC (Z)	-0.004	-0.004	-0.003	0.003	0.003	0.005
	(-0.48)	(-0.48)	(-0.29)	(0.44)	(0.44)	(0.73)
CMIC (Z)	-0.005	-0.005	-0.004	-0.002	-0.002	-0.001
	(-0.80)	(-0.74)	(-0.63)	(-0.54)	(-0.51)	(-0.20)
Firm FE	YES	YES	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Firm and Year-Quarter Cluster	YES	YES	YES	YES	YES	YES
Observations	125,984	125,984	125,983	102,984	102,984	102,984
R^2	0.389	0.389	0.390	0.372	0.372	0.373

Panel C: *RFC*

	$WAFE$ (avg. of q1(t+1) and q2(t+1))			$WAFE$ (avg. of q3(t+1) and q4(t+1))		
	(1)	(2)	(3)	(4)	(5)	(6)
RFC(Z)	-0.025***	-0.025***	-0.022***	-0.010	-0.010	-0.007
	(-3.64)	(-3.67)	(-3.35)	(-1.12)	(-1.12)	(-0.79)
Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Firm and Year-Quarter Cluster	YES	YES	YES	YES	YES	YES
Observations	125,984	125,984	125,983	102,984	102,984	102,984
R^2	0.389	0.389	0.390	0.371	0.372	0.373

Table 5: Within-Analyst Earnings Forecast Errors - *IMGC* and *FOG* Interaction

This table extends the analysis conducted in Table 4 by exploring the interaction between *IMGC* and *FOG*. We keep all observations with non-missing *FOG* values. *IMGC(Z)* × *FOG(Z)* in the interaction between *IMGC(Z)* and *FOG(Z)*. (Z) stands for a Z-Score adjustment. All visuals metrics are winzorised at the 99% of their sample distribution.

	WAFE (avg. of q1(t+1) and q2(t+1))			*WAFE* (avg. of q3(t+1) and q4(t+1))		
	(1)	(2)	(3)	(4)	(5)	(6)
IMGC(Z)	-0.020***	-0.022***	-0.020**	-0.021*	-0.023*	-0.021*
	(-2.70)	(-2.90)	(-2.63)	(-1.94)	(-1.97)	(-1.73)
FOG(Z)	0.029***	0.029***	0.029***	0.016*	0.017*	0.017*
	(3.57)	(3.61)	(3.54)	(1.80)	(1.85)	(1.84)
IMGC(Z) × *FOG(Z)*		-0.014***	-0.013**		-0.012	-0.012
		(-2.68)	(-2.58)		(-1.39)	(-1.27)
Pages	0.000	0.000	0.000	0.000	0.000	0.000
	(1.63)	(1.64)	(1.50)	(1.54)	(1.55)	(1.37)
DaysToEarnAnn	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(5.05)	(5.03)	(5.04)	(4.35)	(4.33)	(4.17)
Analyst Disp	0.654***	0.657***	0.637***	1.665***	1.666***	1.636***
	(3.44)	(3.44)	(3.49)	(7.37)	(7.39)	(7.26)
LnNews	0.061**	0.061**	0.060**	0.050**	0.050**	0.052**
	(2.50)	(2.54)	(2.40)	(2.24)	(2.27)	(2.34)
AnnRet	0.008	0.007	0.002	-0.022	-0.023	-0.021
	(0.50)	(0.45)	(0.10)	(-1.30)	(-1.35)	(-1.07)
ROA	-0.190	-0.189	-0.070	-0.065	-0.065	0.041
	(-1.52)	(-1.50)	(-0.55)	(-0.39)	(-0.39)	(0.24)
insthold	-0.030	-0.030	0.006	-0.147**	-0.147**	-0.113*
	(-0.40)	(-0.41)	(0.08)	(-2.29)	(-2.29)	(-1.77)
AdvExpToSale	1.802**	1.801**	1.843**	1.645**	1.643**	1.652**
	(2.27)	(2.26)	(2.34)	(2.37)	(2.37)	(2.61)
LnAssets	0.216***	0.214***	0.301***	0.215***	0.213***	0.286***
	(7.63)	(7.61)	(7.49)	(7.78)	(7.70)	(5.96)
LnBM			-0.082***			-0.057**
			(-3.91)			(-2.36)
SdRet			4.479***			3.099*
			(4.18)			(1.73)
Turnover			-3.521**			-4.331*
			(-2.33)			(-1.86)
LnSize			-0.080***			-0.072
			(-2.88)			(-1.58)
Firm FE	YES	YES	YES	YES	YES	YES
Analyst FE	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Firm and Year-Quarter Cluster	YES	YES	YES	YES	YES	YES
Observations	96,264	96,264	96,263	78,895	78,895	78,895
R^2	0.403	0.403	0.405	0.390	0.390	0.391

Table 6: Regression of Subsequent-Year Analyst Forecast Dispersion on visuals Metrics

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. We report results based on semi-annual fiscal periods, where the first (second) period's $AnalystDISP_{i,j}$ values are based on the average of the $AnalystDISP_{i,j}$ in quarters 1 and 2 (quarters 3 and 4). Panel A report results for *AVC* including the full set of control variables. Panels B and C report results for *AVC*components (*IMGC*, *TC* and *CMIC*) and *RFC*, respectively, where controls are excluded for brevity. See Table B.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-quarter fixed effects. Standard errors are clustered by firm and year-quarter, and t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. All visuals metrics are winzorised at the 99% of their sample distribution. (Z) stands for a Z-Score adjustment.

Panel A: *AVC*

	AnalystDISP (avg. of q1(t+1) and q2(t+1))			*AnalystDISP* (avg. of q3(t+1) and q4(t+1))		
	(1)	(2)	(3)	(4)	(5)	(6)
AVC (Z)	-0.028**	-0.027**	-0.015	-0.022**	-0.021**	-0.011
	(-2.47)	(-2.45)	(-1.55)	(-2.40)	(-2.37)	(-1.24)
LagDEP	0.188***	0.187***	0.150***	0.186***	0.185***	0.135***
	(4.73)	(4.70)	(3.76)	(3.91)	(3.90)	(2.87)
Pages	0.000**	0.000**	0.000	0.000	0.000	0.000
	(2.31)	(2.32)	(1.40)	(1.15)	(1.14)	(0.26)
LnNews	0.061**	0.059**	0.059**	0.064***	0.063***	0.055***
	(2.44)	(2.43)	(2.22)	(2.91)	(2.86)	(2.73)
AnnRet	-0.139***	-0.140***	-0.069**	-0.091**	-0.091**	-0.086***
	(-4.61)	(-4.64)	(-2.62)	(-2.44)	(-2.44)	(-3.65)
ROA	-2.129***	-2.116***	-1.257***	-1.632***	-1.625***	-0.994***
	(-11.21)	(-11.21)	(-5.73)	(-9.02)	(-8.95)	(-5.45)
insthold	-0.137	-0.140	-0.088	-0.193**	-0.196**	-0.145*
	(-1.52)	(-1.56)	(-1.02)	(-2.21)	(-2.26)	(-1.68)
AdvExpToSale	0.484	0.487	0.607	-0.032	-0.027	0.031
	(0.77)	(0.77)	(1.03)	(-0.04)	(-0.04)	(0.05)
LnAssets	-0.022	-0.028	0.164***	-0.015	-0.017	0.130***
	(-0.68)	(-0.88)	(4.49)	(-0.46)	(-0.53)	(2.95)
FOG(Z)		0.033***	0.030**		0.009	0.007
		(2.65)	(2.51)		(0.69)	(0.58)
LnBM			0.005			-0.029
			(0.17)			(-1.05)
SdRet			6.189***			8.619***
			(3.22)			(5.32)
Turnover			2.690			2.006
			(1.60)			(0.90)
LnSize			-0.244***			-0.171***
			(-4.65)			(-4.01)
Firm FE	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Firm and Year-Quarter Cluster	YES	YES	YES	YES	YES	YES
Observations	13,016	13,016	13,016	13,098	13,098	13,098
R^2	0.395	0.396	0.408	0.375	0.375	0.385

Panel B: *IMGC* vs. *CMIC* and *TC*

	AnalystDISP (avg. of q1(t+1) and q2(t+1))			*AnalystDISP* (avg. of q3(t+1) and q4(t+1))		
	(1)	(2)	(3)	(4)	(5)	(6)
IMGC(Z)	-0.026**	-0.026**	-0.017*	-0.020**	-0.019**	-0.012
	(-2.61)	(-2.59)	(-1.85)	(-2.20)	(-2.17)	(-1.39)
TC (Z)	-0.006	-0.006	-0.001	-0.007	-0.007	-0.003
	(-0.46)	(-0.48)	(-0.09)	(-0.99)	(-0.97)	(-0.35)
CMIC (Z)	0.002	0.003	0.005	0.007	0.007	0.009
	(0.35)	(0.41)	(0.61)	(1.15)	(1.14)	(1.27)
Firm FE	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Firm and Year-Quarter Cluster	YES	YES	YES	YES	YES	YES
Observations	13,016	13,016	13,016	13,098	13,098	13,098
R^2	0.395	0.396	0.408	0.375	0.375	0.385

Panel C: *RFC*

	AnalystDISP (avg. of q1(t+1) and q2(t+1))			*AnalystDISP* (avg. of q3(t+1) and q4(t+1))		
	(1)	(2)	(3)	(4)	(5)	(6)
RFC(Z)	-0.029**	-0.029**	-0.020*	-0.016*	-0.016*	-0.007
	(-2.59)	(-2.61)	(-1.77)	(-1.99)	(-1.99)	(-0.84)
Controls FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES
Firm and Year-Quarter Cluster	YES	YES	YES	YES	YES	YES
Observations	13,016	13,016	13,016	13,098	13,098	13,098
R^2	0.395	0.396	0.408	0.375	0.375	0.385

Table 7: Brokerage Mergers and Closures Events, Change in Analyst Coverage, and Use of Visuals

This table reports results from an identification strategy based on Kelly and Ljungqvist's (2012) list of brokerage firms closures. Panel A includes the first stage, the 2SLS, and the reduced form estimations. We first construct a dummy variable (*Brokerage_Event_Dummy*) that receives a value of 1 if the firm was covered by one of the brokerage firms in the year of the event, and zero otherwise. Then in the first stage regression we explore the drop in analyst coverage due to the event by using the change in average analyst coverage ($\Delta AnalystCoverage$) between the year of the event and the subsequent year. In our second stage we use the predicted coverage change as an IV to explore the effect of a drop in coverage on the annual report covering that year. In the reduced form estimation we replace the IV with the brokerage event dummy variable. In Panel B, we report a pre- and post-event tests where we explore the relation between *IMGC* and drop in coverage in a window of two years around the event. Specifically, "Event" refers to the annual report year used in Panel A (i.e., year t), "Pre" is a specification that uses the annual reports from the previous two years (t-1 and t-2). "Post" is a specification that uses the annual reports from subsequent two years (t+1 and t+2). Controls include *InstHold*, *LnNews*, *ROA*, *AnnRet*, *LnAssets*, *LnBM*, *SdRet*, *Turnover*and *LnSize*. All visuals metrics are winzorised at the 99% of their sample distribution.

Panel A: Drop in Analyst Coverage and Increase in *IMGC*

	First	2SLS	Red.From
	(1) *AnalystCovIV*	(2) *IMGC*	(3) *IMGC*
Brokerage_Event_Dummy	-0.401***		0.727***
	(-3.92)		(2.90)
AnalystCovIV		-1.812**	
		(-2.32)	
Controls	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Firm Cluster	YES	YES	YES
Observations	3,603	3,693	3,693
R^2	0.293	0.492	0.651

Panel B: Pre and Post Event Analysis

	Pre		Event	Post	
	(1) t-2	(2) t-1	(3) t	(4) t+1	(5) t+2
Brokerage_Event_Dummy	0.374	0.126	0.727***	0.202	-0.372
	(1.32)	(0.49)	(2.89)	(0.75)	(-1.16)
Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Firm Cluster	YES	YES	YES	YES	YES
Observations	3,589	3,598	3,603	3,142	3,086
R^2	0.642	0.641	0.642	0.665	0.661

Table 8: Regression of Subsequent-Year Stock Volatility, Beta and Cost-of-Equity Capital on Visual Metrics

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 Capital*) on fiscal year t+1 on fiscal year t visual metrics and other explanatory variables. See Table B.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 visuals metrics are winzorised at the 99% of their sample distribution. (Z) stands for a Z-Score adjustment.

Panel A: *AVC*

	SdRet (Z)			*MktBeta (Z)*			*Cost-of-Equity Capital (Z)*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AVC (Z)	-0.023***	-0.023***	-0.015**	-0.029**	-0.029**	-0.018**	-0.029**	-0.029**	-0.018**
	(-3.36)	(-3.36)	(-2.80)	(-2.53)	(-2.53)	(-2.65)	(-2.49)	(-2.49)	(-2.67)
LDEP	0.308***	0.308***	0.236***	0.307***	0.306***	0.225***	0.286***	0.285***	0.212***
	(4.26)	(4.27)	(3.25)	(6.50)	(6.51)	(5.30)	(6.46)	(6.48)	(4.72)
Pages	0.000	0.000	0.000	-0.000	-0.000	-0.000	0.000	0.000	-0.000
	(1.20)	(1.20)	(0.68)	(-0.49)	(-0.49)	(-1.19)	(0.09)	(0.08)	(-0.63)
LnNews	-0.005	-0.007	0.022	0.089	0.088	0.070	0.103	0.103	0.083
	(-0.31)	(-0.37)	(1.00)	(1.41)	(1.41)	(1.33)	(1.52)	(1.51)	(1.53)
AnnRet	-0.103**	-0.103**	-0.039	0.107**	0.107**	0.071	0.105**	0.105**	0.074
	(-2.68)	(-2.70)	(-1.01)	(2.41)	(2.42)	(1.47)	(2.34)	(2.35)	(1.52)
ROA	-0.836***	-0.834***	-0.139	-0.732***	-0.728**	-0.097	-0.713**	-0.709**	-0.049
	(-4.81)	(-4.81)	(-0.78)	(-2.90)	(-2.88)	(-0.40)	(-2.80)	(-2.79)	(-0.21)
insthold	-0.119***	-0.124***	-0.100**	0.049	0.047	0.194**	0.052	0.050	0.194**
	(-3.44)	(-3.63)	(-2.88)	(0.74)	(0.70)	(2.51)	(0.80)	(0.76)	(2.54)
AdvExpToSale	-0.271	-0.285	-0.144	0.728	0.718	0.911	0.720	0.709	0.897
	(-0.58)	(-0.61)	(-0.26)	(1.35)	(1.32)	(1.52)	(1.29)	(1.26)	(1.45)
LnAssets	-0.049	-0.047	0.238***	0.013	0.013	0.161**	0.002	0.003	0.151**
	(-1.00)	(-0.98)	(3.27)	(0.22)	(0.22)	(2.39)	(0.04)	(0.05)	(2.38)
FOG(Z)		-0.011	-0.016**		-0.002	-0.001		-0.005	-0.004
		(-1.58)	(-2.19)		(-0.14)	(-0.12)		(-0.40)	(-0.36)
LnBM			-0.112***			-0.080*			-0.071*
			(-4.21)			(-2.04)			(-1.94)
SdRet						16.539**			16.106*
						(2.25)			(2.01)
Turnover			4.007*			-0.768			-0.670
			(1.81)			(-0.29)			(-0.25)
LnSize			-0.347***			-0.127**			-0.132**
			(-5.46)			(-2.36)			(-2.44)
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	13,706	13,706	13,705	13,706	13,706	13,705
R^2	0.715	0.715	0.724	0.577	0.577	0.592	0.601	0.601	0.616

Panel B: *IMGC* vs. *TC* and *CMIC*

	SdRet (Z)			*MktBeta (Z)*			*Cost-of-Equity Capital (Z)*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IMGC(Z)	-0.019**	-0.019**	-0.015**	-0.016*	-0.016*	-0.010	-0.016*	-0.015*	-0.009
	(-2.46)	(-2.45)	(-2.19)	(-2.06)	(-2.05)	(-1.67)	(-1.97)	(-1.96)	(-1.58)
TC (Z)	-0.007	-0.007	-0.002	-0.019*	-0.019*	-0.013	-0.022**	-0.022**	-0.015*
	(-1.23)	(-1.19)	(-0.44)	(-1.91)	(-1.92)	(-1.56)	(-2.18)	(-2.19)	(-1.90)
CMIC (Z)	-0.001	-0.001	0.001	-0.005	-0.005	-0.003	-0.004	-0.004	-0.002
	(-0.17)	(-0.22)	(0.26)	(-0.58)	(-0.59)	(-0.35)	(-0.52)	(-0.54)	(-0.30)
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	13,706	13,706	13,705	13,706	13,706	13,705
R^2	0.715	0.715	0.724	0.577	0.577	0.592	0.601	0.601	0.616

Panel C: *RFC*

	SdRet (Z)			*MktBeta (Z)*			*Cost-of-Equity Capital (Z)*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RFC(Z)	-0.019***	-0.019***	-0.011**	-0.031*	-0.031**	-0.021*	-0.033*	-0.033*	-0.022*
	(-3.39)	(-3.38)	(-2.13)	(-2.10)	(-2.11)	(-1.87)	(-2.05)	(-2.07)	(-1.90)
Controls FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
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	13,706	13,706	13,705	13,706	13,706	13,705
R^2	0.715	0.715	0.724	0.577	0.577	0.592	0.601	0.601	0.616

Table 9: Regression of Subsequent-Year Firm Changes in Bond Ratings *IMGC*

This table reports results from panel regressions of changes in corporate bonds ratings (*ChngRate*) in fiscal year t+1 on fiscal year t *IMGC* and other explanatory variables. 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 B.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 visuals metrics are winzorised at the 99% of their sample distribution. (Z) stands for a Z-Score adjustment.

Panel A: *IMGC*- All Ratings

	ALL				High-Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IMGC(Z)	0.041***	0.041***	0.024*	0.024*	0.094**	0.094**	0.072	0.072
	(3.24)	(3.23)	(1.82)	(1.78)	(2.16)	(2.18)	(1.60)	(1.58)
LDEP	0.137***	0.137***	0.084***	0.084**	0.143**	0.143**	0.113**	0.116**
	(3.68)	(3.70)	(3.02)	(2.57)	(2.57)	(2.60)	(2.24)	(2.24)
AvgRate	0.278***	0.278***	0.325***	0.326***	0.335***	0.339***	0.389***	0.388***
	(9.89)	(9.93)	(10.99)	(11.20)	(9.96)	(10.36)	(10.56)	(10.63)
Pages	-0.000	-0.000	0.000	0.000	0.001	0.001	0.001	0.001
	(-0.51)	(-0.52)	(0.41)	(0.41)	(0.89)	(0.81)	(1.33)	(1.36)
LnNews	-0.017	-0.016	-0.012	-0.014	-0.096	-0.094	-0.128	-0.131
	(-0.28)	(-0.26)	(-0.26)	(-0.30)	(-1.00)	(-0.99)	(-1.53)	(-1.56)
AnnRet	0.240**	0.240**	0.119**	0.119**	0.163**	0.166**	0.054	0.052
	(2.71)	(2.72)	(2.68)	(2.81)	(2.55)	(2.59)	(1.65)	(1.68)
ROA	3.724***	3.719***	2.003***	2.051***	3.691***	3.664***	2.157***	2.125***
	(6.79)	(6.79)	(3.86)	(3.99)	(5.66)	(5.67)	(3.45)	(3.43)
InstHold	0.152	0.155	0.077	0.071	0.249	0.258	0.182	0.175
	(1.51)	(1.55)	(0.74)	(0.69)	(1.29)	(1.36)	(0.99)	(0.97)
AdvExpToSale	-0.979	-1.023	-0.889	-0.917	-0.834	-1.071	-1.166	-1.128
	(-0.98)	(-1.02)	(-0.84)	(-0.86)	(-0.47)	(-0.63)	(-0.62)	(-0.60)
LnAssets	0.311***	0.314***	-0.041	0.019	0.345***	0.360***	0.028	0.132
	(5.13)	(5.15)	(-0.53)	(0.22)	(4.01)	(4.14)	(0.27)	(1.04)
FOG(Z)		-0.007	-0.003	-0.002		-0.051	-0.032	-0.034
		(-0.51)	(-0.18)	(-0.12)		(-1.50)	(-0.95)	(-0.98)
SdRet			-7.956	-7.838			2.051	1.775
			(-1.06)	(-1.04)			(0.27)	(0.24)
Turnover			-9.768**	-9.534**			-9.902*	-9.811
			(-2.20)	(-2.15)			(-1.74)	(-1.73)
LnSize			0.487***	0.424***			0.523***	0.434***
			(6.13)	(4.62)			(5.71)	(3.84)
LnBM				-0.070				-0.114
				(-1.17)				(-1.10)
D/E				-0.030				-0.032
				(-1.56)				(-1.12)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry 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	0.290	0.290	0.324	0.324	0.339	0.340	0.366	0.367

Panel B: *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)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry 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	0.409	0.410	0.433	0.434

Panel C: *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)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry 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 10: Regression of Subsequent-Year Firm Annual Cumulative Returns on Visual Metrics

This table reports results from panel regressions of the firm's annual cumulative returns in fiscal year $t+1$ on fiscal year t visual metrics and other explanatory variables. See Table B.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 visuals metrics are winzorised at the 99% of their sample distribution. (Z) stands for a Z-Score adjustment.

	AVC (Z)			*IMGC(Z)*			*RFC(Z)*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AVC (Z)	-0.010	-0.010	0.014						
	(-0.92)	(-0.92)	(1.56)						
IMGC(Z)				-0.006	-0.006	0.013			
				(-0.59)	(-0.58)	(1.57)			
RFC(Z)							-0.024	-0.024	0.001
							(-1.45)	(-1.45)	(0.15)
LDEP	-0.103**	-0.104**	-0.049	-0.104**	-0.104**	-0.049	-0.104**	-0.104**	-0.049
	(-2.66)	(-2.66)	(-1.68)	(-2.66)	(-2.65)	(-1.68)	(-2.66)	(-2.66)	(-1.68)
Pages	0.001	0.001	0.000	0.001	0.001	0.000	0.001	0.001	0.000
	(1.22)	(1.23)	(0.17)	(1.23)	(1.23)	(0.17)	(1.24)	(1.25)	(0.13)
LnNews	-0.012	-0.014	0.027	-0.013	-0.014	0.027	-0.012	-0.014	0.028
	(-0.41)	(-0.47)	(1.23)	(-0.42)	(-0.48)	(1.24)	(-0.40)	(-0.46)	(1.24)
ROA	-1.418***	-1.415***	1.004**	-1.421***	-1.418***	1.004**	-1.409***	-1.406***	1.007**
	(-5.14)	(-5.16)	(2.70)	(-5.14)	(-5.17)	(2.70)	(-5.16)	(-5.19)	(2.70)
insthold	-0.391**	-0.396**	-0.122	-0.391**	-0.396**	-0.122	-0.392**	-0.397**	-0.122
	(-2.58)	(-2.57)	(-1.45)	(-2.58)	(-2.57)	(-1.45)	(-2.59)	(-2.57)	(-1.45)
AdvExpToSale	-0.572	-0.580	0.188	-0.573	-0.581	0.189	-0.590	-0.598	0.190
	(-0.39)	(-0.39)	(0.12)	(-0.39)	(-0.40)	(0.12)	(-0.40)	(-0.41)	(0.12)
LnAssets	-0.300***	-0.301***	0.251***	-0.301***	-0.301***	0.251***	-0.297***	-0.298***	0.252***
	(-4.35)	(-4.37)	(2.91)	(-4.36)	(-4.38)	(2.90)	(-4.34)	(-4.36)	(2.91)
FOG(Z)		0.002	-0.007		0.002	-0.007		0.002	-0.007
		(0.14)	(-0.55)		(0.14)	(-0.55)		(0.14)	(-0.55)
LnBM			-0.064			-0.064			-0.064
			(-1.55)			(-1.55)			(-1.55)
SdRet			13.954***			13.949***			13.925***
			(3.39)			(3.39)			(3.40)
Turnover			-13.858***			-13.852***			-13.926***
			(-3.22)			(-3.22)			(-3.23)
LnSize			-0.672***			-0.672***			-0.671***
			(-7.45)			(-7.45)			(-7.51)
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	15,099	15,099	15,098	15,099	15,099	15,098	15,099	15,099	15,098
R^2	0.229	0.230	0.304	0.229	0.229	0.304	0.230	0.230	0.304

Table 11: 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. The sample period is from 2002 to 2019. See Table B.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 visuals metrics are winzorised at the 99% of their sample distribution.(Z) stands for a Z-Score adjustment.

	IMGC(Z)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LDEP	0.432***	0.431***	0.432***	0.432***	0.429***	0.428***	0.426***
	(10.57)	(10.49)	(10.47)	(10.47)	(10.38)	(10.35)	(10.32)
Pages (Z)	-0.015	-0.014	-0.014	-0.014	-0.017	-0.015	-0.012
	(-0.83)	(-0.77)	(-0.75)	(-0.75)	(-0.94)	(-0.84)	(-0.66)
LnNews (Z)	0.037**	0.033**	0.034**	0.034**	0.019	0.016	0.029*
	(2.74)	(2.46)	(2.49)	(2.51)	(1.26)	(1.04)	(1.96)
AnnRet (Z)		0.017**	0.017**	0.017**	0.020***	0.014**	0.020***
		(2.78)	(2.79)	(2.79)	(3.18)	(2.40)	(3.20)
ROA (Z)		0.041***	0.041***	0.041***	0.044***	0.034**	0.028*
		(3.04)	(2.90)	(2.89)	(3.14)	(2.44)	(1.99)
InstHold (Z)			0.001	0.001	-0.004	-0.006	-0.003
			(0.10)	(0.09)	(-0.35)	(-0.47)	(-0.25)
AdvExpToSale (Z)			-0.017	-0.017	-0.016	-0.017	-0.015
			(-0.95)	(-0.96)	(-0.89)	(-0.92)	(-0.88)
FOG(Z)				-0.004	-0.008	-0.007	-0.008
				(-0.32)	(-0.70)	(-0.69)	(-0.72)
LnAssets (Z)					0.141***	0.151***	0.132***
					(3.63)	(3.65)	(3.08)
LnBM (Z)						-0.035**	-0.030*
						(-2.27)	(-1.86)
SdRet (Z)							-0.034***
							(-2.98)
Turnover (Z)							-0.042***
							(-3.22)
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	0.597	0.598	0.597	0.597	0.598	0.598	0.599

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 B.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	19656
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	18229
Keeping the sample between 2002 and 2019	16861
Keeping firms with media coverage	15477

Panel B: Time-Series Statistics before Additional Restrictions

FYEAR	*# REPORTS*	# AV	%	*# Report Pages*
ALL	18229	12438	68.2%	2096775
1993	21	7	33.3%	2651
1994	32	14	43.8%	3142
1995	44	19	43.2%	4545
1996	65	31	47.7%	7351
1997	104	59	56.7%	8571
1998	157	100	63.7%	10944
1999	252	188	74.6%	15514
2000	338	272	80.5%	21913
2001	402	325	80.8%	26106
2002	482	402	83.4%	37173
2003	578	485	83.9%	46377
2004	663	569	85.8%	58879
2005	741	624	84.2%	67822
2006	802	675	84.2%	78498
2007	857	682	79.6%	90241
2008	902	681	75.5%	102974
2009	889	671	75.5%	101743
2010	924	687	74.4%	110377
2011	942	694	73.7%	113142
2012	997	715	71.7%	124834
2013	1025	722	70.4%	131987
2014	1072	731	68.2%	139259
2015	1122	772	68.8%	146080
2016	1221	837	68.6%	161373
2017	1218	840	69.0%	160807
2018	1250	891	71.3%	169465
2019	1129	760	67.3%	155007

Appendix B - Variable Definitions

Table B.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.
Other Visual Measures Statistics	
AVR	The ratio of ACV to the total number of pages within an annual report.
$IMGR$	The ratio of $IMGC$ to the total number of pages within an annual report.
TR	The ratio of TC to the total number of pages within an annual report.
$CMIR$	The ratio of $CMIC$ to the total number of pages within an annual report.
# AV	The number of annual reports with all visual elements (AV) in a given year.
# IMG	The number of annual reports with images-pages (IMG) in a given year.
# T	The number of annual reports with team/management photos-pages (T) in a given year.
# CMI	The number of annual reports with charts-pages, maps-pages, and infographics-pages (CMI) in a given year.
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.

Variable	Definition
<u>Firm Control Variables</u>	
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 Capital	The cost of equity capital (*Cost-of-Equity Capital*) 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 $\textit{Cost-of-Equity Capital} = r_f + \beta E(r_M - r_f)$. 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.

Appendix C: Annual Report Pages Classification Process

In this Appendix, we describe how we classify pages into the categories depicted in Figure 2 (C.1), as well as the additional steps to construct meaningful labels for the *RFC* measure (C.2).

C.1. Classification of Visual Pages using Machine Learning Tools:

We first manually classified report pages into those with and without visual elements (AV) and trained TensorFlow to do the same. We then applied TensorFlow to a test sample and ascertained that classification accuracy was 96%, after which we used TensorFlow to classify the remaining sample into AV and non-AV pages.

Combined artificial intelligence and a rule-based system, we classify visual elements found on the AV pages into a set of five distinct predefined hierarchical categories: charts ($CHAR$); team or management photos (T); images, excluding team photos (*IMG*); infographics (*INFO*); maps (MAP). We remove pages that include colorful elements that do not belong to these categories, as they mostly capture pages with some coloring that do not carry relevant information content. We categorize each AV page by the dominant visual category that best described its visual content.

Images (*IMG*) were categorized with an accuracy rate of about 97%. The remaining five visual categories were classified with an accuracy rate of roughly 71%. We augmented our algorithms using GV and heuristic rules to increase the accuracy of the other categories. We also identified the top colors used on the page and their distribution to better fine tune accuracy of the colorful elements (CE) category. This combined approach improved classification accuracy rates of *MAP*, *CHAR*, *T*, and *IMG* to approximately 86%, and of *INFO* to about 78%.

Infographics (*INFO*) include a healthy 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, further exacerbated by by the general inability of GV to attach labels in a readily usable way. We therefore resort to using Google Tesseract Optical Character Recognition to capture the location 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 other categories.

C.2: *RFC*—Filters Required to Construct a Meaningful Reinforcement Measure

C.2.1 Focusing on the *IMG* Category:

A precursor to using GV is distinguishing amongst different types of visual elements and pages. The machine learning algorithm can only extrapolate content from what the human mind chooses to feed it. Pages dominated by graphs, charts, maps, team photos, and infographics tend to produce spurious labels. For example, the vast majority of management team photos yield labels such as "smile," "shoulder," "suit," and nearly all chart pages yield labels such as "line," and "blue," which do not adequately describe the image content. In contrast, the error rate of classifying content in image (*IMG*) pages is strikingly low. To mitigate the limitations of machine algorithms in emulating human cognitive processes, we minimize the incidence of spurious error by first classifying pages into the six dominant visual content subgroups depicted in Figure 2, and then including only (*IMG*) pages to derive our informativeness and *RFC* measures.

C.2.2 Page Level Analysis versus Individual Element Analysis:

Page level analysis is essential for capturing information and reinforcement metrics. Figure 6 illustrates how erroneous inferences could be derived if we had instead, extracted each image on a page and processed them individually. Panel A of Figure 6 presents a report page from the IDEXX Laboratories, Inc. 2005 annual report and Panel B of Figure 6 presents each extracted image in isolation.[17] Since page layout choices involve not only the number and choice of elements to include on a page but also their sizing, position, rotation, placement and other factors, treating each image in isolation can lead to improperly weighting or skewing the relative importance of each one, potentially distorting the impressions of readers. As an example, consider the top label from each extracted image, listed in no particular order: horse, computer, font, eyelash, smile, jaw, rectangle, rectangle, rectangle, gesture, and atmosphere. The top eight labels corresponding to the full page shown in Panel A are in descending order of probability: horse, working animal, halter, organism, horse tack, gesture, font, and bridle. Based on the full set of labels (not listed) only one of the images (the horse) would likely have been found to be reinforcing, and 10 images would have

[17]According to Wikipedia, IDEXX Laboratories, Inc. is an American multinational corporation engaged in the development, manufacture, and distribution of products and services for the companion animal veterinary, livestock and poultry, water testing, and dairy markets.

been found to be either uninformative or not reinforcing. Had we treated each image as a single data (image) point, thereby equally weighting (implicitly) each image, we likely would have miscalibrated the importance which investors attach to any one visual, thus potentially understating the level of reinforcement of the textual narrative in the report.