Visual Disclosure and Attention: Evidence From IPO

MV Shivaani
The University of Texas at Dallas

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Abstract

I examine whether and how the use of visuals in the prospectus is related to the attention of market participants. I find that firms that go public with more visuals in their prospectus have greater listing day trading volume, more trades by retail investors, and greater media coverage during the filing period. Further, I use machine learning algorithms to identify the content of visuals used in the prospectus. I find that the above results are primarily driven by qualitative visuals (product and consumer-centric images), specifically emotion-evoking visuals rather than quantitative visuals (graphs and charts). These findings suggest that firms use visuals to summarize financial information and create an emotional connection with prospective investors. Consistent with prior literature documenting managers' strategic use of visuals, I find that greater prevalence of visual disclosure benefits issuing firms' regular investors and pre-IPO shareholders. Having experienced these benefits, managers continue providing visual disclosures in subsequent filings such as 10Ks. Overall, the paper contributes to accounting literature by documenting a positive relationship between visual disclosure in regulatory filings and investor attention.

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1. Introduction

Investors possess limited attention, which compels them to concentrate only on a portion of the information presented to them (Hirshleifer & Teoh, 2003). They are particularly drawn to more noticeable or prominent information (Hockley, 2008). A salient form of information is visuals (Shepard, 1967). Visuals could be graphs, charts, images of people, or products. Recent studies in accounting literature examine the relationship between visual disclosure and capital market outcomes (Christensen et al., 2023; Nekrasov et al., 2022). However, little is known about the relationship between visual disclosure and investor behavior. In this study, I attempt to partially address this gap by examining the association between visual disclosure in corporate filing and investor attention.

A natural setting to examine investor attention is an initial public offering (IPO). Prior literature suggests that firms allocate a significant chunk of shares offered in IPOs to investment bankers' regular customers (Cook et al., 2006). Simultaneously, investment bankers promote the offer to retail investors. Barber and Odean (2002) reveal that one way to promote the offer to retail investors is to grab their attention. Attention induces buying (Barber & Odean, 2008). Much of the trading on the first day of IPO is attributed to retail investors buying the shares. Additionally, short sale constraints in IPO limit the trading to optimistic investors. This further incentivizes firms to devise disclosure strategies that garner investor attention and drum up the demand for the offering (Cook et al., 2006). However, retail investors are prone to limited attention (Nekrasov et al., 2023). Given that retail investors use EDGAR filings in making their trading decisions, a possible avenue for issuers to grab investors' attention and make a connection is through disclosure in the prospectus (Chi & Shanthikumar, 2018). Accordingly, I use the prospectus filed in IPO to examine the role of visuals.

Research in psychology suggests visuals can help overcome the constraint of limited investor attention by contributing to processing fluency (Song & Schwarz 2008; Alter & Oppenheimer, 2009). Relatedly, text with visuals is more engaging than text without visuals (Glenberg & Langston, 1992).

In the accounting context, experiments show that visuals in firms' CSR report increase readers' willingness to invest (Elliott et al., 2017), visual summaries of key information to mutual fund clients make them invest more optimally (Cox et al., 2018), and the aesthetic of the initial pages of annual reports increases the likelihood of investing in the firm (Townsend & Shu, 2010). Therefore, visuals can act as an external stimulus that incites action and attention.

In my empirical analysis, I examine 10,345 visuals used in prospectuses for 1082 US companies for the period 2010–2021. I find that about 93% (1010 out of 1082) of IPO firms in my sample have at least one visual in their filing. On average, a prospectus has ten visuals. Consistent with Christensen et al. (2023) finding of increasing use of visuals in 10K, there is an increasing trend in the mean number of visuals in the prospectus in the sample period.

My primary hypothesis is that visual disclosure in the prospectus is positively associated with attention. I use three measures of attention: media coverage during the offering period and trading volume on day one, as a proxy for investor attention and average trade size on day one, as a proxy for retail investors' attention (Cook et al., 2006). Specifically, I regress the number of visuals used in prospectuses on these attention measures. I control for various textual features(length of prospectus, tone, complexity) and firm characteristics (venture capital backing underwriter reputation, and firms' pre-IPO performance) and find that the number of visuals used in the prospectus is positively related to attention measures. More precisely, on average, including an additional image is associated with 1.3 additional media articles in the offer period and 0.005% higher volume of shares traded on the listing day.

The above analysis assumes that visuals are attention-grabbing because they are salient and vivid. This assumption is grounded in the cognitive psychology principle that human attention is more readily attracted to elements that stand out in our perceptual field, a phenomenon known as salience. This effect is further enhanced by vividness, bright colors, and distinct contrasts that create a stronger sensory impact. Marketing and communication literature also shows that vivid visuals often have a higher engagement and recall rate than text-based content. I directly test the role of the salience of visuals in capturing attention. I proxy salience through the size of the image and vividness through the average saturation of colors within the images. As predicted, using more salient or vivid visuals is associated with higher attention.

Next, I examine the content of visuals to understand the relationship between specific types of visuals and investor attention. I classify visuals as quantitative and qualitative visuals. In the sample, 17 percent of visuals are quantitative, and 83 percent are qualitative. Extant research primarily focuses on quantitative visuals to examine the relationship between visuals and investor behavior. SEC instructs that quantitative visuals be accompanied by complementary text. However, there is no such requirement for qualitative visuals. Therefore, the two types of visuals serve different roles and may differentially affect investor attention. Consistent with this notion, I find that investor attention is associated with qualitative visuals and not quantitative visuals. To better understand the characteristics of qualitative visuals that relate them to investor attention, I further classify qualitative visuals as emotional and non-emotional qualitative visuals. Hou et al. (2023) show that the presence of humans and animals in visuals in fundraising campaigns evokes emotions and incites people to provide more funds. As such, emotion-evoking visuals garner greater attention and desire, inciting action. I follow Hou et al. (2023) and use a deep learning model to classify visuals with humans and animals as emotion-evoking visuals. I find that 16% of qualitative visuals are emotion-evoking visuals. In regression analysis, I find that amongst all visuals, emotional visuals are significantly positively associated with investor attention. This result indicates that visuals can create an emotional connection with investors.

Media is a prominent information intermediary, and prior IPO studies tout media coverage as a means to garner investor attention (Cook et al, 2006; Da et al (2011)). However, I use it as a proxy for investor attention to the IPO. Accordingly, media coverage could be viewed as an omitted correlated variable in the relation between visual disclosure and trading-based measures of investor attention. To alleviate this concern, I re-examine the relationship between visuals and investor attention while controlling for media coverage. I find that the evidence of positive relationship between visual disclosure and investor attention is robust to the inclusion of media coverage.

I conduct a battery of additional tests to better understand visuals' role in the prospectus. Several IPO studies posit that increased investor attention benefits institutional issuers and pre-IPO shareholders through first-day return and wealth creation, respectively. In an IPO, those who do not sell stock in the offering gain from the increased price of their stock (wealth effects) and lose from the sale of stock for less than its early traded price (dilution effects). I find evidence of both: visual disclosure is positively associated with initial returns and visual disclosures is related to wealth creation rather than dilution.

Next, I examine whether firms' use of visual disclosures in the prospectus is related to firms' future disclosure choices. Specifically, I test whether visual disclosure in the prospectus predicts the use of visuals in the first 10K. I find a positive relation between the use of visuals in the two filings. The relationship also holds for different types of visuals i.e., more qualitative visuals in the prospectus are associated with more qualitative visuals in 10K. These results suggest that visual disclosure is a characteristic of specific firms, a persistent component of their overall disclosure strategy.

I next examine the reasons for cross-sectional variation in the use of visuals in the prospectus. I find that firms with more innovative operations, less reporting complexity, more uncertainty, and venture capital backing have significantly more visuals. Interestingly, I do not find evidence of existing competition in the industry that the issuing firm is entering to be a significant driver of the use of visuals.

My study contributes to accounting literature in several ways. First, my findings broaden our understanding of how firms' visual disclosure relates to investor behavior. Nekrasov et al. (2022) show that quantitative visuals in corporate social media communication increase investor attention. I complement their findings by showing that in the IPO context, qualitative, emotion-evoking visuals are positively related to investor attention and not the quantitative visuals. These findings also complement the results of Cao et al. (2023), who show that institutional investors' trades are related to operations-related visuals in managers' presentations. These findings, taken together, suggest that the different types of visuals used by firms on different platforms may be differentially related to investors' attention.

Second, my study contributes to the research stream investigating the drivers of investor attention. Prior studies primarily focus on market-based drivers of investor attention, such as market-wide events or media coverage (Cook et al., 2006). However, only a few studies, such as Lou (2014) and Nekrasov et al. (2022) consider firm-initiated actions (such as advertising) and firm-initiated disclosures (on social media) as means to attract investor attention. I extend this line of inquiry by providing evidence of an association between firm-provided disclosure in a regulatory filing and investor attention.

Third, to the best of my knowledge, no other study uses a comprehensive set of visuals in their analysis. For example, Nekrasov et al. (2022) consider graphs used in a firm's earnings announcement on Twitter. Christensen et al. (2023) consider both quantitative and qualitative visuals but exclude product-related images and executive pictures in their analysis of 10K. In management presentations, Cao et al. (2023) focus on summarized and forward-looking operations-related information. In contrast, I use an expanded set of visuals that include quantitative, qualitative, emotion and non-emotion-evoking visuals and provide the first evidence of the prevalence of usage of these different types. Examining such a more comprehensive set of visuals within a disclosure medium furthers our understanding of the different roles of different visuals.

More broadly, this paper speaks to the extensive literature on IPO outcomes. The finding of high initial returns in IPO is primarily attributed to demand by retail investors (Cook et al., 2006). However, what drives retail investors to buy shares on listing day is hotly debated (Ritter & Welch, 2002). Few studies show that this demand is spurred by media coverage that captures investors' attention (Cook et al., 2006; Liu et al., 2014). Other studies examine the role of voluntary disclosure in explaining initial returns (Guo et al., 2004; Leone et al., 2007). My finding of a positive association between emotion-evoking visual disclosure and investors' attention extends this literature by showing that visual disclosures in the prospectus are another channel that is related to investors' attention. Correspondingly, the evidence of a positive relation between initial returns and visual disclosures suggests that not just textual disclosure but other forms of voluntary disclosure could be missing pieces to the puzzle of initial IPO returns.

The rest of the paper is organized as follows. Section 2 provides an overview of the institutional background. Section 3 provides a review of related literature and develops the hypotheses. Section 4 describes the research design, sample construction and descriptive statistics. Section 5 presents my results. Section 6 discusses some additional analyses and robustness tests. Section 7 provides concluding remarks.

2. Institutional Background

To go public, firms must file a registration statement (including a prospectus therein) with the SEC that provides extensive information about the firm. The registration statement, formally called form S-1, contains information about a firm's business and financial position. The SEC limits a firm's communications with market participants by restricting firms from disseminating information outside the prospectus. Around the time of the filing of the prospectus, the firm enters the quiet period. During this period, the SEC seeks to prevent unequal access to information and to reduce the likelihood that investors are influenced by material that is more promotional in nature. If the firm learns new information, the Securities Act of 1933 requires the firm to amend their registration statement.

The registration statement should include all the information needed to make an informed investment decision. After filing the S-1 and resolving any SEC review comments, the firm's management team visits financial centers to market the offering through a series of roadshow presentations. The firm's legal advisors counsel management to make only factually accurate statements that closely coincide with their S-1 filing.

The Securities and Exchange Commission (SEC) recognizes the significance of disclosures in a prospectus when it states that *"... an important part ... is the "prospectus" that will be used by the company to solicit investors*." Consequently, much of the SEC's guidelines on simplified disclosure focus on the prospectus. For example, SEC's Plain English Rule 421 (d) mandates that issuers adhere to plain English principles and is primarily directed toward the prospectus. The accompanying handbook provides guidelines on the effective use of visuals, and SEC provides additional guidance on using qualitative versus quantitative visuals to protect the interests of investors. As such, both the prospectus and the use of visuals in filings such as prospectus appear important to SEC.

3. Related Literature and Hypothesis Development

3.1. Investor Attention and Disclosure

Attention is a scarce, limited resource (Hirshleifer & Teoh, 2003). Prior literature provides evidence that capital market participants are subject to limited attention, and investors' limited attention affects stock prices (Nekrasov et al., 2023).[1] These findings suggest that rational managers will consider information users' limited attention when making disclosure decisions (Nekrasov et al., 2023).

[1] Prior studies show that sell-side equity analysts (Aslan, 2021), financial analysts (Du, 2021), investors (Hirshleifer & Teoh, 2002), and hedge fund managers (Lu et al., 2016) have limited attention.

Given investors ' limited attention, several studies examine managers' strategic disclosure choices. Early studies examine the strategic timing of disclosure to exploit variation in limited attention. For example, Della Vigna and Pollet (2009) suggest that opportunistic managers release bad news on Friday. Similarly, deHaan et al. (2015) show that investors have lower attention after trading hours, and managers announce bad earnings news during these low attention periods. Recent studies suggest that managers attempt to combat the limited processing of information in mandatory disclosures by spreading the disclosure over multiple days (Chapman et al., 2019) or releasing the information in installments rather than at once (Li et al., 2020).

Investors' attention can also be captured by carefully choosing the form, format, and placement of information (Fiske & Taylor, 2016). Huang et al. (2018) focus on the number of quantitative items in earnings press releases and find that more prominently displayed items are associated with a stronger immediate market reaction. Similarly, Files et al. (2009) show that the market reacts more strongly to restatements when restatements are disclosed in the headlines of a press release than when it is disclosed in the body of the press release. Other studies focus on disclosure vs. recognition of information in financial statements and suggest that investors' underweight information provided footnotes in their decisions (Aboody, 1996; Ahmed et al., 2006). More recently, accounting studies have begun to examine the influence of salient but non-textual information on investor attention.

3.2. Visual Disclosure

Nekrasov et al. (2022) use visuals as a measure of salience and examine the effect of visuals, especially graphs, on investor attention in firms' earnings announcements on Twitter. They find that earnings announcements with graphs get more retweets. They also indicate firms are more likely to use visuals in their earnings tweets when performance is good but less persistent, consistent with managers' opportunistic use of disclosure choices.

Few other recent studies examine the use of visuals in disclosure and its implications for capital market outcomes. Xu (2021) and Fronk (2023) use the setting of earnings call and examine the visual content of earnings call slides. Xu (2021) focuses on the drivers of the use of visuals by managers. She suggests managers are more inclined to use visuals to highlight other KPIs when quarterly earnings fall short of analyst expectations. Fronk (2023) examines the consequences of the use of visuals in earnings call slides. His results indicate that visual disclosure decreases information asymmetry, increases market liquidity, and lowers investor processing costs, specifically for retail investors.

In the context of regulatory filings, Christensen et al. (2023) examine the use of visuals in 10Ks. They provide the first descriptive evidence of a significant increase in the use of visuals by firms in their 10Ks. This increase is concentrated in firms that have more retail focus. While the expectation is that visuals increase transparency and reduce uncertainty, authors find that the use of infographics is associated with greater post-filing volatility of returns. Is it because of the difficulty in interpreting information in graphs or the inherently complex nature of firms using graphs remains an open question.

Ben-Rephael et al. (2021) also exploit the use of visuals in 10K to introduce the concept of visual readability. When visuals complement text, analysts' forecasts are more accurate and aligned with other analysts' assessments. Visuals that reinforce text also have significant capital market consequences in terms of lower risk and cost of equity.

Pertinently, visuals that have capital market consequences are not limited to firm-initiated disclosures. Other market participants' use of visuals has also been found to affect stock prices. Gu et al. (2022) examine the use of GIFs, an attention-grabbing moving image used on social media, in predicting investor sentiment and stock returns of firms discussed in GIFs. Obaid and Pukthuanthong (2022) use photos from news articles on WSJ to construct a daily sentiment index (photo pessimism).

Consistent with behavioral models, their measure of photo pessimism predicts market return reversals and trading volume.

3.3. Hypothesis Development

Market participants have limited attention (Hirshleifer & Teoh, 2003). The attention constraint is especially binding when the information is complex and technical. Research in psychology shows that visuals can help overcome this constraint (Song & Schwarz 2008). Anecdotal evidence suggests that firms are cognizant of investors' limited attention and attempting to mitigate its effects.[2] For example, a March 3, 2020, Wall Street Journal article accounts how firms include videos, graphics, and other elements to engage their readers and to "*keep their annual reports from being a bore*".[3]

Studies show that the inclusion of photos in communication can be attention-grabbing. For example, Garcia and Stark (1991) conduct an eye-tracking study and document how photos are the most common initial attraction to newspaper pages. Powell et al. (2015) document a similar result by showing that content with text accompanied by a photo or photo alone is more attention-grabbing than content with text alone. In the financial reporting context, Elliott et al. (2017) use lab experiments to show that visuals in firms' CSR reports significantly increase readers' willingness to invest in the firm. Similarly, Cox et al. (2018) find that mutual fund clients invest more optimally when critical fund information (fees, past returns) are summarized visually.

Hou et al. (2023), using the setting of a crowd funding campaign, argue that images convey detailed and explicit information, draw readers' attention, guide their line of sight, and trigger emotions that can affect the funding probability. Similarly, Nekrasov et al. (2022) posit that visual disclosure in earnings announcements on social media platforms engages more users. Therefore, when used

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[2] For example, American Science and Engineering, Inc., Covestro AG https://report.covestro.com/annual-report-2019/?mod=article_inline

[3] https://www.wsj.com/articles/companies-find-ways-to-keep-their-annual-reports-from-being-a-bore-11583231402

effectively, visuals act as an external stimulus that incites attention. Accordingly, my first hypothesis in alternate form is:

Ha: Visual disclosure is positively related to investor attention.

3. Empirical Methodology and Data

3.1. Variable construction

Visual disclosure and its features

My main variable of interest is the number and type of visuals the firm uses in its S-1 filing. A major challenge in constructing my variable is recognizing the content within each image (Xu et al., 2021; Cao et al., 2023). An image can contain thousands of pixels, each with millions of possible colors, forming intricate patterns and objects. However, recent advances in machine learning and AI have made it possible to develop image recognition algorithms with capabilities comparable to humans. In this section, I discuss how I utilize deep learning to extract key content from the visuals used by the firm.

No ready-made machine-learning models exist to classify business-related images (Cao et al., 2023). Therefore, I follow the procedure Cao et al. (2023) use to build my model. As the first step, I manually review and classify (label) a random sub-sample of 2,000 images into five categories (Christensen et al., 2023): full-text page; signatures, icons and logos; graphs, charts, maps, and other images. I present the examples of images from each category in Appendix C.[4] These images then serve as the training sample for the deep learning algorithms I later employ.

To build my deep learning model, I utilize a technique called transfer learning (Pratt, 1993; Rajat et al., 2006). Transfer learning uses a pre-trained model as a starting point for a new task. Accordingly, I use a pre-trained Convolutional Neural Network (CNN) model, VGG19, to build my model.

[4] A possible limitation of my training data is human error in the labelling process as I am sole classifier of the images used in the training data.

VGG19 is most suited to my task of image classification as it is built on a dataset containing more than 14 million labelled images and used in recent accounting studies to build deep learning models (Cao et al., 2023). I modify the parameters of the last two CNN layers and fine-tune the model with my training sample. I use the resulting model to classify the images extracted from the prospectus. I provide the details of this procedure in Appendix B.

For my analysis, I exclude full-text pages and signatures as they do not have any real visuals and icons (such as checkmarks and bullets) and logos as they lack meaningful content (Christensen et al., 2023). Therefore, the variable *Num_Images* is the number of visuals in a prospectus, excluding those classified as full-text pages, signatures, and logos. In other words, *Num_Images* is the sum of visuals classified as charts, graphs, maps, and other images.

Since charts, graphs, and data maps represent financial information, I collectively call them *Quant* visuals. In contrast, 'other images' primarily contain non-financial information, I call these visuals the *Qual* visuals.

While the model mentioned above classifies visuals into five categories, it does not identify the content within the *Qual* visuals. To this end, I employ another pre-trained deep learning model, YOLO.v5. YOLO is widely used for real-time object detection in tracking and autonomous vehicles. I use it to detect the objects represented in the *Qual* visuals. Because I aim to classify *Qual* visuals into *Emotional* and *Non_Emotional* visuals, I primarily focus on the presence of humans and animals in an image (Hou et al., 2023). *Qual* visuals that contain either a human or an animal are classified as *Emotional* and the rest of the *Qual* visuals a*re non-emotional*. I provide examples of each type of image in Appendix D.

After classifying the image's content, I extract each image's defining features. Specifically, I use the Python function HSV (which refers to Hue Saturation Value) to calculate each image's saturation, hue, and contrast. Image dimensions, such as height and width, are calculated using the number of pixels in each image.[5] I use these features to create proxies of *Salience* and *Vividness*. *Salience* is measured as the average size of the images presented in a given prospectus. *Vividness* is measured as the average saturation of images within a prospectus.

Measures of attention

I focus on three observable measures that are likely to be associated with investor attention. While none of these measures is a perfect proxy for attention, all three are useful.

One way to infer investors' attention is through observing investors' actions (Da et al., 2011). If a company's disclosure stimulates investor interest, it should be reflected in investors' trading decisions. As such, greater buying or selling can be inferred as greater attention to stock. Because trading volume on the first day of IPO is seen as a sign of greater investor interest, I measure trading volume as a natural log of one plus the number of shares traded on the first day of listing. A disadvantage of this approach is the lack of extensive historical trading data, which makes it difficult to assess whether the observed trading volumes are standard or indicative of heightened investor interest.

My second measure attempts to mitigate these concerns. An important finding in IPO literature is that much of the initial trading in IPO is driven by optimistic retail investors who could not get the company's shares via the allotment process (Cook et al., 2006). As such, increased trading on the first day by retail traders indicates greater interest and demand from retail investors. I proxy retail investors' demand using average trade size (Cook et al., 2006). Specifically, I use a natural log of one plus (number of shares traded divided by number of trades). Admittedly, it is a crude measure of trading by retail investors. Large institutional investors could break down their trades into smaller trades, thereby increasing the number of trades while keeping the volume constant. However, my interpretation of average trade size as a proxy for retail trading is consistent with the evidence in Barber et al. (2006). Coupled with prior evidence that first-day trades in IPO are primarily driven by retail investors and

[5] Each image is represented as an array of pixel values when read in by a computer program.

limits to arbitrage constraint the trade by institutional investors suggests, interpreting average trade size as suggestive of retail trading appears reasonable.

My third proxy for attention relates to the media's decision to cover the firm. According to recent survey data, media outlets are more inclined to cover firms with more captivating content (Call et al., 2022). As such media coverage is an appropriate outcome to examine in my context. To measure media coverage, I utilize the average number of daily media articles written about a firm from the date the prospectus is submitted up until one day before the commencement of trading. I scale the number of media articles by the number of days within this timeframe.

I follow Bushee et al. (2020) to create my measure of media attention. I use news releases from RavenPack Full Edition database[6]. To ensure only relevant stories are included, I exclude stories with a relevance score of less than 100, as assigned by RavenPack. I also exclude several news classifications that likely have limited information content and visibility to retail traders. Specifically, I exclude stories where the (1) RavenPack assigned category equals "earnings", "revenue", or "conference-participant" (typically relate to firms announcing the date of an upcoming earnings announcement, and the third relates to announcements of participation in upcoming conferences); (2) RavenPack type contains "IPO" or "public-offering" (stories announcing the completion of the offering) or equals "trading" (trading halts and resumptions); and (3) RavenPack group equals "insider trading", "order-imbalances", or "investor-relations" (the last typically being stories about upcoming conference calls or institutions reporting holdings). Finally, I exclude firm press releases and articles related to analyst ratings as these represent firm-initiated and analyst-initiated news.

3.2. Empirical Specification

To examine the association between visual disclosure in prospectus and attention, I estimate the following baseline equation:

[6] Full edition combines RavenPack's Dow Jones, Web, and PR Editions data.

$$Attention_i = \alpha + \beta_1 NumImages_i + \theta Controls_i + \gamma_k + \delta_t + \varepsilon \qquad (1)$$

Where attention is a measure of investors' attention. I use three proxies for investor attention: trading volume on the first day, average trade size, and media coverage. I measure media coverage as the number of media articles written about the firm from the day of filing of prospectus to one day before the listing.

My primary variable of interest is *Num_images*, the number of images in the prospectus. *Controls* is the vector of control variables. Following Loughran et al. (2013), I control size, ownership retention, underwriter reputation, and venture capital backing.

I also control for textual features of S-1. I use the word list provided by Loughran and McDonald (2011) to count the total words in the prospectus and to count the number of positive, negative, and uncertain words.

γ_k are industry fixed effects to control for industry-specific unobserved heterogeneity and k represents 12 industries from Fama-French (FF-12) industry classification. δ_t are IPO-year fixed effects to control time-specific effects. All variables are defined in Appendix A. I winsorize all continuous variables at the top and bottom five percent.

3.3. Sample Construction

I construct my sample from the intersection of multiple datasets. My primary data source for IPO data is SDC Platinum from the LSEG database (formerly Refinitiv), which contains detailed information about the initial equity issues of companies. I focus on companies that went public and listed equity on the NYSE, AMEX, and Nasdaq from 2010 to 2021. To be included in my sample, the offering must have *original_issue_flag* in the SDC database set as 'TRUE .'I also eliminate ADRs, unit issues, depositary, and issues with offer prices less than $5 (Loughran & McDonald, 2013; Patatoukas et al., 2022). I then merge the trading data from CRSP using CUSIP.[7] I obtain pre-listing company financial data from Compustat, underwriters' reputation data from Jay Ritter's website, and data on media coverage from Ravenpack. I use Google Search Volume Index to measure a company's search frequency on Google.

Following prior studies, I exclude financial firms (FF12 classification 11).[8] After requiring non-missing observations for all variables, my final sample consists of 1082 firm-level observations. My yearly distribution of the number of companies is mainly consistent with Patatoukas et al. (2022). Table 1 summarizes my sample selection process.

3.4. Descriptive Statistics

My final sample includes 10,345 visuals used by 1,010 firms between 2010 and 2021. 72 of my 1082 sample firms do not use visuals in their prospectus. Figure 1 shows that the use of visuals has gradually increased over the sample period.

To better understand the nature of Qual visuals, I provide a word cloud of the words used in Qual visuals. Figure 2 presents the word cloud. Interestingly, some of the most common words firms use in non-Quant visuals are phase, cell, and development, suggesting usage by Pharma companies, to communicate their drug development stage. Some other common words, customer, management, business, product, etc. are generic and unrelated to any industry. Figure 3 shows the industry-wise mean number of visuals used. Most visuals appear to be used by firms in consumer durable industry and least by firms in oil and gas. This pattern suggests that firms with more B2C consumer models probably use more visuals.

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[7] I follow the procedure outlined in Lowry et al., (2017) to combine SDC and CRSP data.
[8] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library/det_12_ind_port.html

Table 1 Panel B indicates the incidence of sample IPOs industry grouping. I find that the sample of IPOs is not distributed equally across industries. Therefore, I include dummy variables for industry groupings in subsequent analyses, in which accounting for industry effects might be important.

I provide descriptive statistics for my variables of interest in Table 2. Panel A provides a distribution of visuals used over time. On average, a firm uses ten visuals in its prospectus. The average number of Quant visual is 1.6, Qual visuals is 2.6 and Emotional visuals is 1.3. While only one-fourth of the firms use emotion- evoking visuals, the average number of these visuals among firms is about four.

Panel B provides summary statistics for attention measures. On average, about 0.5 articles are written daily about an IPO firm from the day of filing of the prospectus to the day of listing. The mean of trading volume is 5,075,827, with an average trade size of 210 shares.

Panel C provides summary statistics for firm characteristics. The mean (median) of the log of total number of words is 10.55 (10.73), mean (median) of percent of uncertain words (%Uncertain) is 2.01% (2.01%) , mean (median) of negative words (%Negative) is 1.90% (1.90%). These numbers are slightly higher than those reported in Loughran and McDonald (2013). However, the mean (median) of percentage of positive words (%Positive) is 0.75% (0.78%), lower than Loughran and McDonald (2013). About three-fifths of the companies are backed by venture capitalists and an underwriter with a high reputation, and one-thirds have positive EPS in the year before IPO. The average firm has a mean initial return of 21%, comparable with prior studies.

4. Results

4.1. Visual Disclosure and Attention

I first examine how visual disclosure relates to investor attention. I expect firms that use more visuals in their prospectus will subsequently experience greater investor attention. I use three measures of investor attention. My first measure, *Trade_volume*, is based on the number of shares traded on listing day. I estimate equation (1) and tabulate results in column (2) of Table 3. Firms that use more visuals in their prospectus experience greater first-day trading volume. The coefficient on *Num_images*, 0.005 ($p< 0.1$), is significantly positive, suggesting that, on average, the use of an additional visual is associated with .005% greater trading volume, ceteris paribus. In terms of numbers, for each additional image, the shares are expected to increase by about 0.501% ($e^{0.005} – 1$).

My second measure of attention, *Retail attention*, is based on average trade size. Since smaller trade sizes suggest retail trading (Cook et al., 2006), a smaller average trade size indicates more trading by retail investors. I multiply the measure with minus one to facilitate ease of interpretation—column (3). The coefficient of *Num_images* is 0.001 ($p<0.1$). This means that more number of images in prospectus are associated with more trading by retail investors.

My third measure of attention, *MediaCoverage*, is the number of articles written about a firm in the period beginning from the filing of the S-1 to one day before the listing, scaled by the length of this period. The coefficient of *Num_images* in Col (1) of Table 3 is 0.012 ($p<0.01$). Overall, these results suggest that the number of visuals used in the prospectus are positively related to investor attention.

4.2. Salience and Vividness of Visuals and Attention

The above analysis is based on the premise that the salience and vividness of the visuals drive attention. I directly test this assumption. I proxy *salience* through average image size and *vividness* through average saturation of the images. I re-estimate equation (1) with *salience* and *vividness* as additional variables and present the results in Panel A and Panel B of Table 4, respectively.

Columns (1) to (3) show results for *salience*. The coefficient of *salience* is positive and significant in each of the three columns. Columns (1) to (3) of Panel B show the results for *vividness*.

4.3. Content in Visual Disclosure and Attention

Next, I examine the content of visuals to isolate the specific types of visuals that are related to attention. I decompose *Num_images* that capture the number of images into two components: *Quant* and *Qual*, which measure the number of quantitative and qualitative visuals, respectively. I re-estimate equation (1), replacing *Num_images* with its components, and present the results in Panel B of Table 4. In columns (1) to (3) of Panel C, the coefficient of *Qual* is significantly positive, while the coefficient of *Quant* is positive but not significant. This suggests that the association between visuals and attention is primarily through *Qual* visuals.

To better understand *Qual* visuals' content driving the above results, I further decompose *Qual* visuals. I classify *Qual* visuals as *Emotional* and *Non-Emotional*. Columns (1) to (3) of Panel D presents the results based on the above decomposition. The coefficient of *Emotional* visuals is significant and positive while the coefficient of non-emotion-evoking visuals is positive but not statistically significant.

This result extends Nekrasov et al.'s (2022) finding that user engagement on social media is positively related to the use of *Quant* visuals on social media. These results also complement the results in Cao et al (2023), who focus on non-emotional qualitative visuals in corporate presentations and find that investor trade is associated with such visuals.

4.4. Media Coverage, Visual Disclosure, and Investor attention

Extant IPO literature primarily considers media coverage as a mechanism that induces first-day retail buying. As such a natural concern is that results in column (1) and (2) of Table 3 are driven by filing period media coverage. To alleviate these concerns, I re-estimate equation (1) but control for filing period media coverage to re-examine the relation between visuals and attention. I present the results in Table 5. The coefficient of *Num_images* is positive and significant in Columns (1) and (2). Additionally, consistent with prior literature, the coefficient of media coverage is also positive and significant. Overall, these results suggest that visual disclosure is associated with retail investors' attention, which is over and above the effect of media coverage.

5. Additional Analysis

I conduct a battery of additional tests to better understand visuals' role in prospectus. Specifically, I focus on the relationship between the use of visuals and IPO outcomes, the firm's use of visuals in subsequent filings, and factors associated with firms' use of visual disclosure. I also conduct robustness tests to alleviate concerns regarding the effect of existing attention to firms and the form of my measure of visuals.

5.1. Visual Disclosure and IPO Outcomes

IPO literature primarily focuses on first day returns as the outcome of interest. Cook et al. (2006) indicate that issuers and investment bankers attempt to promote the IPO to retail investors. Successful promotion, coupled with short sale constraints limit the first day trading to optimistic retail investors. This in turn drives up the demand and the price of the shares on first day, resulting in high initial returns. Correspondingly, if use of visuals is positively related to investor attention, then firms that use more visuals should exhibit higher initial returns.

I examine the relationship between use of visuals and initial returns and present the results in Panel A of Table 6. I find that using an additional visual is associated with about 20% more initial returns (coeff is .201 ($p < 0.01$)). The result is stronger for qualitative visuals (coeff is 0.173 ($p < 0.1$)), particularly emotion evoking qualitative visuals (0.389 ($p < 0.01$)).

Another outcome of interest in IPO literature is wealth effects for pre-IPO shareholders. In an IPO, those who do not sell stock in the offering gain from the increased price of their stock (wealth effects) and lose from the sale of stock for less than its early traded price (dilution effects).

The main dependent variables in the test of relation between visual disclosure and IPO performance are initial returns and wealth creation. Initial returns is measured as difference between the first trade day closing price and the offer price relative to the offer price (Ritter & Welch, 2002) . Cook et al. (2006) define wealth and dilution effects as follows: wealth effects = (P-midpoint)(shares retained) and dilution effects = (P-OP)(shares sold), where P is the market price, shares retained represent the shares not initially sold in the offering, shares sold include secondary offerings, OP is the offer price, and midpoint is the midpoint of the initial filing range. Using these estimates, I create a dummy variable that takes on the value one if the wealth effects are greater than the dilution effects and zero otherwise. As a first step in estimating wealth effects, I regress the initial return variable on these variables and use the residuals from this regression as the proxy for the separate effect of underpricing on insider wealth gains. In the next step, I use logit regression to estimate the relationship between visuals and wealth effects. Panel B of Table 6 presents the results. The coefficient of *Num_images*, 0.024 is positive and significant. Consistent with above results, the coefficient for qualitative visuals (0.031) and emotion- evoking qualitative visuals (0.049) is larger in magnitude. The evidence suggests that use of visuals in prospectus increases insider wealth gains.

5.2. Subsequent Use of Visuals by Firms

The results in Table 3 and 6 show that firms that use visuals in prospectus tend to benefit in terms of greater investor attention on the first day and greater initial returns. Having experienced these early benefits, do firms continue to use visuals in their subsequent filings with SEC? I focus on the first 10-K filed by the companies after going public to examine whether they use visuals in their subsequent filings. I regress the number of visuals in 10-K on number of visuals in prospectus and control for firm performance in first year (return on assets), firm's post listing market capitalization, BIG4 auditors as proxy for external monitoring factors. I also control the firm's pre-IPO sales, whether the issue was VC backed and underwritten by a reputed underwriter. Lastly, I include industry and year fixed effects. Since the dependent variable, number of images is a count variable, I use Poisson model.

Column (1) of Table 7 shows the results of the above analysis. The coefficient of *Num_images* (number of visuals in prospectus) is positive and significant. The coefficient indicates that for every additional visual in IPO the log of the expected count of images on a Form 10-K (Y) is expected to increase by 0.042. In practical terms, for each additional image in an S-1 filing, the expected number of images on a Form 10-K increases by a factor of about 1.043 (e^0.042).

I repeat the above analysis with the number of quantitative and qualitative visuals in 10-K as the dependent variables and present the results in Columns (2) and (3) of Table 7, respectively. Consistent with column (1), there is a positive and significant relation between use of visuals in the prospectus and use of visuals in 10-K. Most prominently, use of an additional quantitative visual in prospectus is associated with 0.3 additional log of expected count of quantitative visuals in the 10-K.

Christensen et al. (2023) examine the factors related to firms' probability of including the visuals in the 10K and the time elapsed between firms' first occurrence in their sample and firm's first use of visuals. These findings extend their results by showing that it is not only the post-listing environment of the firm that explains firms' use of visuals in 10K. But the firm's use of visuals in filings made before listing is also positively related with subsequent use of visuals in firm's filings. These results are suggestive of underlying characteristics of firms that drive their overall disclosure strategy.

5.3. Drivers of Use of Visuals in Prospectus

The analysis so far suggests that visual disclosure plays a crucial role in determining firms' IPO performance, yet there is huge cross-sectional variation in the use of visuals. Accordingly, it is helpful to examine the determinants of the use of visuals in the prospectus.

Several studies examine the determinants of firms' decision to present information more saliently by placing it in the headline or an earlier part of the document (e.g., Files et al., 2009; Huang et al. 2018). The determinants examined in this research relate to firms' desire to emphasize information that makes the firm look better. Building on this literature, I identify the determinants of firms' choice to use visuals. Since firms' overall disclosure strategy in IPO is shaped by inputs from VC (Guo et al., 2004) and expertise of underwriters, I expect that firms will be more likely to use visuals when they are VC-backed, and the IPO is promoted by a reputed underwriter.

To examine whether firms have stronger incentives to attract attention with visuals when the issue is IPO backed, I estimate a Poisson model with number of images as the dependent variable. I present the results in Table 8. I find that firms backed by venture capitalists, with greater pre-IPO sales, and more research and development expenses have more visuals in their IPO. Interestingly, I do not find evidence of an association between use of visuals and under writer reputation or competition in the industry the firm is entering.

5.4. Robustness Tests

To validate the robustness of my results, I run two modified regressions. First, I test the validity of my measure of *Num_images*. I log-transform the number of visuals and re-estimate my main equation. Panel A of Table 9 presents the results of this analysis. The coefficient on ln*(Num_images)* is similar in statistical and economic significance to coefficients in Table 3. This result provides assurance that the results are not driven by the specific scale used for my measure.

Second, I repeat my analysis with an additional control variable: pre-listing attention to firm. I proxy pre-listing attention by google search volume index (Da et al., 2011). Specifically, I average the search volume ranks provided by Google for the period beginning from the filing of prospectus to the day before the trading starts. Panel A of Table 9 presents the results of this analysis. Both the magnitude and the statistical significance of the coefficient on *Num_images*, across columns, are similar to those reported in Table 3, suggesting that my results are not necessarily driven by existing levels of attention on the firm.

6. Conclusion

This paper examines the role of visual disclosures in the prospectus. I provide initial evidence of the use of visuals by firms in the IPO prospectus. More than 90 percent of firms use at least one visual and the types of visuals used vary from quantitative, qualitative to emotion-evoking visuals. Firms backed by venture capitalists and firms engaged in innovative activities use relatively more visuals.

I also examine the relationship between different types of visuals used in prospectus and investor attention. Using three proxies for investor attention based on media coverage, trading volume and trade size, I show that visual disclosure in prospectuses is positively associated with investors' attention. The association is particularly stronger for emotion- evoking qualitative visuals but not for quantitative visuals. Consistent with the notion that increased investor attention in IPO increases initial returns, I find that firms that use more visuals, particularly emotion-evoking visuals, experience greater run-up of first-day prices.

There are a few limitations of this study. The relationship examined between visual disclosures and investor attention is association-based and does not have a causal connotation. The proxies for investor attention are not perfect measures. Future work could use more nuanced measures of investor attention.

Nevertheless, my study contributes to literature in multiple ways. First, the study adds to the nascent literature examining the use of visuals in corporate communication and documents the relationship between visual disclosure in prospectus and subsequent use of visuals in 10K. Second, the study contributes to the emerging stream of literature investigating the association between visual disclosure and capital market outcomes. Third, to the best of my knowledge, this study is the first to categorize visuals used in firm disclosure into quantitative and, emotional and non-emotional visuals. Finally, the study speaks to longstanding literature in IPO by showing that initial returns are associated with visual disclosures by firms and not just textual features of disclosure.

The major takeaway from my study is that qualitative and quantitative visuals play different roles within different corporate filings. The findings of this study also have important implications for regulators. Considering a prospectus as a document intended to communicate financial information and details of business operations and the SECs mission to protect retail investors' interest, the SEC may want to review the use of emotional visuals as well as firms' motive of using such visuals.

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Appendices

Appendix A: Variable Definitions

Variables	Definition	Source
Num_images	Number of images in S-1	S-1
Quant	Number of quantitative images (contains charts/ graphs) in S-1	S-1
Qual	Number of qualitative images (contains product/factory related images)in S-1	S-1
Emotional Qual	Number of emotion evoking images (contains humans and animals) in S-1	S-1
Non-Emotional Qual	Number of non-emotinal qualittaive images in S-1	S-1
Num_images10K	Number of images in first 10-K filed after listing	S-1
Qual10K	Number of qualitative images in first 10-K filed after listing	S-1
Quant10K	Number of quantitative images in first 10-K filed after listing	S-1
Salience	Average size of image in S-1	S-1
Vividness	Average saturation of image in S-1	S-1
Trading volume	Natural log one plus number of trades on first day of trading	CRSP
Retail trade	Natural log of one plus average trade size, where average trade size is number of shares traded on first day divided by number of trades on first day of trading	CRSP
Media coverage	Average number of media articles written from the date of the filing of S-1 to one day before the listing day.	RavenPack
%Negative	Number of negative words in S-1 divided by total number of words	S-1, Loughran & McDonald(2011)
%Positive	Number of positive words in S-1 divided by total number of words	S-1, Loughran & McDonald(2011)
%Uncertain	Number of uncertain words in S-1 divided by total number of words	S-1, Loughran & McDonald(2011)
Ln(Num words)	Natural log of one plus total number of words in S-1	S-1
Tone	(Number of positive words - Number of negative words)/ (Number of positive words + Number of negative words)	S-1 , Loughran & McDonald(2011)
Fog	Gunning fog index to measure readability of S-1	S-1

Up revision	Percentage upward revision in offer price from the mid-point of the filing range if the offer price is greater than the mid-point, ((offer price -mid-point))/mid-point)X100if offer price> mid-point, else zero	SDC
VC dummy	An indicator variable equal one if IPO firm is backed by venture capitalist, zero otherwise	SDC
UW reputation	An indicator variable equal one if firm's underwriter has a Rnk of 8 or more, zero otherwise	SDC, Jay Ritter's website
Prior Nasdaq 15 day return	Buy-and-hold annual returns of CRSP Nasdaq value-weighted index on 15-trading days prior to IPO date, ending on day t-1.	CRSP
Insider	Selling shates divided by number of shares offered this market	SDC
Positive EPS dummy	An indicator variable set to one if trailing EPS is positive at the time of IPO, else zero	SDC
Ln(sales)	Natural log of trailing annual firm sales at the time of IPO	SDC
Initial returns	Percentage change from offer price to first day closing price	SDC, CRSP
Wealth creation	(Close price-midpoint of offer price)*(shares retained)	CRS, SDC
Wealth Dilution	(Close price-Offer price)*(shares sold)	SDC
Proceeds	Natural log of dollar amount sold	SDC
Float	Ratio of number of shares issued in the offering to the number of shares issued and outstanding after the offering	SDC, Compustat
Resids	Residuals from regressing initial returns on Num_images and float	SDC, CRSP, S-1
Competition	Herfindahl-Hirschman Index for issuing firm's industry in the year prior to the IPO	Compustat
Roa	Return on assets in the first year of listing	Compustat
Ln(MktVal)	Natural log of market value of issuer at the end of first year of listing	Compustat
BIG4	An indicator if issuing firm's auditor is BIG4 in the first year of listing	Compustat
R&D	Research and development expense in the year prior to the IPO year	SDC, S-1
Google search	Search volume index to compute search intensity for each company	Google

Appendix B: Deep Learning Model for Image Category Classification

Collecting Training Data

Collecting training data was a crucial step in our project. To build a robust machine learning model, we followed a systematic process:

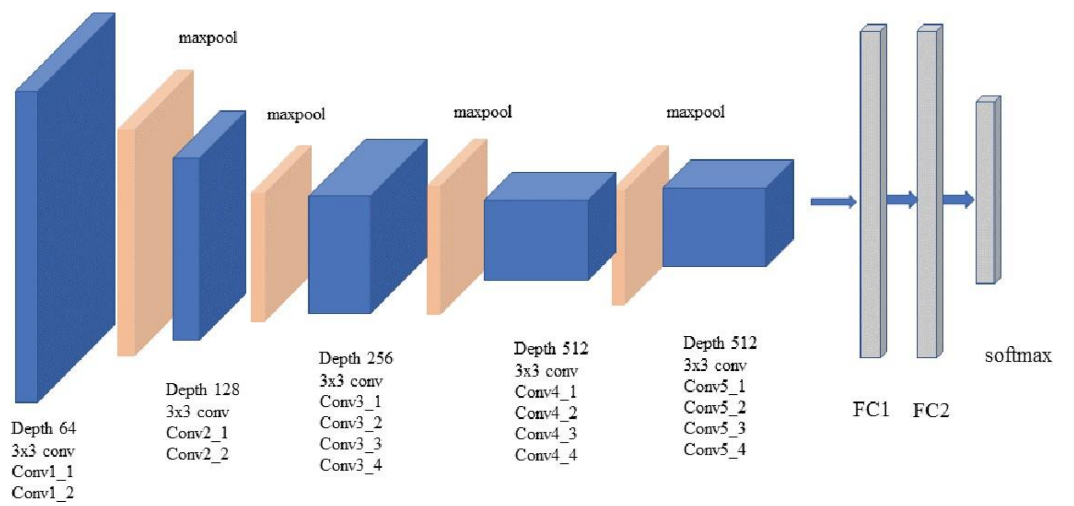
1. **Gathering US IPO Data (2010-2021):** The first phase of my data collection involved navigating the EDGAR website, which serves as the primary repository for SEC filings. I wrote custom Python scripts to programmatically access and extract relevant information about US IPOs. This process included retrieving company names, filing dates, file number etc. for companies that went IPO in years 2010 to 2021.
2. **Image Data Collection:** IPO filings often contain visual elements such as charts, graphs, logos, and product images. To extract these images, I employed web scraping techniques and libraries like BeautifulSoup and Selenium. This automated process allowed me to systematically gather image assets linked to each IPO.
3. **Manual Labeling:** A critical step in my data collection process was the manual labeling of a subset of images. I reviewed and categorized these images into five distinct classes or categories (signatures, icons, graphs, full text pages, others). These categories were chosen to represent the different types of visuals typically found in IPO documents, such as financial charts, product images, company logos, signatures, icons etc. Manual labeling ensured that my machine learning model would have a ground truth reference for learning and making predictions.
4. **Postprocessing:** To enhance the model's ability to generalize and improve its robustness against diverse and previously unseen images, I augmented the training data with slight

modifications. These alterations included random rotations, brightness adjustments, and both vertical and horizontal flips.

5. **Training, Validation and Testing Set:** The manually labeled images formed the core of my training and testing dataset. I split this dataset into three parts: 70% for training the machine learning model, 15% for validation, and remaining 15% for testing its performance.

By following this systematic approach to collecting and preparing my training data, I aimed to build a robust machine learning model capable of accurately categorizing images in IPO documents.

Model Construction



I employed transfer learning to categorize images into five specified categories relevant to S-1 document types. Transfer learning leverages a pre-existing model as a foundational architecture for a secondary, related task. My choice, the VGG19 model, is renowned for its depth, comprising 16 convolutional layers, 3 fully connected layers, 5 MaxPooling layers, and a SoftMax layer. This model has been pretrained on the ImageNet database, an extensive dataset featuring over a million images across 1000 distinct categories.

I adapted VGG19 to focus on five specific classes by modifying the architecture's final layers. I replaced the original last fully connected layer and the SoftMax output layer with a new 512-node fully connected layer and a SoftMax layer tailored to my five target categories.

The training process utilized a batch size of 64 and a modest learning rate of 0.0001 over the course of 50 epochs. This meticulous training regimen was designed to optimize the deep learning model for our specific classification task.

Model Metrics

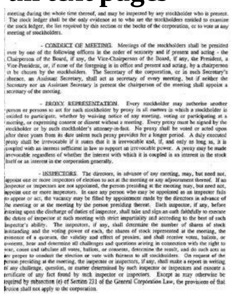
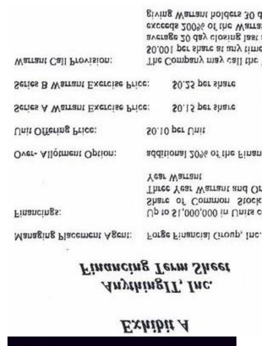
The performance of my model was assessed using accuracy as the primary evaluation metric on the test set kept apart for this purpose. This metric was computed as the proportion of images that were correctly classified into their respective categories out of the total number of images evaluated. In the context of my study, this entailed an exact determination of how well the model identified and categorized each image into one of the five designated classes (signatures, icons/logos, full page texts, graphs, others) pertinent to the S-1 document types. My model demonstrated a commendable proficiency in this classification task, achieving an accuracy rate of 87.9%. This high level of accuracy underscores the model's effectiveness in discerning and classifying the images accurately into the five predefined categories.

Appendix C: Examples of Visual Classification

Examples of Images

1. **Icons/Logos**

2. **Full text pages**

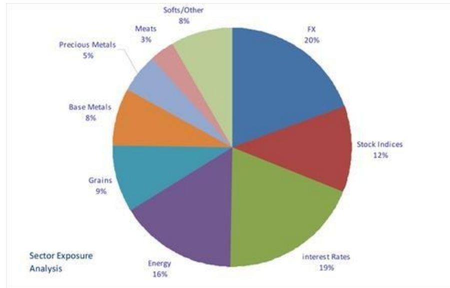



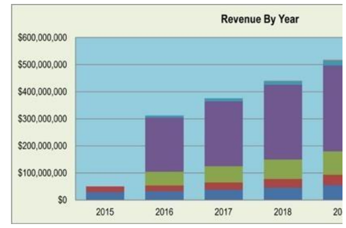


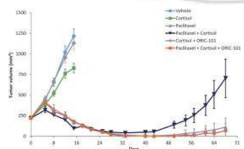
3. **Signatures**

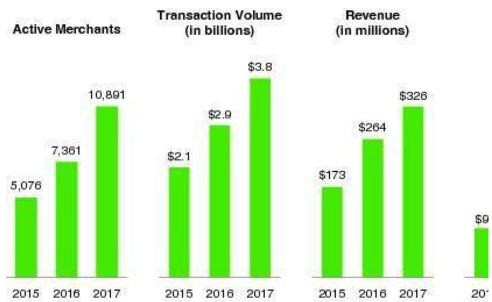


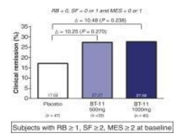
4. Graphs/Charts

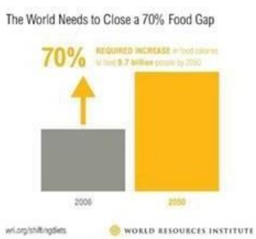


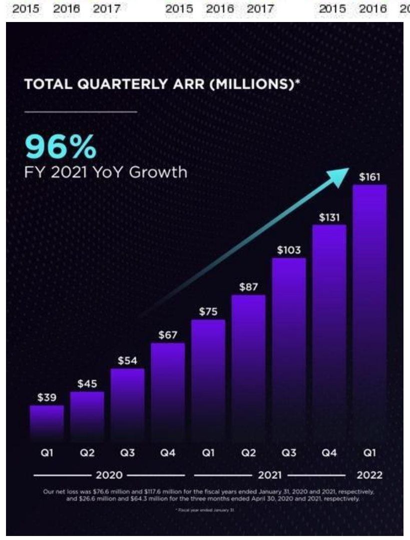


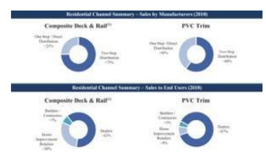




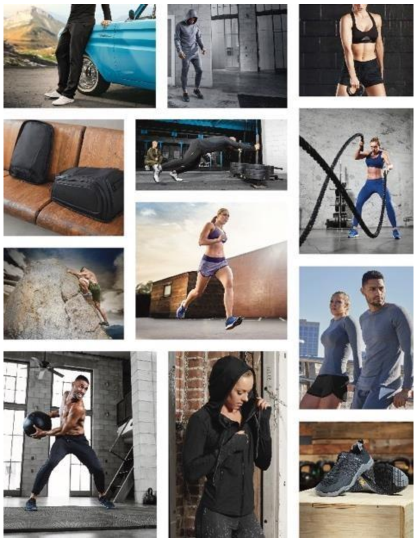




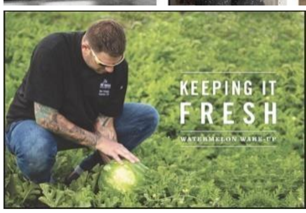




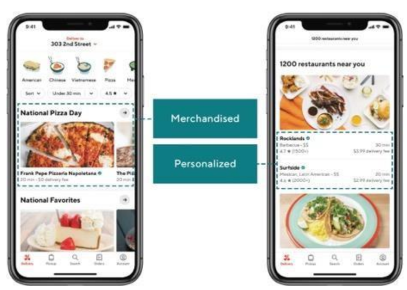
5. Others



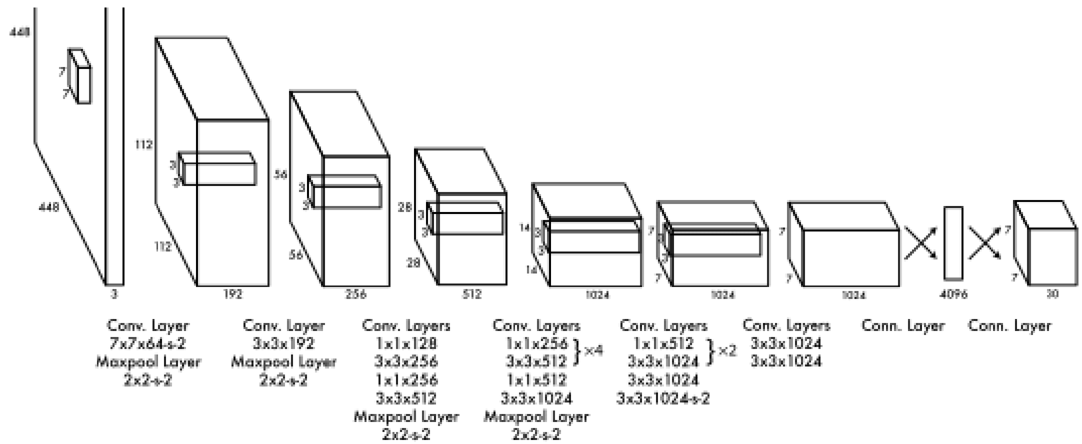

J.ALEXANDER'S
STONEY RIVER


KEEPING IT
FRESH


DENIM:
BREADTH AND DEPTH OF FITS, SIZES AND WASHES


National Pizza Day
National Favorites
1200 restaurants near you
Merchandised
Personalized

Appendix D: Deep Learning Model for Extracting Emotion-Evoking Images



In the S-1 document, we employ the existence of a human or animal within an image as a surrogate indicator for an image's potential to evoke emotions or establish a connection with the viewer. To discern the presence of a human or animal in these images, we leverage the YOLOv5 model.

YOLO, an abbreviation for "You Only Look Once," stands as a deep learning-based object detection algorithm initially introduced by Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi in their 2016 paper titled "You Only Look Once: Unified, Real-Time Object Detection." The model is trained using COCO dataset comprising of more than 80,000 images over 80 categories. YOLO deviates from conventional object detection techniques by treating the problem as a singular regression task, enabling it to execute real-time object detection at remarkable speeds. The YOLO model exhibits resilience in the face of object rotations and scale variations, proficiently identifying objects in images of diverse dimensions.

Figures and Tables

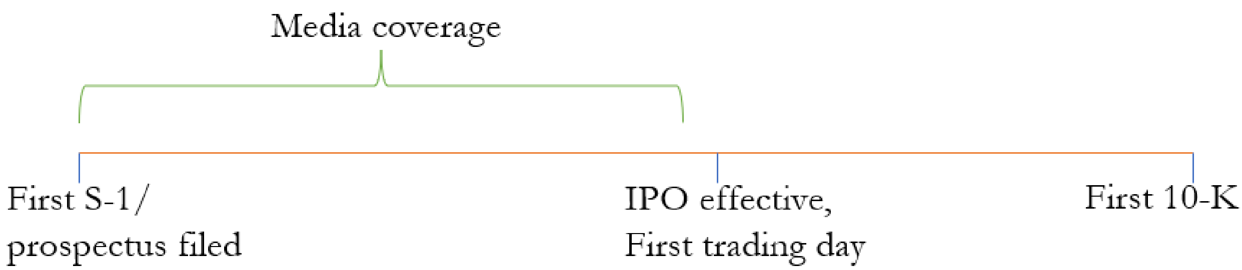
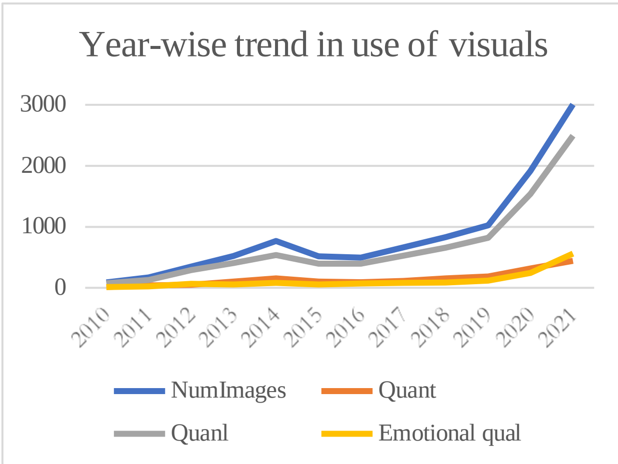


Figure 1: IPO timeline

Figure 2: World cloud of most common words used in qualitative visuals



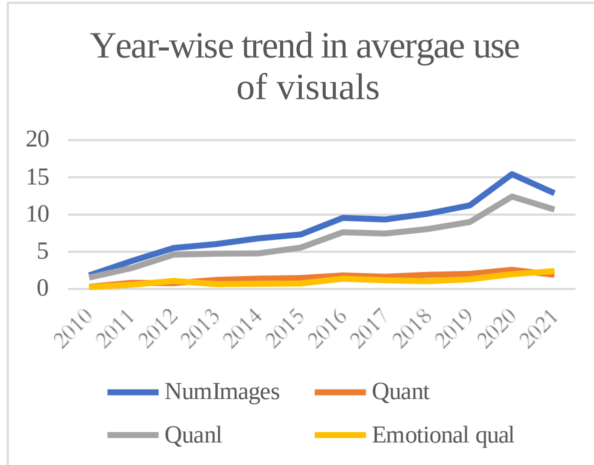


Figure 3: Time-trend in use of visuals in prospectus

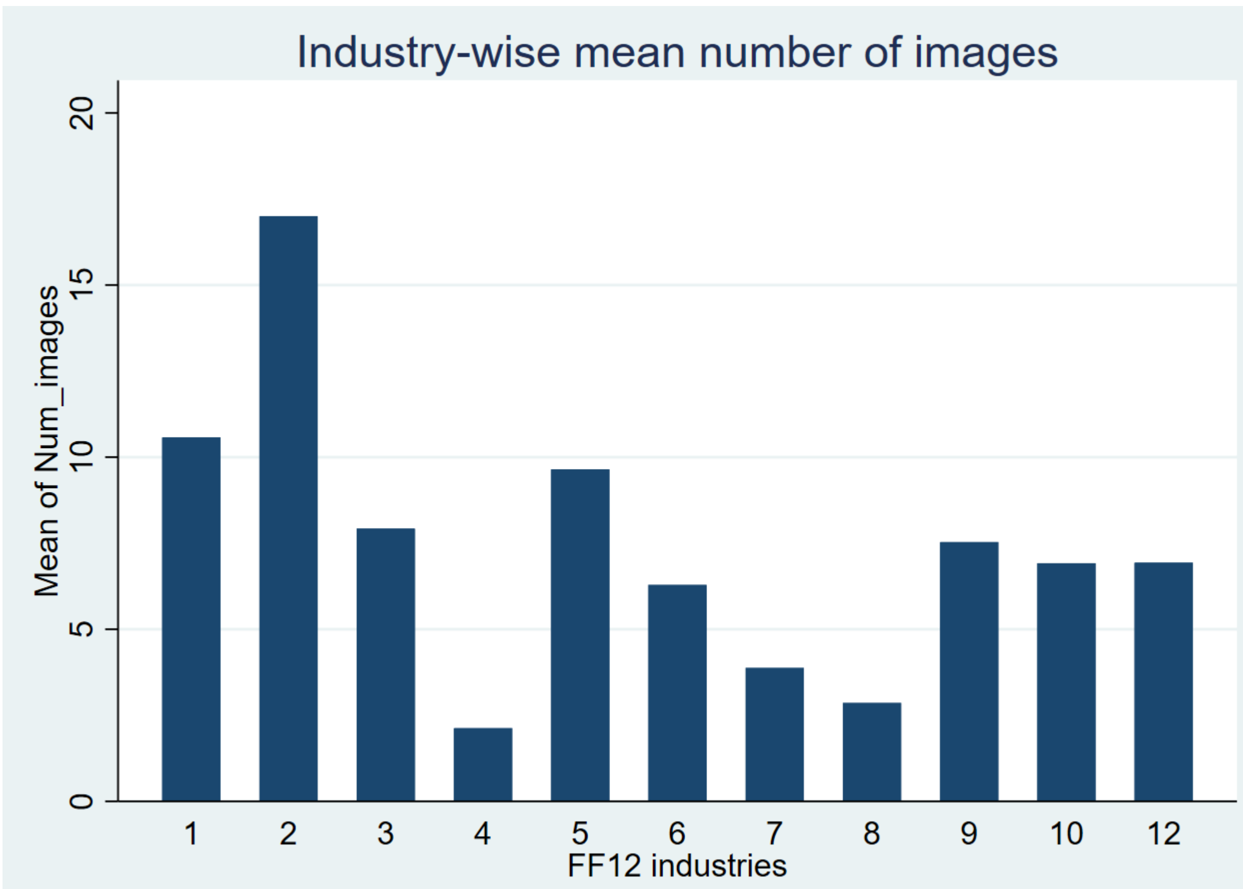


Figure 4: Industry-wise mean number of visuals used in prospectus

Table 1: Sample Description

Panel A summarizes the sample construction process. Panel B provides the distribution of sample across Fama-French 12 industry classification.

Panel A: Sample Construction

Number of equity issues (on major US exchanges) 2010 to 2021 from SDC	16530
Missing identifier	*(5)*
Not Orig_IPO	*(12813)*
Depositary issue	*(266)*
Unit issues	*(1288)*
Offer Price < 5	*(120)*
Base Sample from SDC	**2038**
Missing CompustatCRSP link to SDC data	*(358)*
Not matched to CRSP	*(278)*
Not matched to Compustat	*(80)*
Companies in FF11	*(204)*
Missing controls	*(36)*
Final Sample	**1082**

Panel B: Industry Distribution

FF12 industry	FF12	Freq	Percent	Cum.
Consumer Nondurables	1	28	2.59	2.59
Consumer Durables	2	18	1.66	4.25
Manufacturing	3	39	3.6	7.86
Oil, Gas, and Coal Extraction and Products	4	40	3.7	11.55
Chemicals and Allied Products	5	14	1.29	12.85
Business Equipment	6	300	27.73	40.57
Telephone and Television Transmission	7	8	0.74	41.31
Utilities	8	14	1.29	42.61
Wholesale, Retail, and Some Services	9	98	9.06	51.66
Healthcare	10	434	40.11	91.77
Others	12	89	8.23	100
		1082		**100**

Table 2: Descriptive Statistics

This Table provides descriptive statistics of the visuals in sample prospectus in Panel A, descriptive statistics of attention measures in Panel B, and descriptive statistics of other firm characteristics in Panel C. Panel D presents correlation among variables of interest in Panel B. The sample period is from 2010 to 2021. All continuous variables are winsorized at 5% and 95%. All variables are described in Appendix A.

Panel A: Visuals

Variable	N	Mean	SD	25%	50%	75%
Num_images	1082	9.561	8.588	3.000	7.000	13.000
Quant	1082	1.636	2.090	0.000	1.000	2.000
Qual	1082	7.639	7.154	2.000	5.000	11.000
Emotional Qual	1082	1.345	3.297	0.000	0.000	1.000
Non-emotional Qual	1082	6.294	6.067	2.000	4.000	9.000

Panel B: Attention measures

Variable	N	Mean	SD	25%	50%	75%
Media coverage	1082	0.59	0.90	0.02	0.21	0.70
Trading volume	1082	15.44	0.95	14.79	15.48	16.15
Retail attention	743	5.35	0.25	5.17	5.33	5.56

Panel C: Other firm characteristics

Variable	N	Mean	SD	25%	50%	75%
VC backing	1082	0.58	0.49	0.00	1.00	1.00
UW reputation	1082	0.61	0.49	0.00	1.00	1.00
Initial returns	1082	21.03	28.31	0.00	13.76	36.00
Up revision	1082	4.03	5.72	0.00	0.00	7.14
Prior Nasdaq 15 day return	1082	1.13	2.90	-1.01	1.04	3.12
Insider	1082	0.08	0.17	0.00	0.00	0.00
Positive EPS dummy	1082	0.29	0.45	0.00	0.00	1.00
ln(sale)	1082	4.28	1.91	2.70	4.37	5.68
Age	1082	8.86	7.09	4.00	7.00	12.00
R&D	1082	3.64	4.10	0.00	2.47	5.60
ln(Num words)	1082	10.55	0.66	10.38	10.73	11.01
%Negative	1082	1.90	0.39	1.60	1.90	2.19
%Positive	1082	0.75	0.17	0.65	0.78	0.88
%Uncertain	1082	2.01	0.27	1.82	2.01	2.22
Tone	1082	-0.43	0.09	-0.50	-0.44	-0.37
Fog	1073	19.33	1.13	18.54	19.35	20.04
SVI	983	16.69	15.43	7.85	10.97	17.19

Panel D: Correlation Matrix

	Num_images	Quant	Qual	Emotional	Salience	Vividness	Initial returns	Insider	Positive EPS dummy	Ln(sale)	Ln(words	%Negative	%Positive	%Uncertain	Fog	Trading Volume	Media coverage	Retail trade
Num_images	1.00																	
Quant	0.57	1.00																
Qual	0.95	0.33	1.00															
Emotional	0.51	0.16	0.53	1.00														
Salience	0.04	-0.03	0.06	0.05	1.00													
Vividness	0.15	0.01	0.18	0.19	0.20	1.00												
Initial returns	0.16	0.06	0.16	0.14	0.10	0.10	1.00											
Insider	0.07	0.10	0.04	0.17	0.00	0.05	0.05	1.00										
Positive EPS dummy	-0.04	0.07	-0.07	0.07	0.01	0.01	-0.02	0.33	1.00									
Ln(sale)	0.09	0.14	0.05	0.26	0.06	0.22	0.00	0.36	0.47	1.00								
Ln(words	0.21	0.13	0.21	0.05	0.10	0.01	0.07	-0.05	-0.14	-0.11	1.00							
%Negative	0.10	-0.05	0.13	0.01	-0.04	-0.04	0.11	-0.12	-0.26	-0.31	0.19	1.00						
%Positive	0.23	0.10	0.24	0.10	0.03	0.08	0.07	-0.02	-0.17	-0.09	0.32	0.46	1.00					
%Uncertain	0.08	0.00	0.10	-0.04	-0.08	-0.11	0.07	-0.11	-0.28	-0.41	0.24	0.76	0.44	1.00				
Fog	-0.07	-0.08	-0.05	-0.11	-0.05	-0.16	-0.08	-0.18	-0.11	-0.24	-0.11	0.42	0.15	0.37	1.00			
Trading Volume	0.13	0.09	0.12	0.27	0.10	0.25	0.23	0.28	0.26	0.64	0.01	-0.18	-0.01	-0.30	-0.15	1.00		
Media coverage	0.16	0.07	0.17	0.13	0.04	0.16	0.19	0.03	-0.07	0.09	0.09	0.09	0.10	0.07	-0.04	0.27	1.00	
Retail trade	0.28	0.12	0.29	0.17	0.12	0.08	0.46	-0.03	-0.18	-0.13	0.33	0.27	0.22	0.28	0.12	0.05	0.18	1.00

Table 3: Visual Disclosure in Prospectus And Attention

This table presents the results from regression based on Equation 1 and estimates coefficients for the relation between number of visuals in the prospectus and investors' attention. All variables are defined in Appendix A. All continuous variables are winsorized at 5 and 95 percentiles. t-statistics (based on standard errors clustered by year) are reported in parentheses. ***, **, * indicate significance at the 0.01, 0.05, 0.10 levels, respectively.

	Media Coverage	Trade Volume	Retail Trade
	(1)	(2)	(3)
Num images	0.012***	0.005*	0.001*
	(3.65)	(2.17)	(2.13)
%Negative	0.005	0.201*	0.004
	(0.05)	(2.06)	(0.16)
%Positive	-0.088	0.313**	0.028
	(-0.48)	(2.55)	(0.53)
%Uncertain	0.131	-0.475***	0.050
	(1.41)	(-3.31)	(1.79)
ln(Num words)	0.004	0.043	0.011
	(0.18)	(1.07)	(0.72)
Up revision	0.012*	0.048***	0.006***
	(2.16)	(13.34)	(3.71)
VC dummy	0.429***	-0.019	0.109***
	(5.56)	(-0.27)	(3.92)
UW reputation	0.058	0.175**	0.054*
	(1.08)	(2.26)	(1.99)
Prior Nasdaq 15-day returns	0.002	0.005	0.004
	(0.28)	(0.70)	(1.32)
insider	0.113	0.348***	0.106**
	(0.67)	(6.99)	(2.45)
Positive EPS dummy	-0.104	-0.114**	-0.030**
	(-1.60)	(-2.36)	(-2.67)
Ln(sales)	0.085***	0.236***	-0.013**
	(3.90)	(8.25)	(-2.90)
N	1082	1082	743
R^2	0.15	0.59	0.46
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 4: Characteristics of Visuals and Attention

Panel A of this table presents the relation between salience of visuals used in prospectus and investors' attention. Panel B presents the relation between vividness of visuals and attention. Panel C of this table examines the relationship between specific types of visuals and attention. Panel D presents the relationship between emotional and non-emotional visuals and attention. All variables are defined in Appendix A. All continuous variables are winsorized at 5 and 95 percentiles. t-statistics (based on standard errors clustered by year) are reported in parentheses. ***, **, * indicate significance at the 0.01, 0.05, 0.10 levels, respectively.

Panel A: Salience of visuals and attention

	Media coverage	Trade volume	Retail Trade
	(1)	(2)	(3)
Num images	0.011***	0.005*	0.001*
	(3.58)	(2.18)	(2.18)
Salience	-1.442	1.081***	0.428***
	(-1.15)	(4.91)	(3.34)
%Negative	0.003	0.203*	0.005
	(0.03)	(2.09)	(0.19)
%Positive	-0.086	0.311**	0.027
	(-0.47)	(2.52)	(0.51)
%Uncertain	0.120	-0.466***	0.053*
	(1.20)	(-3.25)	(1.89)
ln(Num words)	0.007	0.041	0.010
	(0.26)	(1.01)	(0.67)
Up revision	0.011*	0.048***	0.006***
	(2.18)	(13.46)	(3.87)
VC dummy	0.437***	-0.026	0.106***
	(5.10)	(-0.34)	(3.95)
UW reputation	0.056	0.176**	0.054*
	(1.05)	(2.30)	(1.99)
Prior Nasdaq 15-day returns	0.002	0.005	0.004
	(0.30)	(0.68)	(1.32)
Insider	0.111	0.349***	0.108**
	(0.65)	(7.14)	(2.50)
Positive EPS dummy	-0.102	-0.116**	-0.031**
	(-1.47)	(-2.43)	(-2.72)
Ln(sales)	0.085***	0.235***	-0.014***
	(4.10)	(8.08)	(-3.13)
N	1082	1082	743
R^2	0.15	0.59	0.46
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Panel B: Vividness of Visuals and Attention

	Media coverage	Trade volume	Retail Trade
	(1)	(2)	(3)
Num images	0.011***	0.005*	0.001*
	(3.85)	(2.10)	(2.10)
Vividness	0.005**	0.003*	-0.000
	(2.83)	(1.83)	(-0.67)
%Negative	0.002	0.199*	0.004
	(0.01)	(2.06)	(0.17)
%Positive	-0.106	0.303**	0.029
	(-0.57)	(2.41)	(0.54)
%Uncertain	0.152	-0.463***	0.049
	(1.71)	(-3.23)	(1.78)
ln(Num words)	0.009	0.046	0.011
	(0.38)	(1.14)	(0.71)
Up revision	0.011*	0.048***	0.006***
	(2.00)	(13.60)	(3.80)
VC dummy	0.425***	-0.022	0.109***
	(5.67)	(-0.31)	(3.93)
UW reputation	0.059	0.176**	0.054*
	(1.17)	(2.29)	(2.00)
Prior Nasdaq 15-day returns	0.003	0.005	0.004
	(0.45)	(0.79)	(1.32)
Insider	0.115	0.349***	0.105**
	(0.64)	(6.36)	(2.42)
Positive EPS dummy	-0.095	-0.109**	-0.030**
	(-1.49)	(-2.32)	(-2.76)
Ln(sales)	0.081***	0.234***	-0.013**
	(3.95)	(8.23)	(-2.85)
N	1082	1082	743
R^2	0.15	0.59	0.46
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Panel C: Content of Visuals (Quant Vs Qual) and Attention

	Media coverage	Trade volume	Retail Trade
	(1)	(2)	(3)
Quant	0.017	-0.008	-0.007**
	(1.03)	(-0.79)	(-2.22)
Qual	0.012*	0.008**	0.003***
	(2.05)	(2.52)	(3.54)
%Negative	0.010	0.190*	-0.004
	(0.08)	(2.00)	(-0.17)
%Positive	-0.096	0.320**	0.031
	(-0.50)	(2.59)	(0.58)
%Uncertain	0.130	-0.463***	0.058*
	(1.25)	(-3.34)	(1.98)
ln(Num words)	0.004	0.044	0.012
	(0.15)	(1.10)	(0.79)
Up revision	0.011*	0.048***	0.006***
	(2.14)	(13.41)	(3.56)
VC dummy	0.428***	-0.024	0.107***
	(5.26)	(-0.35)	(3.72)
UW reputation	0.059	0.176**	0.053*
	(1.12)	(2.27)	(1.95)
Prior Nasdaq 15-day returns	0.002	0.005	0.005
	(0.32)	(0.82)	(1.37)
Insider	0.109	0.359***	0.106**
	(0.62)	(7.11)	(2.34)
Positive EPS dummy	-0.103	-0.111**	-0.028**
	(-1.60)	(-2.27)	(-2.62)
Ln(sales)	0.084***	0.237***	-0.013**
	(3.75)	(8.24)	(-2.78)
N	1082	1082	743
R^2	0.15	0.59	0.47
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Panel D: Content of Visuals (Emotional vs Non-Emotional) and Attention

	Media coverage	Trade volume	Retail Trade
	(1)	(2)	(3)
Quant	0.017	-0.007	-0.006*
	(1.17)	(-0.72)	(-2.01)
Non-Emotional Qual	0.012*	0.006*	0.002
	(1.80)	(1.81)	(1.46)
Emotional Qual	0.013	0.013**	0.008***
	(0.54)	(2.54)	(3.38)
%Negative	0.010	0.187*	-0.006
	(0.08)	(1.99)	(-0.24)
%Positive	-0.096	0.320**	0.034
	(-0.50)	(2.61)	(0.67)
%Uncertain	0.130	-0.463***	0.060*
	(1.25)	(-3.34)	(2.04)
ln(Num words)	0.004	0.045	0.012
	(0.17)	(1.15)	(0.84)
Up revision	0.011*	0.048***	0.006***
	(1.90)	(13.46)	(3.52)
VC dummy	0.428***	-0.028	0.106***
	(4.74)	(-0.39)	(3.70)
UW reputation	0.059	0.174**	0.052*
	(1.14)	(2.25)	(1.95)
Prior Nasdaq 15-day returns	0.002	0.005	0.004
	(0.32)	(0.82)	(1.36)
Insider	0.108	0.351***	0.100**
	(0.71)	(6.66)	(2.30)
Positive EPS dummy	-0.103*	-0.109*	-0.025**
	(-1.88)	(-2.17)	(-2.36)
Ln(sales)	0.084***	0.236***	-0.014***
	(4.44)	(8.18)	(-3.15)
N	1082	1082	743
R^2	0.15	0.59	0.47
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 5: Visuals, Media Coverage, and Investor Attention

This table re-examines the relationship between use of different types of visuals and investor attention but uses filing-period media coverage as a control variable. All variables are defined in Appendix A. All continuous variables are winsorized at 5 and 95 percentiles. t-statistics (based on standard errors clustered by year) are reported in parentheses. ***, **, * indicate significance at the 0.01, 0.05, 0.10 levels, respectively.

	Trade volume	Retail trade
	(1)	(2)
Num images	0.004*	0.001*
	(1.80)	(2.02)
Media coverage	0.018***	0.012
	(3.47)	(1.66)
%Negative	0.208*	0.004
	(2.13)	(0.17)
%Positive	0.317**	0.029
	(2.45)	(0.56)
%Uncertain	-0.481***	0.048
	(-3.40)	(1.75)
ln(Num words)	0.041	0.011
	(1.01)	(0.73)
Up revision	0.048***	0.006***
	(13.22)	(3.62)
VC dummy	-0.047	0.106***
	(-0.66)	(3.88)
UW reputation	0.183**	0.053*
	(2.50)	(1.95)
Prior Nasdaq 15-day returns	0.006	0.004
	(0.87)	(1.30)
Insider	0.330***	0.105**
	(7.19)	(2.47)
Positive EPS dummy	-0.109*	-0.029**
	(-2.19)	(-2.67)
Ln(sales)	0.229***	-0.014**
	(8.26)	(-2.87)
N	1082	743
R^2	0.59	0.46
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 6: Visuals and IPO Outcomes

Panel A of this table presents the relationship between visual disclosure in prospectus and first day returns using OLS model. Panel B of this table uses logit model with the dependent variable in the regression being binary variable that takes on the value one if the wealth effects are greater than dilution effects. All variables are defined in Appendix A. All continuous variables are winsorized at 5 and 95 percentiles. t-statistics (based on standard errors clustered by year) are reported in parentheses. ***, **, * indicate significance at the 0.01, 0.05, 0.10 levels, respectively.

Panel A: Visual disclosure and initial returns

	Initial returns (1)	Initial returns (2)	Initial returns (3)
Num images	0.201***		
	(3.57)		
Quant		0.412	0.443
		(0.81)	(0.84)
Qual		0.173*	
		(1.97)	
Non-Emotional Qual			0.108
			(0.86)
Emotional Qual			0.389**
			(2.30)
%Negative	5.720	5.922	5.820
	(1.68)	(1.62)	(1.63)
%Positive	-8.818	-8.935	-8.917
	(-1.28)	(-1.30)	(-1.29)
%Uncertain	-3.437	-3.592	-3.597
	(-0.71)	(-0.69)	(-0.70)
ln(Num words)	0.325	0.310	0.391
	(0.29)	(0.28)	(0.35)
Up revision	2.054***	2.054***	2.043***
	(14.54)	(14.47)	(14.45)
VC dummy	6.745***	6.810***	6.658***
	(3.88)	(3.69)	(3.73)
UW reputation	1.088	1.110	1.059
	(1.35)	(1.37)	(1.33)
Prior Nasdaq 15-day returns	1.165**	1.161**	1.161**
	(2.84)	(2.84)	(2.83)
Insider	10.993*	10.886*	10.509*
	(2.02)	(2.00)	(1.89)
Positive EPS dummy	2.180	2.171	2.293
	(1.28)	(1.29)	(1.28)
Ln(sales)	-1.005**	-1.020**	-1.088**
	(-2.57)	(-2.62)	(-2.61)
N	1082	1082	1082
R^2	0.31	0.31	0.31
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Panel B: Visual Disclosure and Insider Wealth Gains

	(1)	(2)	(3)
Num images	0.024***		
	(2.81)		
Quant		0.002	-0.004
		(0.05)	(-0.11)
Qual		0.031***	
		(2.81)	
Non-Emotional Qual			0.049***
			(3.87)
Emotional Qual			-0.026
			(-1.07)
Proceeds	0.088	0.092	0.128*
	(1.24)	(1.28)	(1.76)
Float	-0.394	-0.358	-0.477
	(-0.84)	(-0.76)	(-1.00)
Resids	0.029***	0.029***	0.030***
	(9.05)	(9.02)	(9.02)
N	1020	1020	1020
PsuedoR^2	0.1005	0.1015	0.1078

Table 7: Visual Disclosure in Prospectus and Long-term Use of Visuals

This table presents the relationship between the visual disclosure in the prospectus and the use of visuals in the first 10K after listing using Poisson regression model. All variables are defined in Appendix A. All continuous variables are winsorized at 5 and 95 percentiles. t-statistics (based on standard errors clustered by year) are reported in parentheses. ***, **, * indicate significance at the 0.01, 0.05, 0.10 levels, respectively.

	Num Images (1)	Quant (2)	Qual (3)
Num images	0.042***		
	(9.95)		
Quant		0.299***	-0.008
		(11.96)	(-1.05)
Qual		-0.009	0.054***
		(-1.33)	(8.88)
Competition	0.005	0.005	0.005
	(1.35)	(1.34)	(1.15)
Roa	0.096	-0.125	0.090
	(0.34)	(-0.44)	(0.33)
Ln(MktVal)	0.012	0.115**	-0.015
	(0.32)	(2.12)	(-0.32)
BIG4	0.059	0.124	0.059
	(0.55)	(0.96)	(0.57)
VC dummy	0.217	0.298**	0.245
	(1.23)	(2.12)	(1.23)
UW reputation	0.164***	0.122	0.188**
	(2.67)	(1.18)	(2.50)
Positive EPS dummy	-0.166	-0.221	-0.148
	(-1.16)	(-0.95)	(-1.08)
Ln(sales)	-0.114***	-0.092**	-0.130***
	(-5.35)	(-2.27)	(-6.66)
N	1082	1082	1082
Pseuso-R^2	0.3413	0.2124	0.3573
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 8: Drivers of Firm's Use of Visuals in Prospectus

This table presents the results of the analysis that examines the drivers of number of visuals used in the prospectus, number of quantitative visuals used in the prospectus, and number of qualitative visuals used in the prospectus. Estimation is based on Poisson regression model. All variables are defined in Appendix A. All continuous variables are winsorized at 5 and 95 percentiles. t-statistics (based on standard errors clustered by year) are reported in parentheses. ***, **, * indicate significance at the 0.01, 0.05, 0.10 levels, respectively.

	Num Images (1)	Quant images (2)	Qual images (3)
Age	-0.004	0.004	-0.005
	(-0.84)	(0.64)	(-1.09)
Competition	0.001	0.003**	-0.000
	(0.52)	(2.19)	(-0.11)
Ln(Num words)	0.038	0.062	0.028
	(0.80)	(0.89)	(0.54)
%Uncertain	0.216*	0.345*	0.175
	(1.75)	(1.93)	(1.36)
Tone	0.503*	1.407***	0.369
	(1.65)	(3.09)	(1.16)
Fog	-0.068**	-0.082**	-0.062**
	(-2.55)	(-2.09)	(-2.22)
VC dummy	0.191***	-0.112	0.257***
	(2.88)	(-1.21)	(3.61)
UW reputation	-0.007	-0.006	-0.020
	(-0.13)	(-0.08)	(-0.37)
R&D	0.026***	0.031***	0.025***
	(3.96)	(3.32)	(3.59)
Positive EPS dummy	0.045	0.138	0.004
	(0.64)	(1.39)	(0.06)
Ln(Sales)	0.071***	0.075***	0.069***
	(3.52)	(2.75)	(3.16)
N	1067	1067	1067
Pseuo-R^2	0.2074	0.1215	0.1983
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 9: Robustness Tests

This table presents robustness tests. Panel A re-estimates results of Table 3 but uses log transformations of Number of Images. Panel B re-estimates equation 1 but controls google search-based investor attention during the offering period. All variables are defined in Appendix A. All continuous variables are winsorized at 5 and 95 percentiles. t-statistics (based on standard errors clustered by year) are reported in parentheses. ***, **, * indicate significance at the 0.01, 0.05, 0.10 levels, respectively.

Panel A: Log Transformed Visual Disclosure and Attention

	Media coverage (1)	Trade volume (2)	Retail trade (3)	Media coverage (4)	Trade volume (5)	Retail trade (6)
Ln(Num images)	0.102***	0.053**	0.011			
	(3.79)	(3.07)	(1.12)			
Ln(Quant)				0.067	-0.016	-0.014
				(1.11)	(-0.51)	(-1.54)
Ln(Qual)				0.097**	0.053**	0.019*
				(2.59)	(2.28)	(2.07)
%Negative	0.007	0.202*	0.005	0.020	0.193*	-0.001
	(0.06)	(2.06)	(0.20)	(0.16)	(2.07)	(-0.04)
%Positive	-0.077	0.315**	0.030	-0.107	0.326**	0.035
	(-0.42)	(2.62)	(0.58)	(-0.52)	(2.67)	(0.67)
%Uncertain	0.125	-0.477***	0.048	0.120	-0.469***	0.053*
	(1.32)	(-3.29)	(1.78)	(1.17)	(-3.36)	(1.91)
ln(Num words)	0.002	0.041	0.010	0.001	0.043	0.011
	(0.07)	(1.03)	(0.69)	(0.03)	(1.08)	(0.73)
Up revision	0.012*	0.048***	0.006***	0.011*	0.048***	0.006***
	(2.20)	(13.25)	(3.63)	(2.15)	(13.33)	(3.49)
VC dummy	0.431***	-0.020	0.109***	0.425***	-0.022	0.108***
	(5.63)	(-0.29)	(3.91)	(5.56)	(-0.32)	(3.79)
UW reputation	0.053	0.173**	0.053*	0.057	0.174**	0.053*
	(0.99)	(2.21)	(2.00)	(1.10)	(2.24)	(1.95)
Prior Nasdaq 15-day returns	0.002	0.005	0.004	0.002	0.005	0.005
	(0.27)	(0.70)	(1.30)	(0.28)	(0.80)	(1.34)
Insider	0.125	0.351***	0.107**	0.114	0.366***	0.109**
	(0.75)	(7.45)	(2.49)	(0.64)	(8.04)	(2.45)
Positive EPS dummy	-0.107	-0.115**	-0.030**	-0.103	-0.113**	-0.029**
	(-1.64)	(-2.36)	(-2.69)	(-1.56)	(-2.32)	(-2.63)
Ln(sales)	0.085***	0.236***	-0.013**	0.083***	0.238***	-0.013**
	(3.92)	(8.40)	(-2.90)	(3.69)	(8.38)	(-2.89)
N	1082	1082	743	1082	1082	743
R^2	0.15	0.59	0.46	0.15	0.59	0.46
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Google Search Volume and Attention

	Media coverage	Trade volume	Retail trade
	(1)	(2)	(3)
Num images	0.010*	0.005**	0.001
	(2.10)	(2.26)	(1.62)
Google search	0.008***	0.004**	0.000
	(3.86)	(2.73)	(0.74)
%Negative	0.040	0.215*	-0.010
	(0.33)	(2.10)	(-0.34)
%Positive	-0.175	0.349**	0.001
	(-0.95)	(2.81)	(0.01)
%Uncertain	0.118	-0.483***	0.075**
	(1.18)	(-3.76)	(2.45)
ln(Num words)	0.016	0.056	0.011
	(0.49)	(1.46)	(0.74)
Up revision	0.013*	0.048***	0.006***
	(2.16)	(13.88)	(3.73)
VC dummy	0.374***	-0.054	0.111***
	(4.98)	(-0.70)	(4.62)
UW reputation	0.073	0.206**	0.050
	(1.23)	(2.95)	(1.68)
Prior Nasdaq 15-day returns	0.000	-0.000	0.004
	(0.06)	(-0.05)	(1.25)
Insider	0.070	0.276***	0.097**
	(0.40)	(5.20)	(2.69)
Positive EPS dummy	-0.128*	-0.110*	-0.016
	(-1.88)	(-2.15)	(-1.19)
Ln(sales)	0.083***	0.228***	-0.011*
	(4.06)	(7.75)	(-2.06)
N	983	983	670
R^2	0.18	0.61	0.46
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes