

Visual Information in the Age of AI: Evidence from Corporate Executive Presentations*

Sean Cao Yichen Cheng Meng Wang Yusen Xia

Baozhong Yang

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ABSTRACT

This paper constructs and studies a comprehensive data set comprised of corporate executive presentations. Executive presentations are unique in that they provide an abundance of visual information about a firm's project designs and production plans. In the aggregate, these presentations allow us to explore the value of visual information and examine how market participants with varying levels of technological access respond to such information. Using a state-of-the-art deep learning model, we extract forward-looking operational information from presentation slide images. We find that short-term abnormal returns are positively associated with forward-looking operational information, but not with backward-looking or financial information. AI-equipped financial institutions respond strongly to visual signals, whereas other institutions and retail investors do not. Our study provides novel evidence that AI adoption rewards investors with an informational advantage, creating a potential *AI divide* among market participants.

JEL Classification: D83, G12, G14, G23, G30

Key Words: Machine Learning, Artificial Intelligence, FinTech, Corporate Presentation, Image Analysis, Textual Analysis, Information and Market Efficiency, Institutional Investors, Investment

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1 Introduction

Information disclosed by corporations or media plays a fundamental role in the financial markets. Investors rely on such information to form expectations and shape asset prices, and may obtain it from various sources, including financial statement releases, conference calls, annual reports, and the news media. In this paper, we explore information from an relatively unexplored firm information event: corporate executive presentations. These executive presentations are unique in two ways. First, since CEOs must deliver live presentations within a given time limit, their slides tend to include a large amount of visual and graphic elements. Second, complementary to quantitative information and in contrast with other corporate disclosures, executive presentations provide an abundance of visual information about a firm’s product designs and operation plans.

Due in large part to its unique capacity for analyzing alternative data on a massive scale, artificial intelligence is now being deployed with increasing frequency both by the financial services industry¹ and in academia.² Motivated by the potential that emergent AI technologies hold for the effective processing of visual data from corporate presentations, this paper addresses two central research questions. First, we study whether and how state-of-the-art machine learning techniques can extract valuable information from visual data and help investors understand corporate business operations. Second, utilizing this setting, we examine whether AI technologies create disparities between market participants by rewarding AI-equipped investors with information and trading advantages.

We first construct a comprehensive data set of corporate presentation slides from multiple data sources including Bloomberg News and corporate websites from 2005 to 2018. Our sample includes multiple types of executive presentation events, including non-deal road shows (e.g., [Bradley, Jame, and Williams, 2021](#); [Ellis, Gerken, and Jame, 2020](#)), IPO road

¹According to a survey report by BarclayHedge, over half of hedge fund respondents (56%) used AI to inform investment decisions in 2018. The report is available at <https://www.barclayhedge.com/insider/majority-of-hedge-fund-pros-use-ai-machine-learning-in-investment-strategies>. See also a survey of the recent AI literature in financial economics at the end of this introduction.

²See for example the survey [Cong, Liang, Yang, and Zhang \(2020\)](#).

shows (e.g., [Blankespoor et al., 2017, 2020b](#)), broker-hosted investor conferences (e.g., [Green, Jame, Markov, and Susai, 2014](#)), capital market day events, and others. The final sample used for our analysis includes 17,277 corporate presentation slide decks associated with an average of 1,023 unique firms per year and consisting of 464,765 slide pages. Although quantitative financial information is disclosed to the market in various ways (e.g., earnings announcements, SEC filings), corporate presentations provide a unique opportunity for companies to visually showcase the details of their business operations to potential investors.³ Furthermore, managers can utilize graphics to better present forward-looking information that can affect future cash flows and the value of the company. To reflect the nature of information conveyed by corporate images, we use a deep learning algorithm to classify them into three categories: 1) *Operations Forward*: images in this category provide forward-looking operational information, including future products, blueprints, and development plans; 2) *Operations Summary*: images in this category present information about existing products or services; 3) *Others*, which includes graphs of financial and quantitative information and generic images.

In our classification process, we adopt a deep learning model specifically tailored for image recognition: convolutional neural networks (CNN). Furthermore, we utilize the transfer learning method (e.g., [Pratt, 1993](#)) to improve prediction accuracy and reduce the size of the training sample. Transfer learning utilizes and fine-tunes existing deep neural network models that have been pre-trained with large labelled image data sets.⁴

We first examine the value of visual information extracted from corporate presentation images by testing whether visual information can predict stock returns. We hypothesize that *Operations Forward* contains new, valuable information for investment, whereas the information in *Operations Summary* will, for the most part, have already been incorporated

³While companies also disclose graphics in 10-K reports, the images therein are mostly plots of quantitative data. Corporate presentations allow us to focus on images that provide information about corporate operations and products.

⁴In particular, we leverage the pre-trained VGG16 ([Simonyan and Zisserman, 2014](#)) model using the Google ImageNet data. We provide details about CNN and transfer learning models in [Appendix A](#).

into stock prices. As expected, we find that *Operations Forward* is associated with significant and positive short-term cumulative announcement returns ($[-3, 3]$ relative to the presentation date), while other types of visual information are not. A one-standard-deviation increase in *Operations Forward* is associated with an increase in abnormal returns of approximately 14 basis points around the presentation date.

Information can affect stock prices via two channels: the discount rate and future cash flows (Campbell and Shiller, 1988). Given that corporate disclosure of prospective operations is unlikely to be directly related to discount rates, we expect it to influence stock prices through the cash flow channel. Consistent with this hypothesis, we find that *Operations Forward* is positively associated with firms' sales and earnings in the fourth quarter and the second year following the presentation. Interestingly, *Operations Summary* is only significantly correlated with sales and earnings in the next quarter, but not in the long run, indicating that it contains mostly stale and short-term information.

We next explore different market participants' responses to the visual information contained in corporate presentations. Drawing on recent studies showing that unequal access to alternative data and capacity to analyze data at scale increases information asymmetry among market participants (e.g., Katona et al., 2018; Zhu, 2019), we hypothesize that the ability to process and extract unique information from unstructured data provides information advantages to institutions that have adopted AI technologies. Specifically, since extracting visual information from slides on a large scale requires deep learning capabilities, we expect that AI-equipped financial institutions are more likely to trade on visual information, compared with other institutions and retail investors. We measure the extent of AI adoption by institutional investors by calculating the cumulative job postings in the BurningGlass database.⁵ Consistent with our hypothesis, we find that institutional investors with high AI investment trade more around the presentation date when corporate presentations contain more forward-looking visual information related to operations (higher *Operations*

⁵Our calculation follows a similar approach to those in Acemoglu et al. (2020), Abis and Veldkamp (2020), and Babina et al. (2021).

Forward). In contrast, trades by other institutional investors and retail investors are not sensitive to the visual information contained in CEO presentations.⁶

If AI-equipped institutions are more able to process visual information, then stock prices should incorporate such information more quickly when these institutions are present. To test this hypothesis, we separate stocks into two groups, based on the level of ownership by AI-equipped institutions. We find that *Operations Forward* is only associated with significant abnormal returns around corporate presentations when the stock has a high proportion of AI-equipped institutional ownership, suggesting that AI-guided institutional trades are what impound the visual operations information into prices.

This study contributes to several strands of literature. First, our work extends the growing literature on the impact of AI in the financial services industry. For example, [Abis \(2020\)](#) examines how quantitative investment strategies influence mutual fund performance. [Grennan and Michaely \(2020\)](#) study how analysts perform and adjust in response to the advent of AI-processed recommendations in the markets. [Abis and Veldkamp \(2020\)](#) explore the change in labor shares in the financial industry driven by new data management and AI-related jobs. [Coleman, Merkley, and Pacelli \(2021\)](#) compare the performance of robot analysts from FinTech companies to that of human analysts. [Cao, Jiang, Yang, and Zhang \(2020\)](#) study how firms modify their disclosure practices in response to the presence of AI readership in financial markets. Our paper provides direct evidence of the value of visual information extracted by AI. We show that AI technologies can create information and trading advantages for adopting institutions, potentially generating an *AI divide* among investors.

Second, we contribute to the emerging literature on the value of visual content in corporate disclosures and news media. Several recent studies document the importance of visual content in predicting many outcomes. [Deng, Gao, Hu, and Zhou \(2020\)](#) find that firms that increase their use of graphics experience abnormal returns over the next six months.

⁶Retail trades are calculated following [Boehmer et al. \(2021\)](#).

Ben-Rephael, Ronen, Ronen, and Zhou (2021) measure the visual readability of annual reports and find that images serve as an important source of information by reinforcing firms' textual narratives. Christensen, Fronk, Lee, and Nelson (2021) find a substantial increase in the disclosure of infographics in the last decade. Obaid and Pukthuanthong (2022) construct a sentiment measure using photos in news articles, demonstrating that negative sentiment predicts market return reversals and trading volume. In this paper, we construct a new data set, comprised of corporate presentations, which, since such information is more abundant and salient therein, provides a unique setting to study visual information about business operations and products. Different from the above studies that study images and their relation to texts, we study an information environment where the textual narrative is more limited and focus on comparing different types of visual information contained in images. Interestingly, we find that only certain types of visual information (forward-looking, operational information) impact prices, and that investors have differential abilities to utilize such information.

Finally, our paper contributes to a growing body of studies that apply machine learning and deep learning techniques to financial issues by, for example, using it to predict asset prices (Gu, Kelly, and Xiu, 2020; Brogaard and Zareei, 2022), manage portfolios (Chen, Pelger, and Zhu, 2022; Cong, Tang, Wang, and Zhang, 2022), forecast earnings (van Binsbergen, Han, and Lopez-Lira, 2022; Cao and You, 2021), and analyze audio and video information (Mayew and Venkatachalam, 2012; Hu and Ma, 2021). To complement this literature, our paper explores transfer learning techniques and CNN models, ultimately developing a framework for future studies of visual information in important corporate disclosures.

The rest of the paper is structured as follows. Section 2 describes our data, model, and the method used to construct key variables. Section 3 and Section 4 present empirical results. Section 5 concludes.

2 Visual Information and Machine Learning

2.1 Corporate Presentations Data

We collect a comprehensive dataset of corporate presentation slides from multiple data sources, including Bloomberg News and corporate websites, generated in the period from 2005 to 2018. The corporate presentations in our sample include all types of public executive presentations that are hosted either by the corporations themselves (e.g., corporate conferences) or by third parties (e.g., investment banks). The vast majority of presentations in our sample are held externally and are non-road shows. Our initial sample contains 51,879 corporate presentations (slide decks) and consists of 1,467,979 slide pages that include both graphical and textual content. After merging with CRSP/Compustat⁷, our final sample consists of 17,277 corporate presentation slide decks associated with an average of 1,023 unique public US firms per year and includes 464,765 slide pages. Each slide page is converted to an image as the input for the machine learning algorithms. We also use a Python algorithm to extract the textual information contained in the slides.

Visual and graphic information has been difficult to analyze due to its unstructured and high-dimensional nature. An image may contain tens of thousands of pixels, each with millions of possible colors, that form complex patterns and objects. Recent advances in machine learning and AI, however, have made it possible to construct image recognition algorithms with capabilities comparable to humans. In this section, we describe how we apply deep learning to extract key features of firms' operations from corporate presentations.

2.2 Image Labeling and Classification

As the first step, we manually review and classify (label) a random sub-sample of images into several different categories, providing a training sample for the machine learning algorithms we later employ. We classify each image into one of three categories: *Operations Forward*,

⁷All common variables used are defined as in [Appendix A](#).

Operations Summary, and *Others*. Our labeling criteria are as follows:

1) *Operations Forward*: If a slide image mainly provides information regarding a firm’s future operations, constructions, products, or programs, we classify it as an *Operations Forward* image. This would include, for example, images that present new product designs, blueprints, or future business plans. We present examples of images from each category in [Appendix C](#).

2) *Operations Summary*: If an image mostly presents information about a firm’s existing operations and products, we label it as an *Operations Summary* image. For example, such images might show existing products, established factories, or current business strategies.

3) *Others*: If an image is a plot or chart (usually based on financial information that is also disclosed elsewhere), if the image contains mostly text, or if it contains information not directly relevant to the firm’s operations (e.g., generic images, logos), we label it as *Others*.

To minimize human error in the labeling process, we cross-validate and require a consensus on the classification by at least three graduate research assistants. We use a two-step bootstrapping process to construct the training sample. We first label an initial random sample of 3,000 images. We then use this initial sample to train our machine learning model (described in the next section) and make initial predictions on how the remaining images will be classified. We then select a final training sample of 20,000 pre-classified images with a balanced number of images in each category, and manually classify images in the sample.

2.3 Deep Learning Model

Over time, a diverse array of applications have been found for various machine learning models, including random forests, gradient boosting, and neural networks (e.g., [James, Witten, Hastie, and Tibshirani, 2013](#)). Image recognition, however, has long posed a significant problem for deep learning. Hence Google’s development of ImageNet ([Li et al., 2009](#)), which is able to perform on par with humans, represented a major milestone. The primary deep learning model employed by ImageNet and other leading image recognition algorithms is the

Convolutional Neural Network (CNN). The CNN is a multi-layer neural network in which the lower layers capture finer details while the higher layers extract high-level information, such as objects in the image. We include a detailed discussion of the structure and intuition of CNN in [Appendix B](#).

Still, recognizing business-related images is challenging because there are no ready-made models for this purpose, and training a CNN model usually requires a large training dataset. Therefore, we utilize an advanced machine learning technique called *transfer learning* ([Pratt, 1993](#); [Rajat et al., 2006](#)) to build our own deep learning model based on pre-trained CNN models and then train the model with our business image sample. Specifically, we first build a neural network on top of a pre-trained CNN neural network from a state-of-the-art image recognition model VGG16 ([Simonyan and Zisserman, 2014](#)). We then keep the parameters of CNN layers fixed and fine-tune the model with our training sample. The resulting model is what we call the *Transfer CNN* model. Transfer learning allows us to take advantage of existing CNN models trained with very large datasets while adapting the model to our specific business problem. We also employ the model that utilizes both image and text information from presentations (*Transfer CNN + Text*) and the transfer learning technique. More details of our models are described in [Appendix B](#).

2.4 Model Performance

We consider and train four different model architectures: 1) A CNN model that starts from scratch (*CNN*); 2) A deep learning model that processes both images and text (*CNN + Text*); 3) A transfer learning model that relies on a pre-trained CNN model to process images (*Transfer CNN*); and 4) A transfer learning model that processes both images and text (*Transfer CNN + Text*).⁸

⁸Textual information might also be useful in helping classifying forward-looking v.s. backward-looking information. Keywords potentially indicate forward-looking information include “projected”, “prospect”, “expected”, “guidance”, “target”, “potential”, “forecast”, “estimated”, “will”, “plan”, “outlook”, “opportunity”, “explore”, “expand”, “develop”, “future”, “pipeline”, “new”, “proposal”, “schedule”, “next”, “update”, “forward”, “prepare”.

[Insert Table 1 Here]

We use four measures to evaluate the models' out-of-sample performance. *Accuracy* is the ratio of correct predictions to total observations. *Precision* is the ratio of true positives to the sum of true positives and false positives. *Recall* is the ratio of true positives to the sum of true positives and false negatives. We calculate *Precision* and *Recall* for each category and then take an average across all three categories. *F1 score* is the harmonic mean of *Precision* and *Recall*. Among the four architectures, *Transfer CNN* and *Transfer CNN + Text* have the best performance in terms of F1 score and accuracy. *Transfer CNN + Text* outperforms other models with an accuracy of 80.0% and F1 score of 79.4%. We therefore use it as our main model in the paper.

At the same time, it should be noted that the difference in performance between the *Transfer CNN* and *Transfer CNN + Text* is small, amounting to only 1.1% for the F1 score and 3% for accuracy. This suggests that the vast majority of the prediction power of our model comes from visual information rather than textual information. Intuitively, the textual information in the executive presentation slides tends to be brief and is often used only to supplement the visual information.⁹

3 Variable Construction

3.1 Operations Information from Images

We use the trained *Transfer CNN + Text* model to obtain a final classification for the entire sample of 464,765 slide images in 17,277 corporate presentations slide decks. For each presentation, we then calculate the fraction of slide pages in each category to define our main

⁹We were able to obtain presentation transcripts for a small subset of our sample from Bloomberg. Due to the limited size, we cannot conduct a comprehensive analysis using the verbal information from transcripts.

variables of operation information. Specifically, for each presentation i , we define

$$\text{Operations Forward}_i = \frac{\# \text{ of Operations Forward Slides}_i}{\text{Total Number of Slides}_i}, \quad (1)$$

$$\text{Operations Summary}_i = \frac{\# \text{ of Operations Summary Slides}_i}{\text{Total Number of Slides}_i}. \quad (2)$$

These two variables represent the extent of visual information about forward-looking and backward-looking operations in the executive presentations, respectively. They form the main independent variables in our subsequent analyses.

3.2 AI Institutional Ownership

In this section, we briefly describe our methodology for identifying AI-equipped financial institutions and their stock ownership. We also describe our methodology in greater detail in [Appendix D](#). First, we estimate a financial institution’s AI-related labor stock based on job posting data from Burning Glass. This methodology is similar to that of [Acemoglu et al. \(2020\)](#), [Abis and Veldkamp \(2020\)](#), and [Babina et al. \(2021\)](#). Intuitively, a given financial institution’s AI labor stock in a certain year is calculated based on the time series of the number of AI-related job postings, and the estimated hiring/separation rate in the financial services sector. We then classify financial institutions into AI-equipped and non-AI-equipped institutions based on their estimated AI-related labor stock. Finally, we calculate stock-level ownership by AI-equipped institutions.

A given financial institution i in month t is defined as an *AI Institution* if its AI labor stock in the preceding year is among the top 30% of the sample. We aggregate 13F stock holdings of AI institutions to construct stock-level AI institutional ownership or *AI Inst. Ownership*. Specifically, for a stock-month (i, t) ,

$$\text{AI Inst. Ownership}_{i,t} = \frac{\text{AI Institutional Shares}_{i,t}}{\text{Shares Outstanding}_{i,t}}, \quad (3)$$

where *AI Institutional Shares*_{*i,t*} is the aggregate 13F institutional holdings of stock *i* at time *t* (if *t* is not at quarter end, the previous quarter-end holdings are used), and *Shares Outstanding*_{*i,t*} is the total shares outstanding of stock *i* at the end of month *t*.

3.3 Retail Trades

We follow [Boehmer et al. \(2021\)](#) and use Trade and Quote (TAQ) data to calculate marketable retail order imbalance. After identifying marketable retail buy and sell transactions following [Boehmer et al. \(2021\)](#), we aggregate transactions at the stock-day level and calculate the marketable retail trading measures as follows, for stock-day (*i, t*),

$$\text{Retail Order Imbalance (Shares)}_{i,t} = \frac{mrbvol_{i,t} - mrsvol_{i,t}}{mrbvol_{i,t} + mrsvol_{i,t}}, \quad (4)$$

$$\text{Retail Order Imbalance (Trades)}_{i,t} = \frac{mrbtrd_{i,t} - mrstrd_{i,t}}{mrbtrd_{i,t} + mrstrd_{i,t}}, \quad (5)$$

where *mrbvol*_{*i,t*}, *mrsvol*_{*i,t*} are the daily buy and sell share volume, respectively, and *mrbtrd*_{*i,t*}, *mrstrd*_{*i,t*} are the daily number of retail buy and sell trades.

3.4 Textual Variables

We employ the [Loughran and McDonald \(2011\)](#) dictionaries and follow their methodology to construct textual sentiment and tone measures for presentations: *Positive Sentiment*, *Negative Sentiment*, *Uncertainty*, and *Constrained*. For example, *Positive Sentiment* is the ratio of words in the positive LM dictionary to the total number of words in the presentation (*Text Length*). Other measures are similarly defined. We also construct a comprehensive dictionary of forward-looking words by combining the dictionaries from [Li \(2010\)](#), [Muslu et al. \(2015\)](#), [Bozanic et al. \(2018\)](#), and [Grewal et al. \(2019\)](#) and compute *Forward Looking* as the ratio of the number of forward-looking words to the text length of the slides. We also build a neural network based only on textual information from the corporate presentation slides to predict the slide categories and construct the *Textual Operations Forward* and *Textual*

Operations Summary variables, employing methods similar to those used to construct the visual information variables. Given that the focus of this study is on visual information, we include textual variables as controls in our analyses.

3.5 Other Firm Characteristics

We also consider a number of other firm characteristics as control variables in our tests. *Size* is defined as the natural logarithm of the market capitalization. *Book-to-Market* is the total assets over market cap plus the book value of liabilities. *Turnover* is the monthly average of the ratio of trading volume to shares outstanding, multiplied by twelve. *Inst. Ownership* is the ratio of the total shares of institutional ownership to shares outstanding.

3.6 Summary Statistics

Table 2 reports the summary statistics of the variables. On average, 3.6% of the slides in a presentation are *Operations Forward* slides and 11% are *Operations Summary* slides. There is substantial cross-sectional variation in these variables, as the standard deviation of *Operations Forward* is 5.8%, and *Operations Summary* is 12.2%.

[Insert Table 2 Here]

We further identify the industries with the highest concentration of *Operations Forward* information in Table 3. Panel A of Table 3 displays the top 10 two-digit SIC industries arranged by the fraction of presentations that contain *Operations Forward* slides. Panel B shows the top 10 industries by the average *Operations Forward* in the industry. The top industries include capital-intensive industries such as the Metal, Mining, Oil & Gas, Transportation, and Construction industries, for which future investment plans are important, as well as various Consumer Product industries (e.g., Food, Apparel, and Leather), for which new product designs could be influential.

[Insert Table 3 Here]

Figure 2 shows the time series of the number and percentage of presentations with *Operations Forward* information in our sample from 2006 to 2018. The number of presentations with Operations Forward slides increased steadily over our sample period, due in part to the general increase in the total number of presentations. Interestingly, the ratio of presentations with *Operations Forward* images also increases over time, from 35% in 2006 to 47% in 2018. The increasing propensity of firms for including *Operations Forward* visual information in their public presentations may be due to the increasing demand for new, rich information by investors in the era of AI and big data.

[Insert Figure 2 Here]

Figure 3 compares the distribution of presentation dates by month of the year with those of 10-K and 10-Q filings. Unlike 10-Ks and 10-Qs, which are clustered in common fiscal reporting months (primarily February, May, August, and November), corporate presentation events are relatively evenly distributed, indicating that they provide a continuous information flow throughout the year.

[Insert Figure 3 Here]

4 Visual Information and Capital Markets

4.1 Does Visual Information Matter to the Market?

In this section, we explore whether visual information from corporate presentations offers new insights for investors. The literature has shown that textual disclosures, such as 10-K filings and conference call transcripts, provide new information to the market (e.g. Tetlock, 2007; Li, 2010; Loughran and McDonald, 2011; Jiang, Lee, Martin, and Zhou, 2019). Given that visual information about corporate operations extracted from executive presentations is unique and not contained in common corporate disclosures, we hypothesize that they offer investors value-relevant information. Furthermore, since *Operations Summary* information

is largely known to investors, while *Operations Forward* information is forward-looking and can be particularly helpful in forming expectations of future firm value, we expect *Operations Forward* to provide new information to investors. To the extent that managers enjoy discretion over which information is disclosed in corporate presentations, they are more likely to highlight positive outlooks on operations and omit negative prospects when possible. Therefore, we expect *Operations Forward* to be associated with positive stock reactions.

We examine the market’s reaction to visual information in presentations with the following regression for presentation-firm-date (i, j, t) ,

$$\begin{aligned}
CAR(t_1, t_2)_{i,j,t} = & \beta_0 + \beta_1 Operations\ Forward_{i,t} + \beta_2 Operations\ Summary_{i,t} \\
& + (\gamma_1 ML\ Textual\ Variables) + \gamma_2 Textual\ Controls_{i,t} \\
& + \delta Firm\ Controls_{j,t} + \alpha_{SIC2} + \mu_t + \varepsilon_{i,j,t},
\end{aligned} \tag{6}$$

where $CAR(t_1, t_2)_{i,j,t}$ is the cumulative abnormal returns adjusted for the Fama-French three-factor model during the window $[t_1, t_2]$ around the presentation date t . We include a set of firm-level control variables such as *Size*, *Book-to-Market*, *Turnover*, *Nasdaq*, and *Institutional Ownership*. Textual control variables include *Positive Sentiment*, *Negative Sentiment*, *Uncertainty*, *Constrained*, and *Forward Looking*. ML Textual Variables include the ML text-based variables *Textual Operations Forward* and *Textual Operations Summary*. We also include year and industry fixed effects.

[Insert Table 4 Here]

Table 4 reports the results. Consistent with our hypotheses, columns (1) and (2) show that cumulative abnormal returns in window $[-3, 3]$ are significantly and positively correlated with forward-looking visual operational information, but insignificantly correlated with backward operational information. In particular, column (2) shows that, in the model including control variables and industry and year fixed effects, a one-standard-deviation increase (0.058) in *Operations Forward* is associated with an increase of 14 basis points in

$CAR(-3, 3)$ around the presentation date, or 5% annualized abnormal returns.

Column (3) includes *Textual Operations Forward* and *Textual Operations Summary* as additional control variables and displays quantitatively similar results. Furthermore, the coefficients on *Textual Operations Forward* and *Textual Operations Summary* are statistically indistinguishable from zero, suggesting that visual information is more important than textual information in our setting. We further explore the market’s reactions in different windows. Columns (4) through (6) show that the relationship between visual information and announcement returns holds for the shorter window $[-2, 2]$. Columns (7) through (9) indicate that $CAR(4, 13)$ is not significantly correlated with either *Operations Forward* or *Operations Summary*.

Overall, the results support the hypothesis that visual information about firm operations gleaned from corporate presentations provides new signals to investors. Such signals are concentrated in forward-looking visual information and are quickly incorporated into stock prices.

4.2 Visual Information and Future Cash Flows

Information can affect stock prices via two channels: discount rates and future cash flows (Campbell and Shiller, 1988). Given that a firm’s disclosure of prospective operations is unlikely to be directly related to discount rates, we expect it to influence stock prices via the cash flow channel. We use *Earnings* (operating earnings before depreciation scaled by assets) as our primary measure for cash flows. Since revenues from new projects can be better measures of long-term profitability than short-term earnings, we also use *Sales* (scaled by total assets) as an alternative measure. Specifically, we expect a high figure for *Operations Forward* to be associated with higher future earnings and sales for the disclosing company.

We estimate the following regressions, for presentation-firm-date (i, j, t) ,

$$\begin{aligned}
 Y(t_1)_{i,j,t} = & \beta_1 \text{Operations Forward}_{i,t} + \beta_2 \text{Operations Summary}_{i,t} \\
 & + \gamma_1 \text{Textual Controls}_{i,t} + \delta \text{Firm Controls}_{j,t} + \alpha_{SIC2} + \mu_t + \varepsilon_{i,j,t}, \quad (7)
 \end{aligned}$$

where $Y(t_1)$ is *Earnings* or *Sales* in quarter (or year) t_1 after the presentation date.

[Insert Table 5 Here]

Panel A of Table 5 reports the results of the relationship between visual operational information and future *Earnings*. While *Operations Forward* is insignificantly correlated with future *Earnings* in the 1st through 3rd quarters after the presentation (columns (1) to (3)), it significantly and positively predicts *Earnings* starting in the 4th quarter (column (4)), and continues to predict *Earnings* in the second year (column (5)). The primary reason for this may be that new operations and projects could take time to materialize and affect the firm’s performance. Notably, *Operations Summary* is only significantly (and positively) related to the 1st quarter’s *Earnings* following the presentation. These results are consistent with our conjecture that *Operations Forward* indeed contains longer-term information than *Operations Summary*, which also validates our machine-learning-based approach to extracting these variables from corporate presentation images.

We next examine the relation between visual operational information and revenues by replacing the outcome variable *Earnings* with *Sales*. Similar to the results for *Earnings*, Panel B of Table 5 shows that *Operations Forward* significantly and positively predicts *Sales* starting from the 4th quarter (column (4)) following the presentation, and the predictive power continues in the second year (column (5)). In addition, *Operations Summary* is not significantly correlated with long-term sales.

Overall, the evidence presented in this section indicates that forward-looking operational visual information contains important information about the disclosing firm’s future revenue and profits, which in turn can influence expectations for stock prices.

4.3 Do Analysts Incorporate Visual Information?

Analysts are important information intermediaries. Investors often rely on them to provide key information through their earnings forecasts and revisions (e.g., [Womack, 1996](#); [Francis and Soffer, 1997](#)). To the extent that *Operations Forward* contains important information regarding future earnings and sales for the disclosing company, analysts may incorporate visual information into their forecast revisions after corporate presentations. To explore this possibility, we examine the following regression at the presentation-analyst-firm-quarter level (i, k, j, t) ,

$$\begin{aligned} \textit{Revision Action}_{i,k,j,t+1} = & \beta_1 \textit{Operations Forward}_{i,t} + \beta_2 \textit{Operations Summary}_{i,t} \\ & + \gamma_1 \textit{Textual Controls}_{i,t} + \delta \textit{Firm Controls}_{j,t} + \alpha_{SIC2} + \mu_t + \varepsilon_{i,j,t}. \end{aligned} \tag{8}$$

The dependent variable, *Revision Action*, is either *Revision Direction*, a variable equal to 1 (-1) if the analyst revises the forecast upwards (downwards) after the focal presentation date and before the subsequent earnings announcement date, or *Revision Change*, which is the change in forecasted earnings for such a revision.

[Insert Table 6 Here]

In Table 6 columns (1) and (2), we observe a significant positive relationship between *Revision Direction* and both *Operations Forward* and *Operations Summary*. Columns (3) and (4) exhibit a similar relationship between *Revision Change* and both *Operations Forward* and *Operations Summary*, which is more pronounced for *Operations Forward*. The above evidence suggests that analysts incorporate visual information into their forecasts, further validating our machine learning approach in extracting visual information from corporate presentations.

5 The AI Divide in Information Processing

In recent years, big data and AI technology have fundamentally reshaped the financial services industry, including asset management. Recent studies document how sophisticated analysts and investors are using more alternative data in recent years (e.g., [Huang, Tan, and Wermers, 2020](#); [Chi, Hwang, and Zheng, 2022](#)). However, in light of the large volume of available data, such as may be gleaned from corporate disclosures en masse, disparities in information processing costs for different types of investors may affect their information set, trades, and market outcomes ([Blankespoor et al., 2020a](#)). Unequal access to alternative data and the capacity for utilizing such data at scale can also increase the information asymmetry between sophisticated investors and individual investors (e.g., [Katona et al., 2018](#); [Zhu, 2019](#)).¹⁰

To the extent that AI talent and capability can be expensive and time-consuming to acquire (e.g., [Deloitte Insights, 2020](#)), differential access to AI may be creating an *AI divide*, which compounds information asymmetry among market participants. Executive presentations are public information that can be downloaded and read by any investor. Nonetheless, extracting visual information at a large scale would require sophisticated AI and machine learning capabilities. Still, the cost of processing visual information would be relatively low for AI-equipped financial institutions as compared to other institutions and retail investors. We conjecture that financial institutions with AI capacity are more likely to extract and utilize visual information from corporate presentations. We conduct several tests to further examine the issue.

5.1 Investor Trades, AI Capacity, and Visual Information

Our first test involves how different market participants trade a firm’s stocks around corporate presentation dates. When forward-looking visual operational information is made available through executive presentations, AI-enabled institutions should trade more intensively

¹⁰Such a market is described as “efficiently inefficient” in [Pedersen \(2019\)](#).

than other investors because they have a greater capacity for processing visual information. We consider the following regression at the presentation-firm-date level (i, j, t) ,

$$\begin{aligned} Trades_{i,j,t} = & \beta_1 Operations\ Forward_i + \beta_2 Operations\ Summary_i \\ & + \gamma Textual\ Controls_{j,t} + \delta Firm\ Controls_{i,t} \\ & + \alpha_{SIC2} + \mu_t + \varepsilon_{i,j,t} \end{aligned} \tag{9}$$

where *Trades* are trades made by different market participants around the presentation date t .

We first consider *AI Inst. Trade* and *Non-AI Inst. Trade* in Table 7. *AI Inst. trade* is defined as the change in the quarterly *AI Inst. Ownership* (defined in Section 3.2) during the quarter containing the presentation date.¹¹ Columns (1) and (2) reveal a significant and positive relationship between AI institutional trades around the presentation date and forward-looking visual operational information. In addition, AI institutional trades are insignificantly correlated with visual operational summary information. In contrast, columns (3) and (4) show that non-AI institutional trades are insignificantly correlated with both *Operations Forward* and *Operations Summary*. These results support our hypothesis that AI-equipped institutions are more likely to trade on visual operational information in presentation slides, thanks to their ability to process unstructured data at a large scale.

[Insert Table 7 Here]

In Table 8, we examine the relationship between retail trades and visual operational information. We follow Boehmer et al. (2021) and use marketable retail trade imbalance to proxy for retail trades.¹² In Panel A, the dependent variable is *Retail Order Imbalance*

¹¹We proxy institutional trades by quarterly holdings change in this study due to data limitations, similar to most studies of institutional trading behavior (e.g., Griffin and Xu, 2019; Agarwal, Jiang, Tang, and Yang, 2013). The ANCC dataset provides a subset of transaction-level institutional trades prior to around 2011, but its intersection with our sample is too small to carry out a formal study.

¹²Since we impose the availability of the retail trade measures from TAQ, the sample size is reduced compared to earlier regressions.

(*Shares*), the marketable retail order imbalance calculated based on the number of shares traded. Columns (1) through (4) indicate that retail trades around the presentation date are insensitive to visual operational information for the $[-3, 3]$ and $[-3, 14]$ windows. To examine whether retail investors lag in processing visual information, in columns (5) through (8), we consider retail trades for longer windows from 30 to 90 days and do not find that cumulative marketable retail order imbalance is sensitive to visual information in the long run. Panel B finds similar results for the alternative retail trade measure *Retail Order Imbalance (Trades)*, calculated based on the number of trades.

[Insert Table 8 Here]

In sum, the results above indicate that only AI-equipped institutions' trades are sensitive to the forward-looking visual operational information extracted from presentation slides, suggesting that AI-equipped institutions, as compared to non-AI-equipped institutions and retail investors, are more likely to have the ability to process unstructured image data and utilize visual information from corporate presentations.

5.2 Announcement Return and AI Institutional Ownership

If AI-equipped institutions are more able to process unstructured image data and extract visual information, we would expect to see a stronger relation between cumulative announcement returns and forward-looking visual operational information for stocks with high *AI Inst. Ownership*. To test this hypothesis, we separate stocks into two groups, based on the level of ownership by AI-equipped institutions, and we run the same specification as in Table 4 for the two groups with high and low AI institutional ownership.¹³

[Insert Table 9 Here]

¹³A stock is classified as one with high *AI Inst. Ownership* if the stock's *AI Inst. Ownership* is above the cross-sectional median for the year of presentation.

Table 9 reports the results. Columns (1) and (2) show that the cumulative announcement return in window $[-3, 3]$ is significantly and positively correlated with forward-looking visual operational information for stocks with high *AI Inst. Ownership*. Columns (5) through (8) further show that short-term announcement returns are insignificantly correlated with *Operations Forward* for stocks with low *AI Inst. Ownership*. These findings support our hypothesis that AI-equipped institutions, as compared to non-AI-equipped institutions and retail investors, facilitate the incorporation of visual operational information into stock prices.

6 Concluding Remarks

In this paper, we use machine learning techniques to extract information from visual contents in corporate presentation slides. By using a comprehensive dataset of 464,765 slide pages associated with 17,277 corporate presentation slide decks, we examine the value of visual information in predicting stock returns and study how different market participants respond to it.

We find predictive power only exists in forward-looking visual operational information. Specifically, a one-standard-deviation increase in forward-looking visual operational information in presentation slides is associated with an increase of 14 basis points in cumulative announcement returns within window $(-3, 3)$. Forward-looking visual operational information also predicts the presenting firm's sales and earnings in the fourth quarter and second year following the presentation. We also find that trades made by AI-equipped institutional holding changes are significantly and positively correlated to forward-looking visual operational information in executive presentations, while the trades of non-AI-equipped financial institutions and retail investors are not. Moreover, the relation between short-term cumulative announcement returns and forward-looking visual operational information is stronger for stocks followed by institutions with high AI utilization. The results indicate that AI-equipped institutions, as compared with non-AI-equipped institutions and retail investors, are likely to have a great capacity to process unstructured image data and extract visual

information on a large scale.

Appendix A: List of Variables

Variables	Definition
<i>Operations Summary</i>	The ratio of the number of operations-summary-related pages to the total number of pages in a presentation. Construction methodology is described in Section 2.
<i>Operations Forward</i>	The ratio of the number of operations-forward-related pages to the total number of pages in a presentation. Construction methodology is described in Section 2.
<i>Textual Operations Forward</i>	The ratio of the number of operations-forward-related pages to the total number of pages in a presentation, where operations forward pages are identified by a separate CNN + transfer model using the text in slides only.
<i>Textual Operations Forward</i>	The ratio of the number of operations-forward-related pages to the total number of pages in a presentation, where operations summary pages are identified by a separate CNN + transfer model using the text in slides only.
<i>Positive Sentiment</i>	The number of Loughran-McDonald (LM) finance-related positive words in a presentation divided by the total number of words in the presentation, expressed as a percentage.
<i>Negative Sentiment</i>	The number of Loughran-McDonald (LM) finance-related negative words in a presentation divided by the total number of words in the presentation, expressed as a percentage.
<i>Uncertainty</i>	The number of Loughran-McDonald (LM) uncertainty-related words in a presentation divided by the total number of words in the presentation, expressed as a percentage.
<i>Constrained</i>	The number of Loughran-McDonald (LM) constraining-related words in a presentation divided by the total number of words in the presentation, expressed as a percentage.
<i>Forward Looking</i>	The number of forward-looking words in a presentation divided by the total number of words in the presentation, expressed as a percentage. We construct a comprehensive set of forward-looking words including all dictionaries in Li (2010), Muslu et al.(2015), Bozanic et al.(2018), and Grewal et al.(2019)
<i>Text Length</i>	The total number of words in the presentation.
<i>Size</i>	The natural logarithm of the market capitalization.
<i>Book-to-Market</i>	Total assets over market cap plus the book value of liabilities.
<i>Turnover</i>	The monthly average of the ratio of trading volume to shares outstanding, multiplied by 12.
<i>NASDAQ</i>	NASDAQ indicator that equals one if the stock is traded on the NASDAQ.
<i>Inst. Ownership</i>	The ratio of the total shares of institutional ownership to shares outstanding.
<i>Prior Return</i>	Average FF3 alpha in window [-71,-11] in terms of trading days prior to presentations.

(continued)

Variables	Definition
<i>Revision Direction</i>	A dummy variable that equals one if the analyst changes their forecast for the focal stock during the period between the presentation date and the subsequent earnings announcement date.
<i>Revision Change</i>	The magnitude of the change an analyst makes to their forecast for the focal stock during the period between presentation date and the subsequent earnings announcement date.
<i>General Experience</i>	An analyst's general experience.
<i>Industry Experience</i>	An analyst's industry experience.
<i>Star Analyst</i>	A dummy equal to one if the analyst is a star analyst
<i>Brokerage Size</i>	The size of the brokerage firm that the analyst belongs to.
<i>Earnings</i>	Operating earnings before depreciation scaled by assets.
<i>Sales</i>	Sales scaled by total assets).
<i>AI Inst. Ownership</i>	The AI institutional ownership for a given stock. Please refer to Section 2 for detailed construction method.
<i>AI Inst. Trades</i>	The holdings change among AI-equipped financial institutions. Please refer to Section 2 for detailed construction method.
<i>Aggregate Inst. Size</i>	The sum of the sizes of all institutions holding the focal stock.
<i># of Institutions</i>	The number of institutions holding the focal stock.
<i>Retail Order Imbalance (Shares)</i>	Marketable retail order imbalance trade volume. Please refer to Section 2 for detailed construction method.
<i>Retail Order Imbalance (Trades)</i>	Marketable retail order imbalance trades. Please refer to Section 2 for detailed construction method.

Appendix B: Convolutional Neural Networks

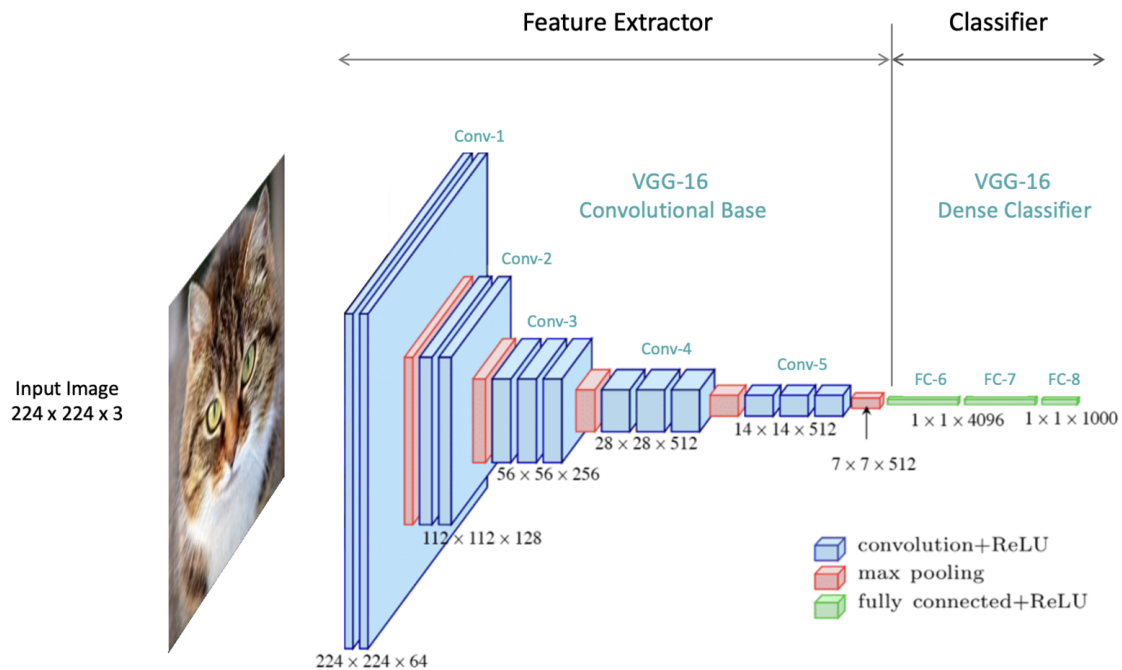


Figure 1: Illustration of the VGG CNN Model. (Source: Learnopencv.com)

In this section, we review details of the Convolutional Neural Network (CNN or ConvNet) and transfer learning models. One limitation of neural networks is that they do not explicitly consider the grid topology or variable dependency, and so fail to model complex interactions between predictors in our context. To overcome this challenge, we apply the CNNs as a feature extractor. CNNs have been tremendously successful in applications ranging from image to text classifications. The CNN architecture we used consists of an *input layer* that takes the pixels of the image into its nodes, one or more *convolutional layers* that utilize the convolution operator to model the complicated nonlinear interactions between the input pixels and generate intermediate features that capture progressively higher-level information from the image (such as shapes and objects), one or more *batch normalization layers* and *max-pooling layers* that reduce the computation time, extract the local dependency across predictors and yield a robust model, and a final *fully connected layer* and *output layer* to

finish the classification and makes prediction for the category the image belongs to. Figure 1 provides an illustration of the VGG-16 CNN network, on which our final model is based.

Convolutional Layer. Based on the input image block $A_{i,j}$, the convolutional layer applies the convolution operator to generate the intermediate features as follows:

$$c_{i,j} = \sigma(W^{conv} * A_{i,j} + b^{conv}), \quad (\text{A1})$$

where $\sigma(\cdot)$ is the ReLU activation function, W^{conv} and b^{conv} respectively represent the weight of the filter and the bias, and $*$ is the convolution operator.

Max-Pooling Layer. The pooling operation replaces the output $c_{i,j}$ of the convolutional layer at a certain location with a summary statistic of the nearby neighborhood. The max-pooling operation reports the maximum output within a rectangular neighborhood,

$$m_{i,j} = \max(c_{k,l}), \quad k = i - 1, i, i + 1; \quad l = j - 1, j, j + 1; \quad (\text{A2})$$

Fully Connected Layer. The output $M = [m_{i,j}]$ from the max-pooling layer is flattened and concatenated with a vector of text input into a vector F , which is further transformed in the fully connected (FC) layer,

$$fc^k = \sigma(W_k^{fc} F + b_k^{fc}), \quad k = 1, \dots, K \quad (\text{A3})$$

where $\sigma(\cdot)$, W_k^{fc} , b_k^{fc} , and K represents the ReLU function, input weights, biases and the number of classification categories. The nonlinearity introduced by the fully connected layer further enhances the model’s ability to learn the internal nonlinearity and to generate better prediction results.

Output Layer. The final output layer consists of K neurons, which represent the probability of each category. Based on the output of the fully connected layer $fc = [fc^1, \dots, fc^K]$,

the softmax activation function yields

$$p(k) = \text{Softmax}(W_k f c + b_k), \quad k = 1, \dots, K \quad (\text{A4})$$

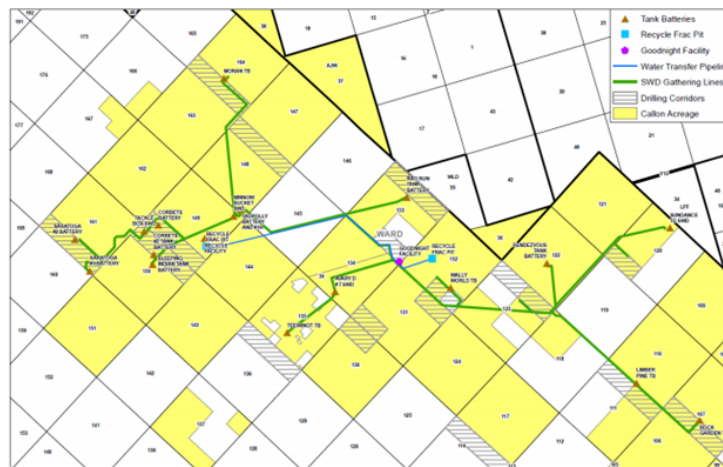
Transfer CNN. The weights of the CNN network need to be estimated using the training data. When the number of observations is large enough, the neural network can learn and produce a model with high accuracy. When the data size is not sufficiently large, it is possible for the model to "learn" from similar image classification problems. We refer to the CNN model that was learned by combining the knowledge learned from our data and other existing data sets as the *Transfer CNN* model. The basic premise of transfer learning is simple: take a model trained on a large data set and transfer its knowledge to a smaller data set. For our specific training task, we build on the pre-trained VGG16 ([Simonyan and Zisserman, 2014](#)) using ImageNet data ([Deng et al., 2009](#)), by keeping the network structure and the trained parameters from all the layers except the fully connected layer. That is, we train a VGG16 network by treating only the parameters in the fully connected layer as unknown.

Appendix C: Examples of Visual Information

Operations Forward



MAJOR PROJECTS



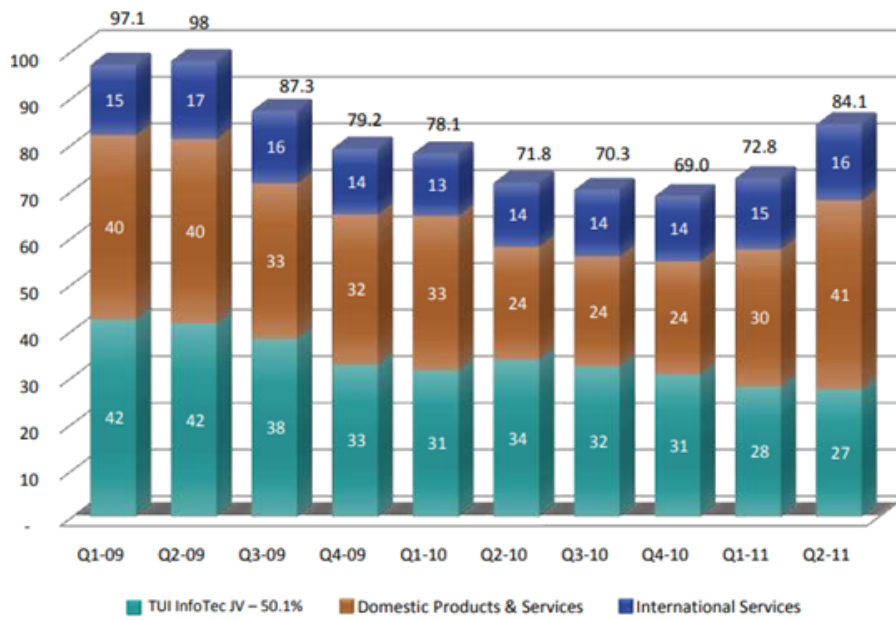
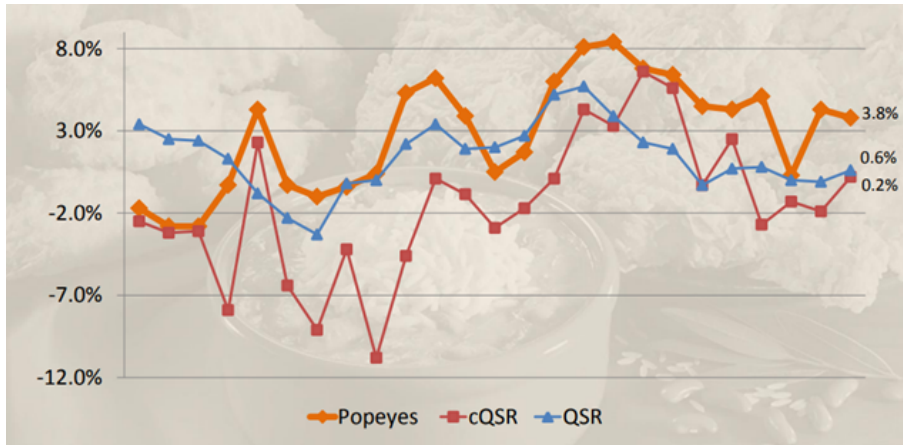
Operations Summary



► Taipei's 101 Mall



Others



Appendix D: AI Labor Stock Estimation

Step 1: Identify AI-related Skills

We first identify AI-related skills following Babina et al. (2021). Intuitively, jobs requiring a certain ability related to AI should also require other core AI skills, and a skill that frequently co-occurs with unambiguous core AI skills might be related to AI. The calculation method is summarized as follows. We start by creating a sample of job postings that require four core AI skills—"Machine Learning," "Natural Language Processing," "Computer Vision," and "Artificial Intelligence." We then measure the AI-relatedness of any given skill as the fraction of job postings requiring that skill, as well as four AI skills mentioned to the total number of job postings requiring that skill. Specifically, for each skill s , the AI-relatedness w of that skill is:

$$w_s^{AI} = \frac{\# \text{ of jobs with skill } s \text{ and } \{AI, ML, NLP, \text{ or } CV\} \text{ in job title or in skills}}{\# \text{ of jobs with skill } s} \quad (\text{A5})$$

Step 2: Identify AI-related Job Postings

After identifying AI-related skills, we calculate AI-relatedness for each job posting by taking the average of the AI-relatedness of the skills associated with that job posting. This gives us a continuous AI-relatedness measure (ranging from 0 to 1) for each job posting. Specifically, letting N denote the number of required skills listed for job posting j , our job-level AI-relatedness measure is:

$$w_j^{AI} = \frac{1}{N} \sum_{s=1}^N w_s^{AI}. \quad (\text{A6})$$

Step 3: AI-relatedness for Institutions

After obtaining AI-relatedness for each job posting, we calculate AI-relatedness at the institution-year level. To be specific, for institution i in year t , its AI-relatedness is the number of AI-related job postings posted by the institution scaled by the total number of

job postings:

$$p_{i,t}^{AI} = \frac{1}{K} \sum_{j=1}^K 1_j(w_j^{AI} > \varphi), \quad (\text{A7})$$

where φ is the cutoff for whether a job is AI job.¹⁴ We conduct fuzzy name matching complemented with manual verification to match Burning Glass institutions to Thomson Reuters 13F institutions.¹⁵

Step 4: Accumulated AI Labor Stock

We estimate accumulated AI labor stock following a similar method to [Abis and Veldkamp \(2020\)](#). First, we use data from the Bureau of Labor Statistics to estimate the probability that a vacancy is filled and the probability that an employed worker separates from their job.¹⁶ Then we calculate the labor stock as follows, for institution-year (i, t) ,

$$l_{i,t}^{AI} = l_{i,t-1}^{AI} (1 - s_t^{AI}) + p_{i,t}^{AI} \times h_t^{AI}, \quad (\text{A8})$$

where $l_{i,t}^{AI}$ is the AI labor stock, s_t^{AI} and h_t^{AI} are the separation rate and vacancy fill rate for the financial services sector¹⁷, and $p_{i,t}^{AI}$ is the AI-relatedness calculated in Step 3. For example, if fund A has 20 AI employees in year 2016, and it posts 10 AI job postings in year 2017, with the estimated average separation rate of 0.1 and hiring rate of 0.6, then fund A's AI labor stock in 2017 is calculated as $20 \times (1 - 0.1) + 10 \times 0.6 = 24$.

¹⁴Intuitively, a higher cutoff imposes stricter criteria for AI jobs. In our main analysis, we set φ to 0.1.

¹⁵We keep asset management companies with type code = 3, 4, 5 in TR 13F data for our main analysis. Approximately 30% of TR 13F institutions can be matched to Burning Glass in our sample.

¹⁶Data are available at <https://www.bls.gov/jlt/#data>.

¹⁷Finance and Insurance (NAICS 52) industry according to the BLS classification.

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Figure 2: Time Series of Corporate Presentations

This figure plots the annual number of presentations (as the bar plots and corresponding to the left axis) and the ratio of the number of presentations with *Operations Forward* images to the number of all presentations (as the line plot and corresponding to the right axis) in our sample from 2006 to 2018. A presentation contains *Operations Forward* images if any slide in the presentation is classified to the *Operations Forward* category.

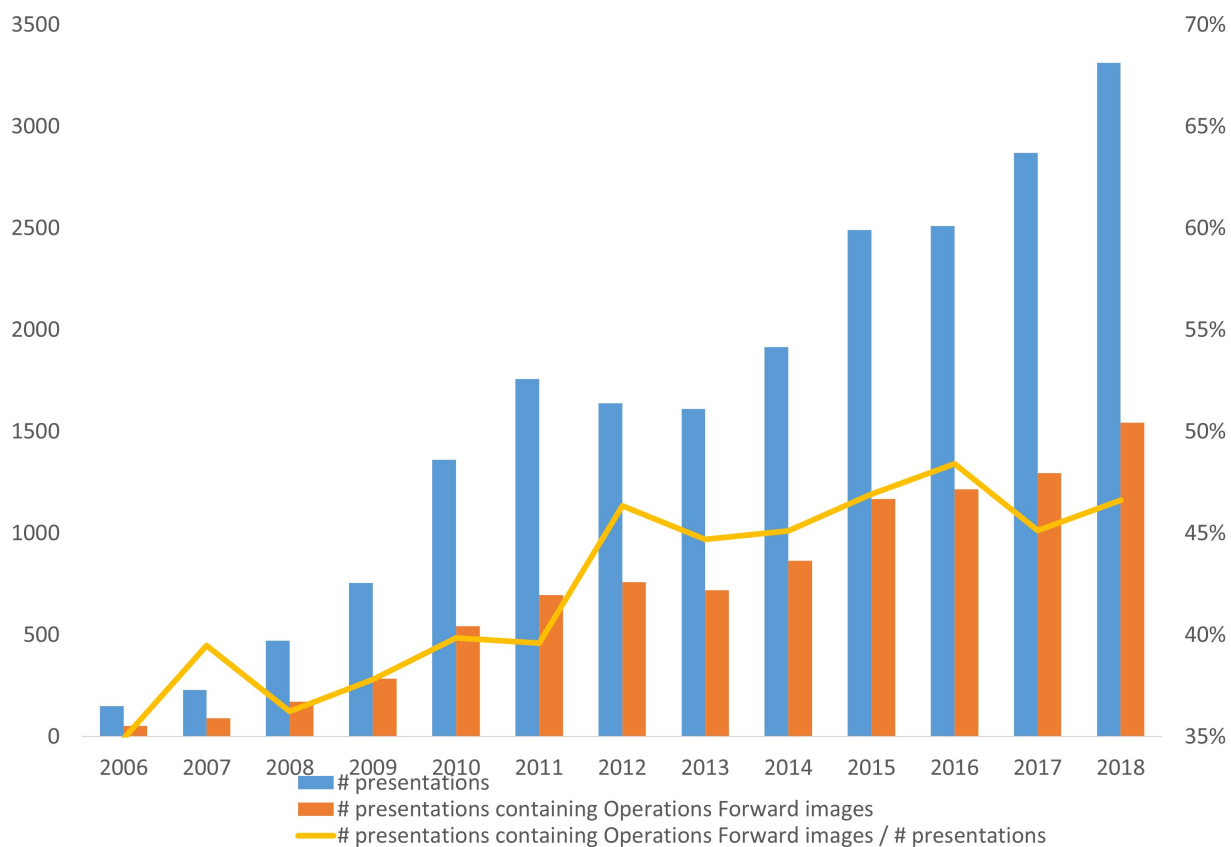


Figure 3: Monthly Distribution of Corporate Presentations

This figure plots the distributions of presentation dates and 10-K/10-Q filing dates in the calendar months.

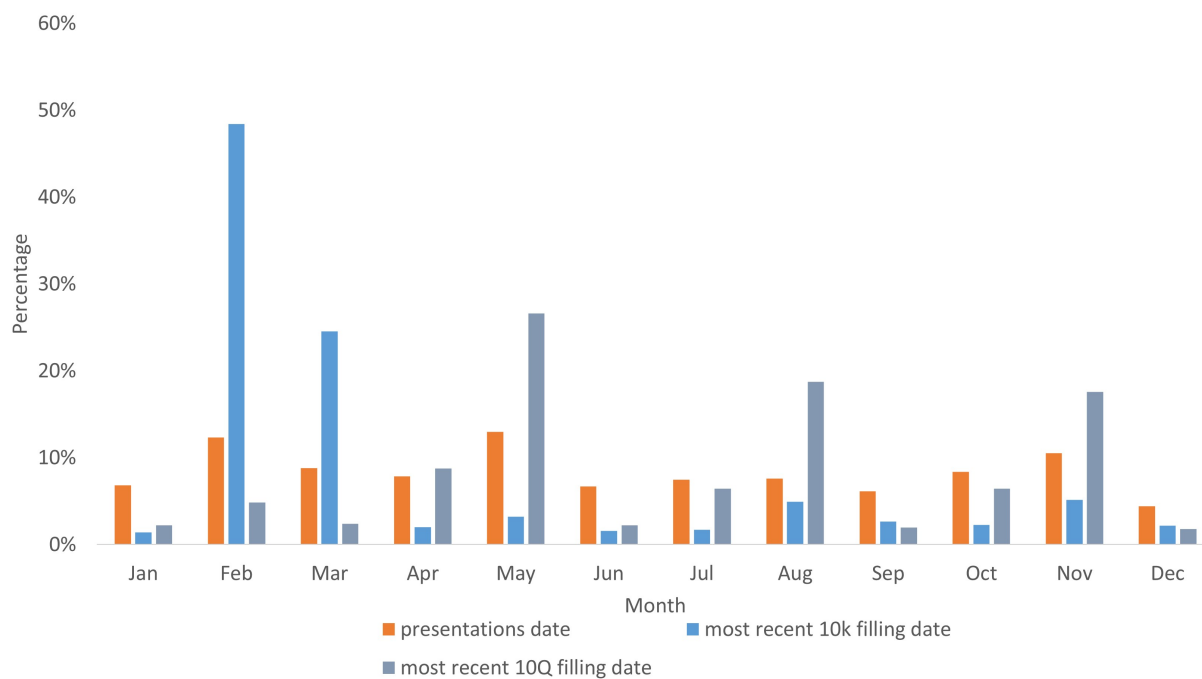


Table 1: Performance of Machine Learning Models

This table summarizes the performance of different machine learning methods to identify and classify corporate image information. We report the out-of-sample performance calculated by the ten-fold cross-validation method. *Accuracy* is one minus the ratio of incorrect category predictions to total observations. For each category, *Precision* is the ratio of true positives to the sum of true positives and false positives; *Recall* is the ratio of true positives to the sum of true positives and false negatives. We calculate *Precision* and *Recall* for each category and then average across the three categories. *F1 Score* is the harmonic mean of *Precision* and *Recall*. Model parameters are selected to maximize the *F1 score* in cross-validation.

Model	<i>CNN</i> (%)	<i>CNN + Text</i> (%)	<i>Transfer CNN</i> (%)	<i>Transfer CNN + Text</i> (%)
<i>Accuracy</i>	75.0	76.5	77.0	80.0
<i>Precision</i>	77.3	70.7	77.5	78.9
<i>Recall</i>	75.0	76.5	77.0	80.0
<i>F1 Score</i>	76.1	73.5	77.2	79.4

Table 2: Summary Statistics

This table presents the descriptive statistics of key variables used in the paper. Panel A reports the statistics for presentation-level variables (i.e., variables constructed using information in slides); Panel B reports the statistics for firm-level variables. All variables are defined as in [Appendix A](#). *AI Inst. Ownership* is constructed as in [Section 2](#).

<i>Variables</i>	Mean	Median	Std	P25	P75	N
Panel A: Presentation-level Variables						
<i>Operations Summary</i>	0.110	0.075	0.122	0.000	0.167	17,277
<i>Operations Forward</i>	0.036	0.000	0.058	0.000	0.056	17,277
<i>Positive Sentiment</i>	0.014	0.012	0.008	0.009	0.017	17,277
<i>Negative Sentiment</i>	0.012	0.011	0.005	0.008	0.014	17,277
<i>Uncertainty</i>	0.010	0.009	0.006	0.006	0.013	17,277
<i>Constrained</i>	0.003	0.003	0.002	0.001	0.004	17,277
<i>Forward Looking</i>	0.043	0.040	0.019	0.030	0.053	17,277
<i>Text Length</i>	3088	2480	2381	1586	3864	17,277
Panel B: Firm-level Variables						
<i>Size</i>	13.10	3.12	30.33	1.08	10.48	17,277
<i>Book-to-market</i>	0.615	0.529	0.421	0.306	0.833	17,277
<i>Prior Return</i>	0.000	0.000	0.001	-0.000	0.001	17,277
<i>Nasdaq</i>	0.311	0.000	0.463	0.000	1.000	17,277
<i>Turnover</i>	1557	1268	1213	8721	1888	17,277
<i>Inst. Ownership</i>	0.775	0.819	0.200	0.705	0.914	17,277
<i>AI Inst. Ownership</i>	0.377	0.380	0.134	0.298	0.457	17,277

Table 3: Top Industries by Operations Forward

This table lists the top ten 2-digit SIC industries with forward-looking operational information. In Panel A, industries are ranked by the number of presentations with at least one *Operations Forward* slide, scaled by the number of all types of presentations. In Panel B, industries are ranked by the industry average of the variable *Operations Forward*, which is the number of slides in this category relative to the total number of slides. We exclude industries with fewer than 50 presentations in the sample.

Panel A: Top 10 industries by proportion of *Operations Forward* presentations

SIC2	Name	% of <i>Operations Forward</i> Presentations
10	Metal, Mining	78%
13	Oil & Gas Extraction	78%
45	Transportation by Air	72%
51	Wholesale Trade (non-durable Goods)	71%
31	Leather & Leather Products	59%
79	Amusement & Recreation Services	58%
49	Electric, Gas, & Sanitary Services	57%
23	Apparel & Other Textile Products	55%
55	Automotive Dealers & Service Stations	53%
20	Food & Kindred Products	53%

Panel B: Top 10 industries by average proportion of *Operations Forward* slides

SIC2	Name	Average <i>Operations Forward</i>
10	Metal, Mining	8.7%
40	Railroad Transportation	8.3%
13	Oil & Gas Extraction	7.8%
44	Water Transportation	7.7%
16	Heavy Construction, Except Building	6.9%
45	Transportation by Air	6.5%
51	Wholesale Trade (non-durable Goods)	5.9%
32	Stone, Clay, & Glass Products	5.6%
33	Primary Metal Industries	5.2%
20	Food & Kindred Products	5.0%

Table 4: Visual Information and Market Response

This table examines the relation between visual information in corporate presentation slides and announcement returns. The dependent variables are *Cumulative Announcement Returns* in different windows, where returns are adjusted by *Market*, *Size*, and *Book-to-Market*. The sample period is from 2006 to 2018. *Operations Forward* and *Operations Summary* measure the forward-looking operational visual information and backward-looking operational visual information in presentation slides. All variables are defined as in [Appendix A](#). Industries are defined by 2-digit SIC codes. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the firm level. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tailed), respectively.

Dependent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		<i>CAR</i> (-3,3)			<i>CAR</i> (-2,2)			<i>CAR</i> (4,13)	
<i>Operations Forward</i>	0.027** (0.014)	0.024* (0.014)	0.030* (0.016)	0.020 (0.013)	0.021* (0.013)	0.025* (0.014)	-0.016 (0.011)	-0.016 (0.011)	-0.019 (0.013)
<i>Operations Summary</i>	-0.009 (0.008)	-0.009 (0.008)	-0.005 (0.008)	-0.003 (0.006)	-0.002 (0.007)	-0.003 (0.008)	0.005 (0.006)	0.005 (0.006)	0.002 (0.007)
<u>Controls Variables</u>									
<i>Positive Sentiment</i>	0.685*** (0.145)	0.613*** (0.154)	0.606*** (0.151)	0.649*** (0.121)	0.580*** (0.129)	0.565*** (0.138)	-0.280 (0.177)	-0.280 (0.177)	-0.405*** (0.129)
<i>Negative Sentiment</i>	-0.449** (0.204)	-0.300 (0.203)	-0.299 (0.196)	-0.391** (0.194)	-0.277 (0.193)	-0.277 (0.180)	0.286* (0.161)	0.286* (0.161)	0.506*** (0.169)
<i>Uncertainty</i>	0.179 (0.158)	0.028 (0.159)	0.029 (0.160)	-0.057 (0.143)	-0.167 (0.146)	-0.164 (0.148)	0.289** (0.118)	0.289** (0.118)	0.269* (0.138)
<i>Constrained</i>	0.139 (0.336)	-0.054 (0.355)	-0.066 (0.400)	0.085 (0.305)	-0.004 (0.323)	-0.014 (0.368)	-0.134 (0.296)	-0.134 (0.296)	-0.044 (0.344)
<i>Forward-Looking</i>	-0.154** (0.060)	-0.126** (0.063)	-0.130* (0.070)	-0.164*** (0.056)	-0.143** (0.058)	-0.146** (0.064)	-0.024 (0.047)	-0.024 (0.047)	0.024 (0.060)
<i>Text Length</i>	0.000 (0.002)	0.000 (0.002)	0.000 (0.001)	-0.001 (0.001)	0.000 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)

(continued)

Dependent Variables	(1)	(2) <i>CAR(-3,3)</i>	(3)	(4)	(5) <i>CAR(-2,2)</i>	(6)	(7)	(8) <i>CAR(4,13)</i>	(9)
<i>Size</i>	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.002*** (0.000)	-0.002*** (0.001)	-0.002*** (0.001)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
<i>Book-to-Market</i>	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.001)	0.002* (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.002** (0.001)
<i>Turnover</i>	0.000 (0.002)	0.003 (0.002)	0.003* (0.002)	-0.001 (0.002)	0.002 (0.002)	0.002 (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
<i>Nasdaq</i>	-0.001 (0.002)	-0.002 (0.002)	-0.002 (0.002)	0.002 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.003* (0.002)	-0.003* (0.002)	-0.001 (0.002)
<i>InstOwnership</i>	0.005 (0.006)	-0.002 (0.006)	-0.002 (0.005)	0.011** (0.005)	0.003 (0.006)	0.003 (0.005)	-0.002 (0.004)	-0.002 (0.004)	-0.005 (0.005)
<i>Prior Return</i>	-1.328 (1.199)	-1.531 (1.188)	-1.532** (0.714)	-2.053** (1.029)	-2.106** (1.027)	-2.104*** (0.657)	-0.475 (0.819)	-0.475 (0.819)	0.006 (0.614)
<i>Textual Operations Forward</i>			0.001 (0.013)			-0.002 (0.012)			-0.026 (0.022)
<i>Textual Operations Summary</i>			0.002 (0.004)			0.002 (0.004)			-0.005 (0.004)
Industry FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,326	17,277	17,273	17,326	17,277	17,273	17,275	17,275	17,271
R-squared	0.009	0.016	0.013	0.009	0.016	0.013	0.017	0.019	0.019

Table 5: Visual Information and Future Cash Flows

This table reports the relation between visual information in corporate presentation slides and firms' future cash flows. Panels A and B examine whether visual information can predict *Earnings* and *Sales*, respectively. *Operations Forward* and *Operations Summary* measure the forward-looking operational visual information and backward-looking operational visual information in presentation slides. We include the same set of control variables as in Table 4. All variables are defined as in Appendix A. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the firm level. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tailed), respectively.

Panel A: Visual Information and Earnings					
	(1)	(2)	(3)	(4)	(5)
	1st Qtr	2nd Qtr	3rd Qtr	4th Qtr	2nd Year
<i>Operations Forward</i>	-0.002 (0.004)	0.002 (0.005)	0.003 (0.004)	0.008** (0.004)	0.032* (0.017)
<i>Operations Summary</i>	0.006*** (0.002)	0.002 (0.002)	0.005 (0.003)	-0.002 (0.002)	0.002 (0.008)
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	16,884	16,808	16,722	16,134	13,129
Adjusted R-squared	0.521	0.476	0.602	0.626	0.715
Panel B: Visual Information and Sales					
	(1)	(2)	(3)	(4)	(5)
	1st Qtr	2nd Qtr	3rd Qtr	4th Qtr	2nd Year
<i>Operations Forward</i>	0.003 (0.007)	0.009 (0.01)	0.008 (0.008)	0.022*** (0.008)	0.125*** (0.042)
<i>Operations Summary</i>	0.009** (0.004)	0.000 (0.005)	0.008 (0.005)	-0.001 (0.004)	0.025 (0.021)
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	17,230	17,192	17,131	16,539	13,562
Adjusted R-squared	0.965	0.952	0.959	0.967	0.955

Table 6: Visual Information and Analyst Revision

This table presents regression results for the relation between analyst revision and visual information in corporate presentation slides. *Revision Direction* is equal to 1 (-1) if the analyst revises up (down) the forecast after the focal presentation date and before the subsequent earning announcement date, and *Revision Change* is the change in forecasted earnings for such a revision. The independent variables of main interest are *Operations Forward* and *Operations Summary*, which measure the forward-looking operational visual information and backward-looking operational visual information in presentation slides. We include the same set of control variables as in Table 4. All variables are defined as in Appendix A. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the firm level. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tailed), respectively.

Dependent Variables	(1) <i>Revision Direction</i>	(2)	(3) <i>Revision Change</i>	(4)
<i>Operations Forward</i>	0.419*** (0.085)	0.655*** (0.081)	0.393*** (0.121)	0.366*** (0.117)
<i>Operations Summary</i>	0.211*** (0.045)	0.281*** (0.043)	0.104* (0.062)	0.106* (0.060)
<u>Controls Variables</u>				
<i># of Prior Forecasts</i>	-2.343*** (0.160)	-2.588*** (0.121)	-4.654*** (0.225)	-4.664*** (0.168)
<i>General Experience</i>	0.001** (0.000)	0.001 (0.000)	0.000 (0.001)	0.000 (0.001)
<i>Industry Experience</i>	-0.003*** (0.000)	-0.002*** (0.000)	0.000 (0.001)	0.000 (0.001)
<i>Firm Experience</i>	-0.007*** (0.000)	-0.007*** (0.000)	-0.006*** (0.000)	-0.006*** (0.000)
<i>Star Analyst</i>	0.054 (0.070)	0.034 (0.070)	-0.001 (0.102)	-0.023 (0.106)
<i>Brokerage Size</i>	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Observations	337,953	337,953	337,944	337,944
Adjusted R-squared	0.411	0.409	0.643	0.640

Table 7: Visual Information and Institutional Trades

This table examines the relation between institutional holding change and visual information in corporate presentation slides. *AI Inst. Trade* and *Non-AI Inst. Trade* are changes in aggregate institutional holdings for AI-equipped and non-AI-equipped financial institutions, defined in Section 3.2. We restrict our sample to events from 2010 to 2018 due to limited data coverage in Burning Glass before 2010. The independent variables of main interest are *Operations Forward* and *Operations Summary*, which measure forward-looking operational visual information and backward-looking operational visual information in presentation slides. We include the same set of control variables as in Table 4. We also control for *Aggregate Institutional Ownership* of the stock and *# of Institutions* holding the stock. All variables are defined in Appendix A. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the firm level. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tailed), respectively.

Dependent Variables	(1) <i>AI Inst. Trade</i>	(2) <i>AI Inst. Trade</i>	(3) <i>Non-AI Inst. Trade</i>	(4) <i>Non-AI Inst. Trade</i>
<i>Operations Forward</i>	0.011** (0.005)	0.012** (0.006)	-0.001 (0.004)	-0.001 (0.004)
<i>Operations Summary</i>	0.003 (0.003)	-0.001 (0.003)	0.002 (0.003)	0.002 (0.003)
Controls	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	15,850	15,850	15,850	15,850
Adjusted R-squared	0.001	0.003	0.001	0.003

Table 8: Visual Information and Marketable Retail Order Imbalance

This table reports the results on the relation between marketable retail order imbalance and visual information in corporate presentation slides. In Panel A, the dependent variable is the marketable retail order imbalance calculated based on the number of shares traded; in Panel B, the dependent variable is the marketable retail order imbalance calculated based on the number of trades. Detailed definitions are given in Section 2. *Operations Forward* and *Operations Summary* measure the forward-looking operational visual information and backward-looking operational visual information in presentation slides, respectively. We include the same set of control variables as in Table 4. All variables are defined in Appendix A. Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the firm level. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tailed), respectively.

Panel A: Marketable Retail Trade Imbalance based on # of Shares Traded								
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Window	[-3,3]		[-3,14]		[-3,30]		[-3,90]	
<i>Operations Forward</i>	0.028 (0.043)	0.029 (0.043)	0.022 (0.036)	0.023 (0.036)	0.039 (0.027)	0.040 (0.027)	0.033 (0.023)	0.033 (0.023)
<i>Operations Summary</i>	-0.028 (0.021)	-0.029 (0.021)	-0.009 (0.018)	-0.010 (0.018)	0.006 (0.016)	0.006 (0.016)	0.004 (0.012)	0.005 (0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,531	9,503	9,550	9,522	9,551	9,523	9,531	9,503
Adjusted R-squared	0.001	0.001	0.002	0.002	0.004	0.004	0.001	0.001

Panel B: Marketable Retail Trade Imbalance Trades based on # of Trades								
Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Window	[-3,3]		[-3,14]		[-3,30]		[-3,90]	
<i>Operations Forward</i>	0.024 (0.039)	0.024 (0.039)	0.062 (0.031)	0.063 (0.036)	0.057 (0.038)	0.057 (0.038)	0.047 (0.043)	0.048 (0.043)
<i>Operations Summary</i>	-0.014 (0.018)	-0.015 (0.018)	-0.010 (0.016)	-0.001 (0.016)	-0.015 (0.012)	-0.014 (0.013)	0.002 (0.010)	0.002 (0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,531	9,503	9,550	9,522	9,551	9,523	9,531	9,503
Adjusted R-squared	0.001	0.001	0.002	0.002	0.008	0.008	0.015	0.015

Table 9: Visual Information, Announcement Returns, and AI Institutional Ownership

This table examines how the relation between visual information and announcement return depend on the *AI Institutional Ownership* of stocks. High and low *AI Inst. Ownership* stocks are determined by the cross-sectional annual average of *AI Inst. Ownership* in the year of presentation. The independent variables of main interest are *Operations Forward* and *Operations Summary*, which measure the forward-looking operational visual information and backward-looking operational visual information in presentation slides. We include the same set of control variables as for Table 4. All variables are defined in [Appendix A](#). Heteroskedasticity-consistent standard errors (in parentheses) are clustered at the firm level. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tailed), respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>High AI Inst. Ownership</i>				<i>Low AI Inst. Ownership</i>			
Dependent Variables	<i>Car(-3, 3)</i>		<i>Car(4, 13)</i>		<i>Car(-3, 3)</i>		<i>Car(4, 13)</i>	
<i>Operations Forward</i>	0.038**	0.035**	-0.019	-0.005	0.002	0.005	-0.006	-0.02
	(0.017)	(0.017)	(0.017)	(0.018)	(0.025)	(0.025)	(0.019)	(0.020)
<i>Operations Summary</i>	0.006	0.008	0.005	0.005	-0.021	-0.020	0.006	-0.001
	(0.009)	(0.009)	(0.009)	(0.009)	(0.013)	(0.013)	(0.011)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,773	7,752	7,771	7,750	7,780	7,763	7,775	7,750
Adjusted R-squared	0.018	0.034	0.026	0.046	0.009	0.02	0.01	0.028