Seeing is Believing: Annual Report "Graphictiy" and Stock Returns

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ABSTRACT

Why do firms graphically enhance their annual reports that appear redundant to the 10-Ks? We develop a novel rational model to explain this. Using a large dataset, we report the first evidence that firms earn approximately 3.5% abnormal returns in the next 3 to 6 months after they initiate graphic annual reports. This is accompanied by an increase in institutional investors' holdings, consistent with our theory that firms create visuals to overcome investor inattention and help communicate subtle information to fundamental investors. This is also consistent with the fact that such firms tend to increase their R&D investments afterwards.

Keywords: Graphic Annual Reports, Attention, Fundamental Strategy, Anomaly, Big Data

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Companies find ways to keep their annual reports from being a bore. Videos, graphics and other elements can provide information in ways that engage and go beyond what regulators request. Wall Street Journal, 3/3/2020

As perhaps the most important financial document for investors, the annual report of a public firm has two versions: one is the mandatory electronic 10-K filing with the U.S. Securities and Exchange Commission (SEC), the other is the user-friendly annual report available on the firm website or delivered to investors. Under the SEC Regulation S-T, there should be no material differences between the two versions, although the latter version can be customized by including large, colorful graphics which are generally absent in the plain 10-Ks.[1] In fact, more than half of the firms listed in the S&P 1500 are releasing such *graphic annual reports*. This raises an economic puzzle: why are so many companies producing aesthetically designed annual reports if they are informationally redundant to the plain 10-Ks?

At first glance, the added visuals in annual reports seem to be cosmetic and marketing-oriented.[2] If so, they should have little impact on stock valuations or perhaps only trigger some short-term sentiment and noise trading. On second thought, it is plausible that those appealing graphics may help deliver certain information not visible in the plain 10-Ks.[3] Visuals can not only draw investors' attention but also help them comprehend subtle information in the business world. This paper reports the first theoretical and empirical study on the value of information directly associated with the graphics in firms' annual reports. Financial research on graphics seem in its infancy. To the best of our knowledge, Obaid and Pukthuanthong (2021) provide the only other study on how news media photos affect investor sentiment and stock returns. In comparison with their pioneer work, we study the graphics in firm annual reports which arguably contain the most fundamental information. Moreover, we provide a rational theory to understand why they emerge in the first place.

Theoretically, we develop a simple model which is sufficient to explain the phenomena and formulate three testable predictions. Our model is inspired by the seminal framework of Kyle (1985),[4] but relaxes a critical assumption that all public information has been fully incorporated by all market participants. We assume that some extra value or payoff of a firm is too subtle to be conveyed effectively and thus slips most traders' minds (in light of the literature on investor inattention, e.g., Hirshleifer and Teoh (2003), Peng and Xiong (2006),

[1] See Section I for the institutional background and Internet Appendix A for more details.

[2] Regulators may view them as "glossy"; see, for example, `https://www.sec.gov/files/reada10k.pdf`.

[3] Regulation S-T Rule 304(b) requires firms to disclose in their electronic filings any graphic elements contained in their annual reports delivered to investors. However, "a good faith effort" is acceptable, which may leave room for extra subtle information embedded in graphic annual reports but not visible in 10-Ks.

[4] Among others, our model setup is perhaps most closely related to Holden and Subrahmanyam (1992).

Barber and Odean (2008), Hou, Xiong, and Peng (2009), Da, Engelberg, and Gao (2011), Lou (2014), and Alldredge and Cicero (2015)). Consequently, the stock can be undervalued, motivating the firm manager to put efforts for more creative communication. Some attentive investors may notice this change and do research on the subtle information (called alpha). It is uncertain who may discover and capitalize this alpha. Based on rational expectations, the manager chooses to act only when the expected alpha is above an endogenous threshold.[5] On average, this can lead to positive abnormal returns subsequent to the manager's efforts (as measured by the surge of graphics in annual reports). When the expected alpha is below the threshold, the manager chooses inaction (as reflected by the cease of issuing graphic reports), which catches no one's attention and promotes no research or discovery of alpha. Our model predicts that if there is no speculative trading on the manager's information-driven choice and if the extra information is identified and processed by fundamental investors, then there will be an apparent delay in stock price reactions. Thus, a finding of delayed anomaly can suggest that the return predictability of graphic annual reports is novel to the market.

Empirically, we collect the annual reports of 1,879 companies from 1994 to 2019. In order to test the theoretical predictions, we customize a machine-learning algorithm to quantify the use of graphics in each annual report. After processing 4.9 million pages of reports and 2.5 million images, our program returns 378,172 image files that have strong visual impacts in terms of colors and sizes. We find that firms experience approximately 3.5% abnormal returns in 3 to 6 months after they switch to releasing graphic reports. The market response shows a delay of at least one month which may be the amount of time it takes investors to identify and process the extra information hinted in graphic reports. We also find that those firms increase their R&D expenditures in the following years, consistent with our theory that the initiation of graphic reports may indicate the presence of new fundamental information. Such information appears subtle and suggestive, calling for humans rather than machines. In this regard, the observed positive abnormal returns can reflect the merit of fundamental analysis (Sloan (2019)), in spite of the wide popularity of quantitative trading nowadays.

In summary, this paper demonstrates the predictive power of a non-textual, highly unstructured dataset — the graphics embedded in firms' annual reports. These graphics turn out to be a valuable source of financial information overlooked by most market participants. Interestingly, they seem to appeal to fundamental investors who may receive some visual hints useful for analysis. Our model not only explains the economic puzzle raised at the beginning, but also validates the novelty of our empirical findings.

[5]This is also related to the literature on voluntary disclosures, following the seminal works of Grossman (1981), Milgrom (1981), Verrecchia (1983, 1990, 2001), Diamond (1985), and Diamond and Verrecchia (1991). Our model focuses on the relationship between firm communication efforts and abnormal stock returns.

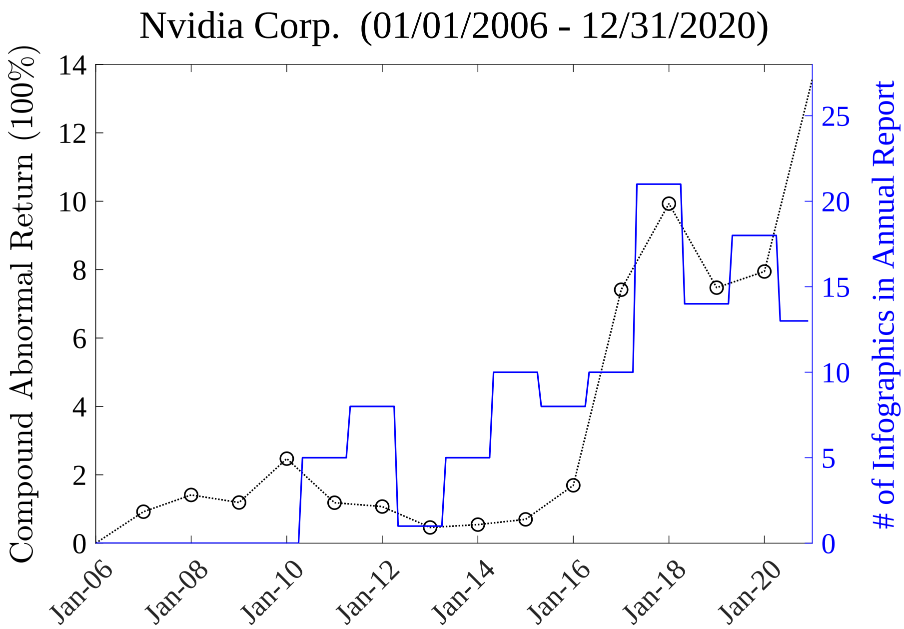

Figure 1. The compound abnormal returns of Nvidia's stock (dashed line) versus the numbers of infographics embedded in its annual reports (solid line) from 2006 to 2020.

As an anecdotal example, Nvidia Corp., the industry leader in developing graphics processing units (GPUs), has started releasing image-rich annual reports ever since 2010, and prior to that, it simply used the plain 10-Ks in its annual reports. Some of their cover pages are provided in the Internet Appendix that accompanies this paper. Figure 1 shows Nvidia's compound abnormal returns[6] versus the numbers of infographics in its annual reports from 2006 to 2020. We exclude uninformative images such as logos and headshots. Graphics that relate to the firms' products and services or that illustrate the firm performance and executive compensations are counted as infographics; the Internet Appendix provides exhibitions of both types. The surge of infographics in Nvidia's reports preceded its accelerated equity growth in recent years. This brings a general conjecture, consistent with our theory, that the abrupt, substantial use of graphics in a firm's annual report may forecast its stock returns.

While our model explains why firms may engage in producing graphic reports, it is of interest to understand why graphics can have impacts on investors. There are two important channels. The first one is about the comprehension of information. Cognitive studies show that the graphic representations of information appeal to humans much more than the textual forms; see Larkin and Simon (1987), Kosslyn (1989), Pinker (1990), Stenning and Oberlander

[6]This is estimated by the CAPM model. We use the CRSP data of Nvidia's betas (with the Nasdaq index as the benchmark portfolio) to calculate its annual excess returns which are then compounded over time.

(1995), and Roth and Bowen (2003), among others. In general, there are unique advantages of using graphics, as they can catch eyeballs, enhance memory, improve understanding, and transcend language. This can explain why data visualization has gained immense popularity across different fields[7] and also why graphic presentations can benefit investors.

The second channel is about learning capacity. "*The average investor is confused and overburdened by the volume and detail of the annual report, unable to comprehend its complexities and jargon, and unable to use all of the information contained in the annual report.*" (Hawkins and Hawkins (1986), p.20). Visuals can solve the problem by quickly engaging the audience and organizing their attention to the key takeaways. In the business world, it is intrinsically difficult to quantify or textualize various types of information. For example, the prospect of a new product may not be well reflected by its performance numbers or technical description. The picture may instead be better painted by its novel applications. One example is Nvidia's GPUs which enabled a major breakthrough in HIV research. Perilla and Klaus (2017) simulated the HIV capsid on a supercomputer with 3880 GPU-accelerated nodes and published their finding in *Nature*. This fact was weaved into Nvidia's annual report, together with *Nature*'s cover page that features a 3D art of the HIV particle (see Appendix D). It can quickly direct audience attention to an impressive application. Moreover, visuals can convey implicit messages that exert subtle influences. They may enable managers to hint at hidden strengths or intangible assets not yet reflected in the financial statements. For all the above reasons, we postulate that when firm managers intend to convey subtle information beyond words and numbers, they will preferentially use graphic presentations.

In order to formally test our model predictions, we divide our sample into three groups: (1) firms that switch to publishing graphic annual reports, (2) firms that do not change their reporting formats relative to the previous year, and (3) firms that just stop issuing graphic reports. For example, Nvidia's first graphic report in 2010 makes it enter the first group in that year, whereas Nvidia joins the second group in 2011 and afterwards (see Figure 1). We examine the abnormal returns for each group of firms around their report release dates. The first group of firms experience significant abnormal returns, approximately 3.5 percent, at an intermediate horizon of three to six months at the time when available. In contrast, the other two groups of firms do *not* show any statistically significant abnormal returns. Our finding is robust to different return measures and to various market or firm characteristics. Combined with our model, these results demonstrate the critical role of graphics in triggering this anomaly and also confirm the informational motive of firms issuing graphic reports.

[7] See, for example, Tufte (1985), Friel, Curcio, and Bright (2001), Kastellec and Leoni (2007), Healey and Enns (2011), Smiciklas (2012), Schwabish (2014), among others.

Interestingly, the extra information takes one to two quarters to be well incorporated into prices. To investigate when the stock price reaction starts, we conduct an event study around the report release dates. The cumulative abnormal returns are not significant over daily event windows or for post-event windows of at least 20 trading days. Combined with our model, this result suggests that the informational motive of firms initiating graphic reports is not anticipated or exploited by speculators. Instead, the abnormal returns that show up later should be caused by the delayed response of fundamental investors. This is supported by the observation that there is an extra fund flow from institutional investors to such firms. Fundamental investors may have first noticed some hints in the graphic reports and then, after a period of research and verification,[8] discovered the superior information of alpha. Consistent with this inference, we find that after releasing graphic reports, firms experience a significant increase in their R&D investments in the following years. Graphics in annual reports may serve as a tool for firms to whisper forthcoming changes in their fundamentals.

It may be surprising that stock prices do not respond immediately to the eye-catching graphics, considering that they have played some informational role. This is because those graphics cannot directly convey *extra* material information. Under Regulation S-T Rule 304 (discussed in Section I), any material information presented in graphics must be disclosed in the 10-K filings as well. If that were not the case, we would have seen prompt, market-wide responses which might ruin the predictive power of graphic annual reports. Given that graphics may only convey extra *non-material* information[9] and they play a critical role in triggering the abnormal returns, one can infer two functions of graphics in our sample: raising investors' attention and giving hints about some extra material information (not required for disclosure at that moment). Fundamental investors do not bet on hints. They do homework and collect various types of data (e.g., firm investments) to develop a picture of nonpublic material information which they can use more readily to evaluate investment opportunities.

Based on our results, the extra information associated with the graphic reports seems to be subtle, suggestive, and uncertain. These features can challenge both managers' communication and investors' comprehension. Investors may lose interest in ineffective firm disclosures and reduce investments on firms with poor communication. The resulted undervaluation of stocks can create the managerial incentive to employ a more engaging communication strat-

[8]The delay can have various sources. For example, the information may be *soft* so that it requires extra time for analysis and verification (Liberti and Petersen (2019)). Hierarchical organizations may also delay investment decisions, especially for fundamental investors (Evans, Rohleder, Tentesch, and Wilkens (2022)).

[9]By definition, non-material information does not directly affect security prices but may provide some hints or insights to investors regarding the possible future performance of the security. See the SEC's Rule of *Selective Disclosure and Insider Trading* at https://www.sec.gov/rules/final/33-7881.htm and a related discussion at https://www.sec.gov/rules/proposed/s73199/zeikel1.htm.

egy, leading to a sizable shift from verbal to visual presentations. Not every type of data or investment decision can be automated by computers. With limited cognitive resources (e.g., Kahneman (1973) and Sims (2003)), human investors tend to exploit the data they are capable to process and ignore the data that is too difficult to consume. This can increase the value of information derived from the data that receives little attention. Intuitively, fundamental analysis is more rewarding if the fundamental information is more challenging for investors, consistent with the observed strong yet sluggish market responses.

Our model captures the above mechanism which drives the interplay between investors' attention problem and firms' aesthetic communication strategy. As new efforts to engage investors, firms have used graphics, videos, and other creative elements in communications.[10] The positive abnormal returns suggest that such changes are effective for some investors. Yet, there is much room for improvement. Our finding may enrich the regulators' consideration when they reform the current regulatory framework for corporate disclosures. This study may also trigger a broad appreciation of the point that the reporting format shift (from text to visuals) is not simply for decoration, but for a worthwhile improvement in communication.

The past decade has witnessed a trend of applying content analysis in finance.[11] Most studies use textual analysis of firm disclosures or news media; see the survey by Loughran and McDonald (2016). For example, Tetlock (2007) uses textual analysis to measure the interactions between the media sentiment and the stock market. Tetlock, Saar-Tsechansky, and Macskassy (2008) show that media language content reflects firms' fundamentals, which are quickly incorporated by investors into stock prices. Hanley and Hoberg (2010) find that greater informative content in the IPO prospectus results in more accurate offer prices and less underpricing. Jiang, Lee, Martin, and Zhou (2019) construct a manager sentiment index based on the textual tone of corporate financial disclosures and report that this sentiment index predicts market returns. Huang, Tan, and Wermers (2020) find that institutions trade rapidly on the tone of corporate news, with return predictability over the following weeks.

In contrast, non-textual analysis in financial research seems quite limited and is emerging most recently. To the best of our knowledge, there are only a few formal applications. Obaid and Pukthuanthong (2021) analyze the sentiment in news photos and find that their photo pessimism index predicts market return reversals and trading volumes, consistent with the behavioral theory (for example, De Long, Shleifer, Summers, and Waldmann (1990)).

[10] As another anecdotal example, the German chemical company Covestro AG published a digital version of their 2019 annual report which incorporates video messages, interactive graphics, and even some quiz.

[11] Content analysis can be applied to a wide range of "texts", including but not limited to written texts, images, animations, speeches, gestures, and music. There are two major branches. One is to analyze the verbal information. The other is to analyze the meaning derived from the use of multiple semiotic resources such as signs, emoticons, brand logos, photos, and other visual components (Ventola and Guijarro, 2009).

Edmans, Fernandez-Perez, Garel, and Indriawan (2022) propose a music-based sentiment measure and document relationships between music sentiment and stock returns. Jiang, Kelly, and Xiu (2021) apply image analysis methods on stock price charts to extract predictors for stock trends. In the real estate research, Carrillo (2008) find that visuals have a large and positive effect on marketing outcomes. Adding a virtual tour may increase the transaction price and reduce the expected duration on the market. Benefield, Cain, and Johnson (2011) use the number of interior and exterior photos as the measure of information and find similar effects.

Our work is contemporaneous but fills a void in the literature. Unlike music songs or news photos, we study graphics in firm annual reports which contain the most relevant and important corporate information. By law, the graphics embedded in those reports should be fair and accurate. In our sample, most graphics appear positive or at least neutral. This feature saves us from the technical problem of assigning positive or negative values to a large number of image files. Instead, we construct a *nonnegative* measure called *Graphicity* to quantify the use of graphics in annual reports. This simple measure is a proxy for the managerial efforts in seeking investors' attention and delivering subtle information.

In the recent accounting literature, Nekrasov, Teoh, and Wu (2021) find that visuals in firms' Twitter earnings announcements can trigger more retweets and Google search queries. Christensen, Fronk, Lee, and Nelson (2021) document descriptive evidence on the trend of data visualization in 10-Ks. By Regulation S-T Rule 304, a typical 10-K does not contain large, colorful images. As a result, the sample size of graphics in 10-Ks is much smaller than that in firms' annual reports. Our findings suggest the necessity to carefully distinguish firms' graphic annual reports from their plain 10-Ks. These two versions are not as interchangeable as it is widely perceived. The graphic reports can be *informationally* larger than the 10-Ks.

Finally, our work can add to the emerging literature on financial big data research (e.g., Begenau, Farboodi, and Veldkamp (2018), Martin and Nagel (2022)). Our sample has the features of big data as discussed by Goldstein, Spatt, and Ye (2021). Visual data is diverse, unstructured, and high-dimensional, with lots of interacting variables as one can envision. These properties pose challenges when researchers attempt to extract useful information from a large sample of visual data. In this regard, we take a step forward by demonstrating the value and predictive power of such a dataset, with both statistical and economic significance.

The rest of this paper is organized as follows. Section I discusses the institutional background. Section II presents our model and its predictions. Section III describes our data and methodology. Section IV presents our empirical results. Section V concludes. An Internet Appendix contains all the supporting information.

I. Institutional Background

Publicly listed companies must submit various reports (e.g., 10-Ks), schedules, and other filings electronically to the SEC, in compliance with Regulation S-T which outlines the rules and procedures pertaining to the SEC's EDGAR (Electronic Data Gathering, Analysis and Retrieval) system. Regulation S-T Rule 304 provides the regulatory code regarding the use of graphic, audio or video elements in corporate disclosures. To the best of our knowledge, this rule has not been mentioned in the academic literature. In Appendix A, we quote and discuss Rule 304, which has six key implications for our study, as summarized below:

1. **Equivalence in Principle.** Rule 304(a) acknowledges the use of graphic content in firms' documents delivered to investors. However, there should be no material differences between such documents (e.g., graphic annual reports) and the corresponding electronic filings with the SEC (e.g., plain 10-Ks). By Rule 304(a), if the delivered version (of annual report) contains graphic content that is not reproduced in the electronic filing (of 10-K), then the latter must simultaneously "*include a fair and accurate narrative description, tabular representation or transcript of the omitted material.*" From the legal perspective, the two documents are supposed to be informationally equivalent.

2. **Legal Liability.** Under Rule 304(b), the graphic content in delivered annual reports "*is deemed part of the electronic filing and subject to the civil liability and anti-fraud provisions of the federal securities laws.*" This requires the graphic content to be fair and accurate. Also, the narrative description, tabular representations or transcripts of the omitted material included in an electronic filing are deemed part of the filing.

3. **Subtle Differences.** Rule 304(b) states that "*However, to the extent such descriptions, representations or transcripts represent a good faith effort to fairly and accurately describe omitted graphic, image, audio or video material, they are not subject to the civil liability and anti-fraud provisions of the federal securities laws.*" The acknowledgement of "a good faith effort" may indicate the reality that both regulators and firms have to accept, considering that *one picture is worth a thousand words*. This item seems to leave room for some subtle information which may be embedded in the graphic annual reports but not readily visible in the plain 10-Ks.

4. **Easy Ignorance**. Under Rule 304(a), market participants may take for granted the "interchangeability" of graphic annual reports and plain 10-Ks, and thus overlook the subtle differences between these two versions of disclosures. Under Rule 304(b), various subtle differences may be tolerated by regulators or may simply escape from their eyes.

5. **Record Keeping.** By Rule 304(c), firms are required to keep records for five years of their publicly distributed annual reports and make those accessible. This explains the abundance and continuity of our sample data.

6. **Plainness of 10-Ks**. Rules 304(d)(e)(f) set more stringent rules and specific guidelines for the electronic filings. For example, firms "*may not include animated graphics in any EDGAR document*". Rule 304(e) states that "*filers may not present in a graphic or image file information such as text or tables that users must be able to search and/or download into spreadsheet form (e.g., financial statements).*" These rules can push firms to follow the plain format in electronic filings, with minimal use of graphics.

Overall, Rule 304 gives much room for firms to use graphics in their published documents, provided that there is no material difference between those documents and their counterparts of electronic filings. However, there could be subtle differences between these two versions of disclosures. Rule 304, on the other hand, discourages the use of graphics in electronic filings, consistent with the observed plain style of 10-Ks. The above institutional background explains why the sample data of graphics in our study is both large and informational.

II. Model

We consider a two-period setup of Kyle (1985) with multiple privately informed traders as in Holden and Subrahmanyam (1992). On top of those traders, we add another player, the firm manager, who has the correct belief about the fundamental value of her firm's stock. One component of this value has not been recognized by the market, probably due to the intricate process of realizing its payoff or value. The information about this component is subtle and not easily discernible. The manager cannot effectively convey this information through standard disclosures. In an alternative venue, the manager can make extra efforts which may help some attentive traders find and capitalize this information.

A. Setup

Consider a market with one risky asset (stock) and two trading dates, denoted $t = 1, 2$. The stock liquidation value, $\tilde{v}$, is a sum of two independent normal random variables, $\tilde{v} = \tilde{v}_0 + \tilde{\alpha}$. The first component, $\tilde{v}_0 \sim \mathcal{N}(1, \sigma_v^2)$, has been commonly recognized by the market and privately observed at time $t = 0$ by M attentive traders, indexed by $i = 1, ..., M$. The second component, $\tilde{\alpha} \sim \mathcal{N}(\overline{\alpha}, \sigma_\alpha^2)$, is subtle and not recognized by the entire market.

	$t=0$	$t=1$	$t=2$	$t=3$
Firm Manager	choose $s \in \{0,1\}$	...	...	see $v = v_0 + \alpha$
Attentive Traders	see v_0 and s	trade $x_{i,1}$	may see α; trade $x_{i,2}$	receive payoff
Market Makers	set $p_0 = 1$	set $p_1(y_1)$	set $p_2(y_1, y_2)$	see $v = v_0 + \alpha$

As a business insider, the manager has the correct vision about her firm, knowing that the stock liquidation value $\tilde{v}$ is actually drawn from the normal distribution $\mathcal{N}(1+\overline{\alpha}, \sigma_v^2 + \sigma_\alpha^2)$. The manager does not observe the value of $\tilde{v}$, nor trade this stock.[12] The manager is aware that $\tilde{\alpha}$ has not been recognized by the market and thus the stock is currently mispriced by an average amount of $\overline{\alpha}$.[13] As a major stakeholder, the manager has incentives to improve the market valuation of her firm. However, she cannot convey her belief of $\tilde{\alpha}$ to investors via standard disclosures (e.g., plain 10-Ks). In an alternative venue, the manager can make extra efforts with indirect informational effects, in terms of catching investors' attention and promoting their research about $\tilde{\alpha}$. At $t=0$, the manager makes a choice $s \in \{0,1\}$ which is publicly observable. Choosing $s=1$ incurs some cost $c>0$ for the manager, but it can raise the attention of all attentive traders and enable some of them to discover the value of alpha. Choosing $s=0$ is costless for the manager, while it raises no trader's interest and has no informational impact on any trader.[14] In our empirical context, $s=1$ is represented by the manager's initiation of graphic annual reports and $s=0$ is represented by her choice to cease issuing graphic reports. The manager rationally anticipates how the trading game would evolve. Similar to Verrecchia (1983), the manager's objective function is described by

$$\max_{s\in\{0,1\}} \mathrm{E}^{\mathcal{F}}[\tilde{p}_2(s) - p_0] - s \cdot c, \tag{1}$$

where $\mathcal{F}$ represents the manager's correct belief that $\tilde{v}$ is drawn from $\mathcal{N}(1+\overline{\alpha}, \sigma_v^2 + \sigma_\alpha^2)$ and where $\tilde{p}_2(s)$ denotes the firm's stock price at $t=2$ indirectly affected by the choice of s.

[12] Insider trading by firm managers is common in the real world. It can be driven by different motivations such as diversification, hedging, and liquidity needs. If the manager in our model is allowed to trade this stock, she may not fully exploit her informational advantage due to various constraints. If other traders do not interpret the manager's trading as information-driven, then, after subtracting the price impacts of the manager's trading, the resulted model will be similar to the one we presented here.

[13] If the existence and distribution of $\tilde{\alpha}$ had been recognized by the market, then our model would collapse to a standard Kyle-type model where the stock is efficiently priced, without any abnormal returns.

[14] This choice may withhold important proprietary information (Darrough and Stoughton (1990)) or avoid miscommunication with investors when firms are uncertain about their preferences (Bond and Zeng (2022)).

The above table illustrates all the players and the timeline of events in our model. While the manager's choice $s \in \{0, 1\}$ is publicly observable, it is only noticed by those attentive traders who have privately observed $\tilde{v}_0$ at the beginning. This assumption is made to simplify our exposition. The key model implications do not depend on the identities or the actual number of traders attentive to the manager's action. Upon observing $s = 0$, each trader receives no hint and cannot find any new information. Upon observing $s = 1$, each trader may discover the value of alpha with probability $\mu > 0$ after his research for at least one period of time. One may interpret the length of the first period as the minimum amount of time for traders to discover alpha. Due to the subtlety of alpha, each trader may fail to find it with probability $1-\mu$. In reality, delays and failures can arise during the research process. They may also happen within the hierarchical organizations that govern the decision process of institutional investors, consistent with the theory literature such as Radner (1993), Bolton and Dewatripont (1994), and Stein (2002). This hierarchy effect, as documented by Evans et al. (2022), is more prominent for fundamental investors than for quantitative traders.

Regardless of the research outcome, each attentive trader can sequentially submit two orders, $x_{i,1}$ and $x_{i,2}$, to maximize his expected trading profit. The objective function is:

$$\max_{x_{i,1}, x_{i,2}} \mathrm{E}^{\mathcal{A}} \left[(\tilde{v} - \tilde{p}_2) \cdot x_{i,2} + (\tilde{v} - \tilde{p}_1) \cdot x_{i,1} \right] \tag{2}$$

where $\mathcal{A}$ represents the trader's belief system. Specifically, each trader observes both v_0 and s at $t = 0$ and believes that v_0 is the actual stock value before his trading at $t = 1$. Each trader observes v_0, s, p_1, and $s\alpha\mathbf{1}_\mu$ before trading at $t = 2$, where $\mathbf{1}_\mu$ is a Bernoulli random variable that equals one with probability μ. Observing $s = 1$ does not immediately change a trader's prior; his belief is updated only after he discovers alpha, as summarized by the product term $s\alpha\mathbf{1}_\mu$. The stock value of $\tilde{v} = \tilde{v}_0 + \tilde{\alpha}$ is realized and publicly revealed at $t = 3$.

In our model, attentive traders are assumed to be fundamental investors whose trading decisions must be backed by material information (e.g., knowing the value of v_0 or α). Seeing the manager's action $s = 1$ is not equivalent to knowing the value of α, although it gives some important hints for alpha. By definition, fundamental investors will not speculate on a hint. In this rational-expectations equilibrium model, the manager also expects that her audience is composed of fundamental investors who do not speculate on her choice of s.

On both trading dates, there are Gaussian noise demands, denoted by $\tilde{u}_1 \sim \mathcal{N}(0, \sigma_u^2)$ and $\tilde{u}_2 \sim \mathcal{N}(0, \sigma_u^2)$. All the random variables, $\tilde{v}_0$, $\tilde{\alpha}$, $\tilde{u}_1$, and $\tilde{u}_2$, are mutually independent. The parameters M, σ_v, and σ_u are common knowledge. The parameter μ is known among attentive traders and the manager. For each auction, the aggregate order flow, $\tilde{y}_t = \sum_{i=1}^{M} \tilde{x}_{i,t} + \tilde{u}_t$, is absorbed by competitive market makers. The initial stock price is set to be $p_0 = 1$, based on their common prior that $\tilde{v} \sim \mathcal{N}(1, \sigma_v^2)$. Without recognizing the existence of alpha, market makers set the price $\tilde{p}_t$ to be their posterior expectation of $\tilde{v}$ conditional on the total order flows up to time t, that is, $\tilde{p}_1(\tilde{y}_1) = \mathrm{E}^{\mathcal{P}}[\tilde{v}|\tilde{y}_1]$ and $\tilde{p}_2(\tilde{y}_1, \tilde{y}_2) = \mathrm{E}^{\mathcal{P}}[\tilde{v}|\tilde{y}_1, \tilde{y}_2]$. Here, $\mathcal{P}$ denotes their common belief that $\tilde{v}$ is drawn from $\mathcal{N}(1, \sigma_v^2)$ and there are $M \geq 1$ traders privately informed about $\tilde{v}$ at the beginning. In this setup, the cumulative abnormal returns over the time window $[0, t]$ can be measured by $\mathrm{E}[(\tilde{p}_t - p_0)/p_0] = \mathrm{E}[\tilde{p}_t - 1]$.

B. Equilibrium

Given that the existence of alpha and the manager's action are overlooked by the market, we can find a subgame perfect equilibrium where market makers use linear pricing strategies:

$$\tilde{p}_1 = P_1(\tilde{y}_1) = p_0 + \lambda_1 \tilde{y}_1, \qquad \tilde{p}_2 = P_2(\tilde{y}_1, \tilde{y}_2) = \tilde{p}_1 + \lambda_2 \tilde{y}_2, \tag{3}$$

and each attentive trader follows a pair of linear trading strategies $(X_{i,1}, X_{i,2})$, $i = 1, ..., M$. Kyle (1985), Holden and Subrahmanyam (1992), and Foster and Viswanathan (1996) provide the general procedures for solving the multi-period linear equilibria. Huddart, Hughes, and Levine (2001) present analytical results for the two-period case with one informed trader. In our model, when a trader has found the alpha, he is uncertain about how many other traders have also found it. Each trader uses rational expectations to adjust his trading plan.

Proposition 1. *There exists a subgame perfect linear Markov equilibrium where the linear pricing rule (3) is determined by the two price impact parameters*

$$\lambda_1 = \frac{\sqrt{\eta M(M+1)^2(\eta(M+1)^2 - 2)}}{\eta(M+1)^3 - 2M} \cdot \frac{\sigma_v}{\sigma_u}, \qquad \lambda_2 = \eta\lambda_1 = \sqrt{\frac{\eta M}{\eta(M+1)^3 - 2M}} \cdot \frac{\sigma_v}{\sigma_u}, \tag{4}$$

and their equilibrium ratio, $\eta := \lambda_2/\lambda_1$, is determined by the cubic equation:

$$(M+1)^4\eta^3 - 2(M+1)^2\eta^2 - (M+1)^3\eta + 2M = 0. \tag{5}$$

The unique solution satisfies the second order condition and the inequality, $\eta(M+1)^2 > 2$, to ensure the existence and positiveness of λ_1 and λ_2. The optimal trading strategies are

$$X_{i,1} = \frac{\eta(M+1)^2 - 2}{\eta(M+1)^3 - 2M} \cdot \frac{\tilde{v}_0 - p_0}{\lambda_1}, \qquad X_{i,2} = \frac{\tilde{v}_0 - \tilde{p}_1}{\lambda_2(M+1)} + \frac{s\tilde{\alpha}\mathbf{1}_\mu}{\lambda_2[2 + \mu(M-1)]}, \tag{6}$$

where the product term, $s\tilde{\alpha}\mathbf{1}_\mu$, reflects the impact of manager's efforts $s = 1$ on each trader who may independently discover $\tilde{\alpha}$ with probability μ. Here, $\mathbf{1}_\mu$ denotes a Bernoulli random variable which equals 1 with probability μ and equals 0 with probability $1 - \mu$.

As market markers do not recognize the existence of alpha or the manager's motivation in choosing s, the prices they set are efficient only for $\tilde{v}_0$, i.e., $\tilde{p}_1 = \mathrm{E}[\tilde{v}_0|\tilde{y}_1]$ and $\tilde{p}_2 = \mathrm{E}[\tilde{v}_0|\tilde{y}_1, \tilde{y}_2]$.

Proof. See the Internet Appendix F. □

For the simplest case where $M = 1$ and $\mu = 0$, the trading equilibrium in Proposition 1 reproduces the results in Huddart et al. (2001), as Equation (5) becomes $8\eta^3 - 4\eta^2 - 4\eta + 1 = 0$ and its unique economic solution is $\eta = \frac{\lambda_2}{\lambda_1} \approx 0.901$. Our analytical extension to the general case is necessary and meaningful in this paper, because the theoretical picture is that some subtle information hidden in firm disclosures has been noticed by a small number ($M \geq 1$) of investors and there is uncertainty ($0 < \mu < 1$) about their informedness or decisions. Economically, M can represent the overall attention from investors toward this firm's alpha, whereas μ can reflect the effectiveness of firm communication with those investors.

As mentioned earlier, the attentive traders in our model follow the style of fundamental analysis. Their trading decisions are executed only after they confirm that such decisions are backed by material information. That is why in Equation (6) the initial trading strategy $X_{i,1}$ is only driven by $\tilde{v}_0 - p_0$ and independent of s, whereas the next trading strategy $X_{i,2}$ has an extra term proportional to $s\tilde{\alpha}\mathbf{1}_\mu$ which reflects a trader's potential knowledge of alpha. In a rational-expectations equilibrium, players inside the model are assumed to understand the model structure. Likewise, the manager in our model understands the fundamental style of attentive traders. As a result, there will be no strategic or manipulative considerations when the manager chooses s. A model where traders speculate on s and the manager strategically chooses s can be an interesting extension but beyond the scope of this paper.

Proposition 2. *Anticipating the trading equilibrium in Proposition 1, the manager chooses*

$$s = \begin{cases} 1, & \text{if} \quad \overline{\alpha} \geq K, \\ 0, & \text{if} \quad \overline{\alpha} < K, \end{cases} \qquad \text{where} \qquad K = \frac{2 + \mu(M-1)}{\mu M} c. \tag{7}$$

The threshold K is a decreasing function of μ and M. Clearly, $K \to \infty$ when $\mu \to 0$ and $K \to \frac{M+1}{M} c$ when $\mu \to 1$. Moreover, $\lim_{M \to \infty} K = c$ for any $\mu \in (0, 1)$.

If $\overline{\alpha} \geq K$, the manager chooses $s = 1$ and the stock shows abnormal returns only at $t = 2$:

$$\mathrm{E}[\tilde{p}_1 - p_0 | s = 1] = 0, \qquad \mathrm{E}[\tilde{p}_2 - p_0 | s = 1] = \frac{\mu M \overline{\alpha}}{2 + \mu(M-1)} > 0. \tag{8}$$

If $\overline{\alpha} < K$, the manager chooses $s = 0$ such that there are no abnormal returns on average:

$$\mathrm{E}[\tilde{p}_1 - p_0 | s = 0] = \mathrm{E}[\tilde{p}_2 - p_0 | s = 0] = 0. \tag{9}$$

Proof. See the Internet Appendix G. □

The delayed emergence of abnormal returns, as predicted by Equation (8), seems to be a trivial result from the assumption that it takes traders at least a period of time to discover alpha. This view is partial, as there is an implicit assumption essential for this delay, that is, the manager's informational motivation in choosing s is not anticipated or exploited by any speculators in this market. Suppose we relax this assumption even slightly, there may not be such a delay. Speculative trading (e.g., right after the initiation of graphic reports) can be much faster than fundamental investing because speculators can skip time-consuming research or verification of information. This will create abnormal returns in an earlier stage. In general, traders are not prevented from betting on s given it is public. The assumption that attentive traders do not bet on s is interpreted as their investment style or discipline. They are described as fundamental traders who only trade on material information.

Proposition 3. *Suppose a smart speculator has recognized the equilibrium characterized by Propositions 1 and 2, and this speculator believes that he is the only trader who has noticed the speculative opportunity on the manager's action $s = 1$. For simplicity, if the speculator just bets in one trade, then he must trade at $t = 1$ to avoid competition with fundamental traders at $t = 2$ (who are not informed about alpha when they trade at $t = 1$). The speculator's demand has a positive lower bound, $D_1(s) = \frac{s}{2\lambda_1}\mathrm{E}[\tilde{\alpha}|s = 1] \geq \frac{s\widehat{K}}{2\lambda_1}$, where $\widehat{K} > 0$ denotes the speculator estimate of the manager's threshold K. As a result, there will be on average a positive abnormal return at $t = 1$ after the manager chooses $s = 1$:*

$$\mathrm{E}[\tilde{p}_1 - p_0 | s = 1] = \lambda_1 D_1(s = 1) \geq \widehat{K}/2 > 0. \tag{10}$$

We omit the proof as it is straightforward. In a typical rational-expectations equilibrium, agents may infer valuable information from equilibrium prices or other observable variables. In Proposition 3, the speculator is inferring a trading signal from the manager's action $s = 1$ which is publicly observable and implicitly informational. Taking Propositions 1, 2, and 3 together, we can make a key prediction: if the manager's informational motive in choosing $s = 1$ is not recognized or exploited by any speculators, then we shall observe no abnormal returns in the earlier stage ($t = 1$) but positive abnormal returns in the later stage ($t = 2$).

Of course, there is another type of speculators who infer trading signals from prices. Such speculators may follow price trends right after the emergence of abnormal returns. This is probably more common and easier to understand. However, the trend-following speculation will not affect the above prediction of delayed anomaly caused by fundamental investing.

C. Discussion

It is worth noting that absence of abnormal returns is not indicative of market efficiency, as *absence of evidence is not evidence of absence.* In our model, stock prices are *inefficient* even when $\overline{\alpha} = 0$ (for which the manager always chooses $s = 0$). This is because market makers have overlooked the volatile component $\tilde{\alpha}$ and thus underestimate the volatility of $\tilde{v}$. If the existence and distribution of $\tilde{\alpha}$ had been correctly recognized by market makers, then they would increase the price impact costs λ_1 and λ_2 in Equation (4) by replacing σ_v with $\sqrt{\sigma_v^2 + \sigma_\alpha^2}$. Unlike most Kyle-type models, our model describes a market that lacks the semi-strong-form efficiency. Here, traders may beat the market using fundamental strategy. This involves time-consuming research and relies on some hints from public data. In our model, the hints are provided by the manager's extra efforts ($s = 1$) in improving firm communication. In our empirical study, the signal is extracted from the public data of annual report graphics. The profitability of this fundamental strategy can increase with the alpha's subtlety which may reduce both μ and M and hence suppress traders' competition.

The probability μ can be affected by many factors, such as the manager's communication skills, the firm reputation, the regulatory environment (e.g., formatting requirement), and the organizational structure for investors' decision-making processes. In the extreme case of $\mu \to 0$, our model describes the situation of ineffective communication (e.g., poorly designed disclosures). When the perceived $\overline{\alpha}$ is high, a firm with $\mu \approx 0$ would be significantly undervalued by the market. This inefficient valuation can hurt firm performance so that the manager has incentive to improve the effectiveness (μ) of communication with investors. This then lowers the manager's threshold K for choosing $s = 1$, creating a noticeable shift from inefficient ($s = 0$) to more efficient communication ($s = 1$).

In general, the parameters μ and M can be interrelated. A broader audience may encourage more managerial efforts in improving the effectiveness of communication. More effective communication can attract more attentive investors the other way around. Thus, there can be nontrivial interplay between investors' attention and firms' communication strategies.

The cost parameter c can depend on σ_α^2 and μ. On one hand, more uncertain alpha may require more communication efforts, since the manager may need extra work and considerations to convey such information. On the other hand, more efforts are expected to be paid for more effective communication. The cost c may also depend on the choice variable "s" which we can model as a continuous variable, similar to the alternative flow measure of "Graphicity" to be discussed in Section IV.C. All those variations do not change the main implications from the simple model presented here.

D. *Empirical Implications*

We extend the model to a universe of stocks. Each stock has its own alpha, denoted $\tilde{\alpha}_n$ and indexed by $n = 1, ..., N$. The sample mean of alphas is zero. We assume that each firm's alpha is acknowledged by its own manager but not by the market. Each manager chooses an action $s_n \in \{0, 1\}$ at the beginning based on her threshold, denoted K_n, which depends on the parameters of c_n, μ_n, and M_n. This model generates three testable predictions:

Prediction 1. *There are significant, positive abnormal returns for the group of firms whose managers have made efforts ($s = 1$) that at least provide some hints for their firms' alphas.*

Managers are willing to put such efforts only if the expected benefits are strong enough. For each stock, this occurs if $\overline{\alpha}_n > K_n$ and by Equation (8) we have $\mathrm{E}[\tilde{p}_{2,n} - p_{0,n} | s_n = 1] > 0$. Since the threshold is positive for each manager, the sample average abnormal return for those firms should be positive and statistically significant if the sample size is large enough. Empirically, the manager's action $s_n = 1$ is measured by the surge of graphics in her firm's annual report. If this measure can predict stock returns, then we can tell that the manager's efforts have helped some investors to discover alpha.

Prediction 2. *For the group of firms whose managers have chosen to put no efforts ($s = 0$), their sample average abnormal returns are not statistically different from zero.*

Managers withhold information if the expected gains from their efforts are not promising. Their inaction will raise no attention and leave no hints. By Equation (9), the expected abnormal return is zero for each stock in this group, $\mathrm{E}[\tilde{p}_{t,n} - p_{0,n} | s_n = 0] = 0$. For a large sample, the abnormal return shall not be statistically different from zero. Empirically, the manager's inaction $s_n = 0$ is represented by the cease of issuing graphic reports. If we observe significant abnormal returns for firms with $s = 1$ (Prediction 1) and not for firms with $s = 0$ (Prediction 2), then we can confirm the critical role of graphics added by managers, given there is no pre-announcement drift in either test. This will also confirm our hypothesis of information asymmetry between firm managers (insiders) and financial markets (outsiders).

Prediction 3. *If the above return predictability of $s = 1$ is not expected or exploited by any speculators in this market and if the information about alpha is processed by fundamental investors, then there will be an apparent delay in observing the predicted abnormal returns. Moreover, the holdings of fundamental investors should increase for those firms with $s = 1$.*

The delayed emergence of anomaly is a key implication of Propositions 1, 2 and 3. The predicted increase in institutional holdings given $s = 1$ is an implication of Equation (6) in Proposition 1. If Prediction 3 is empirically confirmed, we can draw two critical implications. First, the delayed abnormal returns should be caused by fundamental investors, since they do not immediately speculate on the hints inferred from the manager's action $s = 1$. Instead, they only trade on material information about alpha. Second, the return predictability of the manager's efforts is novel to the market since it has not been recognized by any speculators.

III. Data and Methodology

We collect the printable versions of annual reports of 1,879 U.S. public firms over the period of 1994 to 2019. Most firms have such versions available as PDF files on their websites under the "Investor Relations" section. We search the Internet or request firms to send us their annual reports if not found on their websites. Firms in our sample must have financial accounting variables and stock return data. After excluding firms in the highly regulated sectors, such as financial (SIC codes 6000 to 6999) and utility (SIC codes 4901 to 4999) sectors, our final sample contains 1,322 firms and 10,105 firm-year observations.

We obtain from CRSP the monthly firm returns and market returns over the period of 1994 to 2019. To estimate abnormal returns, we extract Fama-French Three Factors (FF3), Fama-French-Carhart Four Factors (FF3 plus Up-minus-Down factor), and Fama-French Five Factors (FF5) from the Fama-French database. We obtain the annual firm-level financial and accounting variables from Compustat, institutional holdings data from Thomson's CDA/Spectrum database (form 13F), analyst coverage data from Institutional Brokers Estimate Systems (I/B/E/S), and Fog Readability Index from SEC Analytics database. All the variables used in our empirical tests are defined in the Internet Appendix H.

To process roughly 4.9 million document pages, we customize a machine-learning algorithm which can automatically identify and analyze the graphics embedded in a PDF file. We mainly rely on the PyMuPDF and the Pillow library to process image contents.[15] PyMuPDF is a Python binding for MuPDF, a software package known for its top performance and high rendering quality. PyMuPDF also includes a built-in neural network based OCR engine.[16] Pillow is an image library designed for access to data stored in a few basic pixel formats. It provides a general image processing tool. Our program first captures the graphic items in a file, including graphs, photos, and charts. Then it selects color-print items, filters out meaningless items such as logos and headings, calculates how much space the remaining graphics occupy on a page, and counts how many color-print graphics present in a document. Those output variables allow us to quantify the use of graphics in each PDF file. After analyzing roughly 2.5 million image files, our program returns 378,172 graphics that have high visual salience based on their colors and sizes. As a robustness check, we have also used a random subsample to manually confirm the accuracy of our computer algorithm.

To test our model predictions, we divide the sample into three groups: (1) firms that newly issue graphic annual reports; (2) firms that do not change their reporting formats; and (3) firms that cease graphic annual reports. Our first measure of *Graphicity* is defined to indicate whether a firm has newly issued a graphic annual report in a given year on top of the 10-K. This indicator variable equals one if a firm-year observation falls into Group (1) and equals zero otherwise. For example, Nvidia has kept releasing graphic annual reports ever since 2010 but not before. By definition, Nvidia falls into Group (1) in 2010.

Table I describes our sample data and shows several interesting features. On average, over 80% of firms have used graphics in their annual reports. Many of them show a strong preference for using this graphic reporting format. Moreover, firms do not change their reporting formats frequently, as only approximately 9% of firm-year observations have format changes in terms of initiating or ceasing the graphic annual reports.

[Insert Table I about here]

Table II reports the summary statistics of the key variables for the sample we study. These include raw returns, FF5-factor alphas, *Graphicity*, firm characteristics (e.g., ROE, leverage, size), readability of the annual reports/10-Ks, institutional ownership, short interests, and analyst coverage. For example, after the release of annual reports, the average 3-month and

[15] See `https://github.com/pymupdf/PyMuPDF` and `https://pypi.org/project/Pillow/`.

[16] Optical Character Recognition (OCR) a digital technology that can convert different types of textual files, such as scanned paper documents, PDF files or digital images into editable and searchable data.

6-month raw returns for all sample firms are found to be 6.6% and 8.6%. The FF5-factor alphas based on weekly returns for the same event windows are 8.4 and 6.5 basis points. By compounding these weekly alphas, we estimate that the abnormal returns over the 3-month and 6-month windows are merely 0.01% and 0.02%, respectively. Most firm-year observations are associated with graphic annual reports in our sample. However, only around 4.2% of observations correspond to the format-change events that firms newly issue graphic reports.

[Insert Table II about here]

We also provide the logistic regression results in Appendix I, from which one can see that firms with larger size, higher return on equity, and lower book-to-market ratios are more likely to use graphics in their annual reports. This is consistent with our theoretical intuition. On one hand, larger firms tend to receive more attention from market participants. In our model, this means a greater number of attentive traders, which can lower the managerial threshold for making extra communication efforts. On the other hand, growth firms that enjoy higher profitability are perhaps more likely to have novel growth opportunities underappreciated by the market. This can be interpreted in our model as the manager perceives a higher average alpha unrecognized by the market. In short, both effects, size and growth, can increase the tendency of firms to use graphics in annual reports, consistent with our model.

IV. Empirical Results

A. Abnormal Returns and Annual Report Graphicity

We first estimate the abnormal returns around annual report release dates. As mentioned before, we first estimate the weekly alphas from the standard CAPM model, the Fama-French three-factor model (FF3), the Four-factor model (FF3 factors and the Up-minus-Down factor), and the Fama-French five-factor model (FF5), based on weekly returns. Then we compute the abnormal returns for the event windows of 3 months before, and 3 months, 6 months, and 9 months after the release of annual reports.[17] Panel A in Table III reports both alphas and abnormal returns for the group of firms that newly issue graphic reports, while Panel B reports those results for the group of firms which cease issuing graphic reports in a new fiscal year. The t-statistics are reported in parentheses below the weekly alphas. For either group of firms, we do not find statistically significant alphas (from multi-factor

[17] The abnormal return R^e_t over an event window $[0, t]$ is estimated by compounding the weekly alphas α_F from our regressions, i.e., $R^e_t = (1 + \alpha_F)^L - 1$, where L is the number of weeks within the specific window.

models) over the prior-event window $[-3, 0]$ months before the release of annual reports.

For firms that newly issue graphic reports, the post-event alphas from all four specifications are positive and statistically significant at the 1% level. The abnormal returns over the post-event window $[0, 6]$ months are approximately 3.5%. Such positive stock price reaction lasts for at least 6 months after the release of annual reports. After six months, the abnormal return shows little reversal, indicating that it is not a transient market response. The result shown in Panel A of Table III confirms the model Prediction 1.

[Insert Table III about here]

In contrast, for those companies that cease issuing graphic annual reports, their abnormal returns are not statistically different from zero for any event windows we tested (Panel B of Table III). This finding confirms the model Prediction 2. Intuitively, when firms do not have much information to deliver through graphic reports, they may save resources by reverting to the plain 10-Ks.[18] As a result, the abnormal returns are insignificant for those firms.

B. *Regression Results*

We use panel regressions to formally test Prediction 1 and Prediction 2 from our model. To examine whether the graphics in annual reports contain information that predicts future stock returns, we estimate the following regression equation:

$$R_{i,t+\Delta} = \beta_0 + \beta_G \times Graphicity_{i,t} + \beta_X \times X_{i,t} + \beta_F \times Firm_i + \beta_Y \times Year_t + \epsilon_{i,t}, \qquad (11)$$

where the dependent variable $R_{i,t+\Delta}$ is firm i's stock return in 3 months or 6 months after the report release date in year t. In this regression, the key independent variable is *Graphicity*. As mentioned earlier, *Graphicity* is an indicator variable that equals one for a firm-year observation if the firm newly issued graphic annual reports in a fiscal year and that equals zero otherwise. The regression also includes several controlling covariates, denoted $X_{i,t}$, such as firm size, return on equity, and leverage. To control for the textual effect on stock returns, we also include the Fog Readability Index. All the regressions are estimated with either firm and year fixed effects, or industry and year fixed effects. The results are reported in Table IV. As shown in Columns (1) and (2), when we control for firm and year fixed effects, the coefficients β_G for *Graphicity* are 3.429% and 5.043% over the three-month and six-month

[18]The monetary costs of preparing the graphic annual reports are supposed to be negligibly small for the companies in our sample. There can be little monetary incentive to quit issuing graphic reports. Such a decision may instead be driven by non-monetary costs or concerns, such as proprietary information.

window, respectively. Both values are statistically significant at the 1% level, indicating that firms on average experience positive significant abnormal returns after they switch to issuing graphic annual reports from using the plain 10-Ks. The regression coefficients of firm size and return on equity are also significant, indicating the effects of firm size and profitability. As shown in Columns (3) and (4), the results are similar when we control for both industry and year fixed effects. The coefficients of *Graphicity* for three-month window and six-month window are 2.986% (t-statistics = 3.35) and 5.320% (t-statistics = 4.69), respectively. The six-month coefficient is nearly twice as much as the three-month one, reflecting that the new information is gradually incorporated into stock prices. In sum, the empirical results in this subsection are highly consistent with both Prediction 1 and Prediction 2.

[Insert Table IV about here]

We, then, estimate Fama-Macbeth regressions to ensure that our results are not caused by biases related to cross-sectional correlation. The results are reported in Table V. Now the coefficients of *Graphicity* are 3.165% (t-statistics = 4.29) and 5.322% (t-statistics = 6.56) for three-month window and six-month window, respectively. Their magnitudes and significance levels are similar to those from the panel regressions reported in Table IV.

[Insert Table V about here]

Collectively, the above empirical results show that the surge of graphics in firms' annual reports has predictive power for their future stock returns. By confirming both Prediction 1 and Prediction 2, these results confirm our theory that firms have intentionally used graphics to help convey extra information which is not anticipated or noticed by the market.

C. Robustness

We conduct a battery of robustness tests to verify the pattern of abnormal returns subsequent to the graphic print change of annual reports.

Matched Sample. To avoid the sample selection bias (if any), we use the matched sample as a different benchmark and re-estimate the same regressions in Table IV. Specifically, we compare the group of firms that newly issue graphic annual reports with their matched industry peers that have similar firm characteristics but do not change their reporting formats by issuing graphic annual reports.[19] The results are provided in Table VI. Similar to Table IV, we report the results with firm and year fixed effects in Columns (1) and (2): the regression coefficients of *Graphicity* for the three-month and six-month windows are 3.698%

[19] To ensure comparability, we match firms by industry, firm size, and annual report readability each year.

(t-statistics = 3.35) and 4.695% (t-statistics = 3.61), respectively. Results with industry and year fixed effects are reported in Columns (3) and (4). Again, the coefficients of *Graphicity* have magnitudes similar to those in Table IV, and they are all significant at the 1% level. Therefore, selection bias is unlikely to drive our results.

[Insert Table VI about here]

Institutional Presence. The literature lacks a systematic study on the value of information associated with firms' graphic financial reports. Considering that institutional investors are resourceful and sophisticated, one may wonder if they have already noticed and exploited the anomaly we identified. To examine the implication of investor sophistication, we split our sample based on the institutional holdings (before report release dates) and re-estimate the OLS regressions with stock returns over $[0, 6]$ months as dependent variables. As shown in Table VII, the first two columns report the results for the subsample with low institutional presence, and the last two columns are for the subsample with high institutional presence. If institutional presence could explain our finding, then the measure of *Graphicity* would lose some predictive power in the subsample with high institutional presence. In Table VII, the coefficient of *Graphicity* for the low institutional ownership subsample is 7.206% when including firm and year fixed effects, and 5.435% when including industry and year fixed effects. Both of them are statistically significant at the 1% level, as their t-statistics are 3.46 and 2.71, respectively. For the high institutional ownership subsample, the coefficients of *Graphicity* are 4.265% in Column (3) and 5.110% in Column (4), and their t-statistics are 2.83 and 3.55, respectively. These results suggest that the pre-event institutional presence does not have a significant effect on the post-event abnormal returns.

[Insert Table VII about here]

Analysts Following. The literature suggests that a higher level of analyst coverage is associated with lower information asymmetry. Analyst coverage tends to promote the informational efficiency of stock markets. For example, Hong, Lim, and Stein (2000) find that high analyst following stock prices are more informative, and the profits of momentum strategies are lower for these high analyst following stocks. Yu (2008) finds that firms followed by more analysts tend to engage less in earnings management. In our empirical context, if financial analysts had noticed the extra information in the graphic annual reports, then their coverage would weaken the predictive power of *Graphicity* on future stock returns. To test this possibility, we again split our sample into two groups based on the pre-event level of analyst coverage and then re-estimate the previous regressions. In Table VIII, the first two columns report the results for the subsample of firms with low (below-median) analyst following: the coefficient of *Graphicity* is 5.787% (t-statistics = 2.94) when firm and year fixed effects are controlled in Column (1), and 4.378% (t-statistics = 2.34) when industry and year fixed effects are controlled in Column (2). The results are similar for the subsample of firms with high (above-median) analyst following: the coefficient of *Graphicity* is 5.124% (t-statistics = 3.06) in Column (3) and 5.571% (t-statistics = 3.61) in Column (4). Again, the similar magnitudes and significance levels in both subsamples indicate that the pre-event level of analyst coverage does not have a strong effect on the observed abnormal returns.

[Insert Table VIII about here]

Short Interests. Stock market frictions such as short selling constraints can affect price efficiency (e.g., Diamond and Verrecchia (1987); Nagel (2005); Bris, Goetzmann, and Zhu (2007); Boehmer and Wu (2013); Engelberg, Reed, and Ringgenberg (2018)). If short selling frictions were responsible for the documented results in our study, then the positive relationship between annual report format change and subsequent abnormal returns would be more pronounced for firms that are more constrained in short selling. To test this, we split our sample into two groups based on the annual average short interests in the fiscal year before the release of annual reports, and then re-estimate the previous OLS regressions. In Table IX, the first two columns report our results for the subsample of firms with low short interests: the coefficient of *Graphicity* is 5.629% (t-statistics = 2.78) when firm and year fixed effects are controlled, and it is 3.940% (t-statistics = 2.08) when industry and year fixed effects are controlled. The results are similar for the subsample with high short interests: the coefficient of *Graphicity* is 4.845% (t-statistics = 2.87) in Column (3) and 6.014% (t-statistics = 3.86) in Column (4). Those results suggest that our finding is robust to short selling frictions as they cannot explain the observed positive abnormal returns.

[Insert Table IX about here]

Alternative Measures of Graphicity. We have explored alternative measures of *Graphicity* for robustness check. Based on the output of our image analysis algorithm, we define a flow variable, called $\triangle Pics$, which measures the yearly percentage change in the number of graphics used in each firm's annual reports. We also define another measure called *Jump*, which is a dummy variable indicating whether a firm's annual report has 50% more graphics than it had in the previous year. We then regress the post-event $[0, 6]$ month stock returns on both measures, with the same controls used in Table IV. The new results are reported in Table X. Consistent with our previous findings, the coefficients of $\triangle Pics$ and *Jump* are positive and statistically significant at the 1% levels. The coefficient of $\triangle Pics$ is 0.818 (t-statistics = 3.38) when firm and year fixed effects are included, and it is 0.794 (t-statistics

= 3.39) when we include industry and year fixed effects. When we instead use the *Jump* as the proxy for increasing graphicity in annual reports, we find that the coefficient of *Jump* is 1.822% (t-statistics = 3.15) when firm and year fixed effects are controlled, and it is 1.815% (t-statistics = 3.34) when industry and year fixed effects are controlled. This means that when firms have significant jumps in using graphics in their annual reports, they on average experience roughly 1.82% higher returns than other firms in the next six months.

[Insert Table X about here]

D. *Fundamental Investors*

Our results demonstrate the predictive power of annual report graphicity. This return predictability is not anticipated by the market. *Ex post*, it remains unknown who are actually influenced by the graphic annual reports. Our model assumes that the extra information is identified and processed by fundamental investors, not by speculators or retail traders. In general, fundamental investors are highly concerned about the truthfulness and materiality of the information they possess. They want to confirm that their long-term investments are backed by superior, fundamental information. In contrast, speculators tend to bet on short-term opportunities, mostly based on their conjectures or inferences about those opportunities without solid evidence or information. If the anomaly identified in this paper had been recognized by some speculators, then their trading would have taken place shortly after companies initiated graphic reports, creating abnormal returns in an earlier stage. If, instead, the anomaly is novel to the market and only fundamental investors process the anomaly-related information, then we expect an apparent delay in the emergence of abnormal returns, as stated in Prediction 3. To test this prediction, we conduct an event study on the short-term stock performance around the dates that firms release graphic annual reports for the first time. We compute their abnormal returns based on the market model. As shown in Table XI, the cumulative abnormal returns (CARs) for daily event windows of $[-1, 1]$, $[0, 1]$, and $[-1, 0]$ are not statistically significant. Moreover, the post-event CARs are insignificant for up to 20 trading days. Consistent with Prediction 3, this result shows that there is no speculative trading on events of firms' reporting format changes and thus the return predictability of *Graphicity* is indeed a novel finding to the general market.

[Insert Table XI about here]

The delay in stock price response can be an important feature of fundamental investing. Fundamental investors may spend time collecting more data to substantiate their investment decisions. They may also spend extra time on analyzing soft information. According to Liberti and Petersen (2019), hard information includes quantitative data such as earnings numbers in financial statements. This type of information can be easily absorbed by traders. In contrast, it can be difficult to express (qualitative) soft information in numbers or in text. Comprehension of soft information also requires one's prior knowledge and even talents. As another friction, hierarchical organizations may also delay information communication and investment decisions. Evans et al. (2022) show that the hierarchy effect is way more prominent for fundamental investors than for quantitative traders. This also agrees with theoretical implications of Radner (1993), Bolton and Dewatripont (1994), and Stein (2002).

The absence of speculative trading and the delay in stock price reactions suggest that the information driving the observed abnormal returns is most likely processed by fundamental investors. To examine this implication, we test whether annual report *Graphicity* leads to the post-event changes of institutional holdings. Given the quarterly data we can observe, we regress the percentage changes of firms' institutional ownership during one-quarter, two-quarters, and three-quarters post-event time windows on the measure of *Graphicity*,[20] together with other control variables similar to the regression equation (11). The results are reported in Table XII. The coefficient of *Graphicity* is insignificant for the first quarter. However, its magnitude keeps increasing with the length of post-event time window, and becomes statistically significant after three quarters. Notably, the significant coefficient is 4.07, indicating that institutional investors increase their holdings by about 4% in total in response to the new information embedded in graphic reports. This pattern is consistent with Prediction 3 and with the observed abnormal returns in Table IV.

[Insert Table XII about here]

Combining the results in Tables IV, XI, and XII, we conclude that the observed abnormal returns (with a delay but no reversals) reflect the incorporation of nonpublic material information into stocks prices and this extra fundamental information is processed by fundamental investors (not speculators) who may receive hints or insights from graphic reports.

E. *Real Effects*

If firms mainly use graphic annual reports to hint at extra fundamental information, then the question for investors is whether those hints are credible. Specifically, do firms that release graphic reports experience any improvements in their fundamentals subsequently? To answer this question, we employ a Difference-in-Differences (hereafter, DiD) method to

[20] We have also used the two alternative measures of *Graphicity* and reported the results in Appendix J.

examine the predictive power of *Graphicity* on real corporate activities. We regress various corporate investment variables (including *Asset Growth*, which is the annual percentage growth in total assets, *Capex*, which is capital expenditure, and *R&D*, which is the investment in intangible assets) on an indicator variable *Treatment*, which equals one for all the fiscal years after a firm has issued a graphic report for the first time and equals zero otherwise. Table XIII reports our multivariate DiD results.[21] The coefficients of *Treatment* reflect the changes of corporate investments following the annual report format change. The predictability is weak for *Asset Growth* and *Capex*. However, it is positive and statistically significant for *R&D* at the 1% level. Moreover, the increase of *R&D* is survived with the year and firm fixed effects and with the matched sample. The coefficient of *Treatment* is 1.483 (t-statistics = 2.04) in the matched sample regression, indicating that firms tend to increase their *R&D* investment by 1.483% annually after they switch to issuing graphic reports.

[Insert Table XIII about here]

The above result is consistent with our theory. First, it shows that the hints in graphic annual reports are overall credible. This can also explain why institutional investors may take into account such hints. Second, the *R&D* operations are often complex and may involve proprietary information. Graphics seem suitable tools when firms intend to spread subtle messages about *R&D*-related firm potentials. Third, the result in Table XIII is also compatible with our logistic regression result reported in Appendix I, since larger firms with more growth opportunities and higher profitability are perhaps likely to invest more in *R&D*.

There can be real benefits from using graphic reports to signal *R&D*-related fundamental improvements. This can reduce information asymmetry, boost stock prices, and lower costs of capital, which in turn promote firm investments (Fishman and Hagerty (1989), Diamond and Verrecchia (1991)). Firms may also reduce their perceived risk about investment opportunities and harness the feedback effects of financial markets (see Chen, Goldstein, and Jiang (2007), Bond, Edmans, and Goldstein (2012), Edmans, Goldstein, and Jiang (2012)).

F. Policy Implications

Our results support the managerial incentive to adopt a multimedia approach in preparing and presenting corporate information. Investors may have limited ability to filter valuable information from text-heavy reports (e.g., 10-Ks); they may also struggle with the prior

[21] We have examined the parallel trend assumption as required for a valid DiD test. Following Bertrand and Mullainathan (2003), we include indicators for three pre-treatment periods (in years) along with three during- and post-treatment indicators. The results in Appendix K confirm the parallel trend assumption.

knowledge required for understanding certain information. This may explain why the standard filings can be less attractive to investors, consistent with the finding by Loughran and McDonald (2017) that the activity of investors' requests for 10-Ks on EDGAR of the SEC is surprisingly low and also with the finding by Cohen, Malloy, and Nguyen (2020) that investors are inattentive to format changes in firms' financial reports.

Recognizing those problems, firms may invest more resources in producing attractive reports. This practice shares similarities with marketing but has a different target audience. Visuals can help investors overcome their inattention and capture the big-picture insight. We provide the novel evidence on the positive economic effect of using graphics in firms' annual reports. Appropriate use of visuals can enhance communication with investors and improve the market's informational efficiency. Hence, our findings may help regulators consider going beyond the current regulatory framework and accommodate the needs of firms to make more user-friendly presentations.[22]

Of course, there could be downside risk. The case of WeWork IPO filing is one example. The first Form S-1 that WeWork filed for its IPO is an image-heavy document, beyond the norm followed by most companies that go public. According to the news media,[23] the former WeWork executives spent months and a fortune producing the S-1 report "*like it was the September issue of Vogue*." WeWork had hired a former director of photography at *Vanity Fair* magazine and sent photographers to reshoot the company's locations around the world. Its overuse of photos in the S-1 filing has been viewed by the financial media as glossy and inappropriate. Similar problems may also arise in the graphic annual reports of some firms.

Our empirical approach can expand regulators' tools that monitor misleading or abusive practices. As done in this paper, regulators may construct a database of graphics embedded in firms' disclosures. Regulators may also adopt the simple metric we defined to gauge the *graphicity* of firm documents in real time. This can help detect suspicious activities and urge firms to fairly use graphics in their disclosures.

[22] See https://www.sec.gov/divisions/corpfin/guidance/regs-tinterp.htm for the SEC Compliance and Disclosure Interpretations for Regulation S-T in 2015. Readers are also referred to *A Plain English Handbook: How to Create Clear SEC Disclosure Documents*; see https://www.sec.gov/reportspubs/investor-publications/newsextrahandbookhtm.html.

[23] See, for example, the media coverage and comments from the Bloomberg website at https://www.bloomberg.com/opinion/articles/2019-10-01/dorm-room-hedge-fund-had-its-own-values.

V. Conclusion

Studies that employ content analysis of financial reports have largely focused on standard numerical and textual data, with advances made by Tetlock (2007) and others (see, e.g., Loughran and McDonald (2016)). This is likely due to the complexity of non-textual content (e.g., graphics) that has hindered extracting useful information from such type of dataset in the past. With recent advances in machine learning, our paper takes the challenge to analyze, for the first time, the graphics embedded in public firms' annual reports. We provide not only extensive empirical results, but also a novel theoretical model to explain why firms make the extra efforts to design graphics in their reports to begin with.

We find that those firms that initiate graphic annual reports earn on average significant and positive abnormal returns in the following one to two quarters. This finding is robust to various specifications. It cannot be explained by investor sophistication, short selling constraints, or analyst following. We also find that the positive abnormal returns are accompanied by an increase in holdings of institutional investors. Moreover, firms that issue graphic reports have increased their research and development expenses in the following years, reflecting the positive real effect of annual report graphicity on corporate investment.

Our model helps explain the puzzle as to why a large fraction of firms continue to provide visually aesthetic but seemingly redundant financial reports to the general public. As suggested by our theory, firms are motivated in using graphics to convey information which is of value but not easily discernible, or to hint at potentials not reflected in their financial statements. Therefore, the added visuals in firms' annual reports are more than a decorative advertisement, but constitute a valuable source of information about firm fundamentals.

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Table I: Sample Formation

This table reports the descriptive statistics of the public firms' annual reports (over the period of 1994 to 2019) in our sample data.

Total number of firms	1,879
Firm-year observations	15,372
# of firm-years after excluding observations for financial and utility firms	11,664
# of firm-years after excluding observations with missing accounting and stock return information	10,033
# of firm-years publishing graphic annual reports, in addition to 10-Ks	8,358
# of firm-years changing reporting format by initiating graphic reports (with only 10-Ks in the previous year)	422
# of firm-years changing reporting format by ceasing graphic reports (with graphic reports in the previous year)	517

Table II: Descriptive Statistics

This table reports the descriptive statistics of all major variables for all the sample firms we study. The definitions of variables are provided in the Internet Appendix H.

	N	Mean	Median	STD	P25	P75
Raw Return [0,3]	9,930	6.635	6.346	15.299	-4.151	17.480
Raw Return [0,6]	10,105	8.601	8.617	21.505	-6.186	23.595
FF5 Alpha [0,3]	9,990	0.084	0.096	0.992	-0.566	0.747
FF5 Alpha [0,6]	10,034	0.065	0.067	0.673	-0.402	0.532
Graphic Report	10,105	0.832	1.000	0.374	1.000	1.000
Graphicity	10,105	0.042	0.000	0.200	0.000	0.000
Readability	9,561	20.081	19.996	1.053	19.417	20.651
ROE	10,019	25.680	25.380	27.775	13.678	39.183
Leverage	10,060	28.232	25.185	25.762	2.112	44.132
Size	10,105	6.932	6.838	1.904	5.588	8.214
Capex	10,090	4.970	3.247	5.499	1.669	6.028
R&D	7,098	5.525	1.173	14.795	-2.383	8.974
Asset Growth	10,105	9.271	5.864	17.877	-1.788	16.183
Cash Flow	10,013	8.041	9.638	11.043	4.736	14.460
Past Profitability	10,019	11.558	13.505	17.230	7.740	19.694
INST	9,450	69.752	76.360	26.589	55.708	89.470
Short Interest	9,699	5.250	3.220	5.803	1.520	6.934
Analyst Coverage	9,303	6.625	5.000	5.420	2.750	9.000

Table III: Abnormal Returns around the Release of Firms' Annual Reports

This table reports the abnormal returns for the firms that change their reporting formats. The abnormal returns are obtained by estimating Fama-French-Carhart 4-Factor and Fama-French 5-Factor Models for different event windows around the release of annual reports, using weekly returns. The CAPM alpha measures the weekly abnormal return when restricting the coefficients of *SMB*, *HML*, and *UMD* to zero in the 4-Factor model. The 3-Factor alpha is the intercept from the 4-Factor regression when *UMD* is omitted. The 4-Factor alpha is the intercept from estimating the 4-Factor model. The 5-factor alpha is the intercept from estimating the 5-Factor model. We estimate the regressions within the event windows of 3 months before, and 3 months, 6 months, and 9 months after the report release dates.

Panel A: Firms Initiating Graphic Reports				
	[-3, 0 mo)	[0, 3 mo]	[0, 6 mo]	[0, 9 mo]
CAPM Alpha	0.102**	0.295***	0.139***	0.100***
	(1.92)	(6.43)	(3.72)	(3.21)
Abnormal Returns	*1.338*	*3.898*	*3.688*	*3.975*
3-Factor Alpha	0.089	0.255***	0.135***	0.080**
	(1.56)	(5.60)	(3.61)	(2.47)
Abnormal Returns	*1.166*	*3.365*	*3.579*	*3.180*
4-Factor Alpha	0.042	0.211***	0.134***	0.068**
	(0.66)	(4.28)	(3.57)	(2.10)
Abnormal Returns	*0.541*	*2.780*	*3.544*	*2.681*
5-Factor Alpha	-0.002	0.284***	0.131***	0.080**
	(-0.02)	(5.39)	(3.45)	(2.40)
Abnormal Returns	*-0.021*	*3.752*	*3.472*	*3.186*

Panel B: Firms Ceasing Graphic Reports				
	[-3, 0 mo)	[0, 3 mo]	[0, 6 mo]	[0, 9 mo]
CAPM Alpha	-0.008	0.053	0.010	-0.046
	(-0.18)	(1.11)	(0.26)	(-1.43)
Abnormal Returns	*-0.110*	*0.690*	*0.259*	*-1.788*
3-Factor Alpha	-0.008	0.020	-0.034	-0.042
	(-0.15)	(0.39))	(-0.90)	(-1.28)
Abnormal Returns	*-0.108*	*0.263*	*-0.872*	*-1.623*
4-Factor Alpha	-0.016	-0.005	-0.016	-0.046
	(-0.28)	(-0.10)	(-0.43)	(-1.40)
Abnormal Returns	*-0.207*	*-0.068*	*-0.424*	*-1.789*
5-Factor Alpha	-0.041	0.043	-0.012	-0.013
	(-0.69)	(0.76)	(-0.31)	(-0.37)
Abnormal Returns	*-0.531*	*0.560*	*-0.323*	*-0.501*

Table IV: Annual Report Graphicity and Stock Return Predictability

This table reports the results of panel regressions that examine whether the annual report graphicity predicts future stock returns. Dependent variables are 3-month and 6-month stock returns after the release of annual reports. Columns (1) and (2) report the results with firm and year fixed effects, while Columns (3) and (4) report the results with industry and year fixed effects. Standard errors are adjusted for heteroskedasticity and clustered by firm. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

	(1) Return [0,3]	(2) Return [0,6]	(3) Return [0,3]	(4) Return [0,6]
Graphicity	3.429***	5.043***	2.986***	5.320***
	(3.71)	(4.38)	(3.35)	(4.69)
Size	-1.688***	-3.898***	-0.410***	-0.772***
	(-3.51)	(-5.88)	(-3.16)	(-4.41)
ROE	0.045***	0.100***	0.042***	0.077***
	(3.70)	(5.88)	(4.72)	(6.12)
Leverage	-0.015	-0.046**	0.002	-0.026*
	(-1.03)	(-2.29)	(0.19)	(-1.94)
Readability	0.060	-0.021	0.287	0.207
	(0.26)	(-0.07)	(1.54)	(0.83)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	No	No
Industry Fixed Effect	No	No	Yes	Yes
N	9,297	9,446	8,699	8,825
Adjusted R-Sq.	0.080	0.161	0.056	0.129

Table V: Annual Report Graphicity and Stock Return Predictability: Fama-MacBeth Regressions

This table reports the Fama-MacBeth regression results. Dependent variables are 3-month and 6-month stock returns after the release of annual reports. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

	(1)	(2)
	Return [0,3]	Return [0,6]
Graphicity	3.165***	5.332***
	(4.29)	(6.56)
Size	0.193	0.034
	(1.50)	(0.13)
ROE	0.040	0.099***
	(1.61)	(4.35)
Leverage	-0.011	0.009
	(-1.12)	(0.17)
Readability	0.308	0.368
	(0.74)	(0.92)
N	9,297	9,446
Adjusted R-Sq.	0.0528	0.0413

Table VI: Annual Report Graphicity and Abnormal Returns: Matched Sample

This table reports the results of panel regressions that examine whether the annual report graphicity predicts future stock returns, using a matched sample. Dependent variables are 3-month and 6-month stock returns after the release of annual reports. Columns (1) and (2) report the results with firm and year fixed effects, while Columns (3) and (4) report the results with industry and year fixed effects. Standard errors are adjusted for heteroskedasticity and clustered by firm. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

	(1)	(2)	(3)	(4)
	Return [0,3]	Return [0,6]	Return [0,3]	Return [0,6]
Graphicity	3.698***	4.695***	2.887***	5.208***
	(3.35)	(3.61)	(2.65)	(4.00)
Size	-1.272*	-3.587***	-0.397**	-1.059***
	(-1.85)	(-4.00)	(-1.99)	(-3.97)
ROE	0.038**	0.092***	0.057***	0.097***
	(2.00)	(3.80)	(3.96)	(5.09)
Leverage	0.005	-0.038	0.009	-0.009
	(0.27)	(-1.39)	(0.69)	(-0.46)
Readability	0.318	0.077	0.554*	0.398
	(0.78)	(0.14)	(1.76)	(0.98)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	No	No
Industry Fixed Effect	No	No	Yes	Yes
N	3,871	3,933	3,532	3,582
Adjusted R-Sq.	0.073	0.179	0.061	0.156

Table VII: Annual Report Graphicity and Abnormal Returns, Conditional on Institutional Presence

This table reports the results of panel regressions that examine whether the annual report graphicity predicts future stock returns, conditional on the institutional ownership prior to the annual report release dates. Dependent variables are 6-month stock returns after the release of annual reports. The first two columns report the results for the subsample with low institutional ownership (below median), while the next two columns report the results for the subsample with high institutional ownership (above median). Standard errors are clustered by firm and adjusted for heteroskedasticity. Firm/Industry and year fixed effects are included. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

	Low Institutional Presence		High Institutional Presence	
	Return [0,6]	Return [0,6]	Return [0,6]	Return [0,6]
Graphicity	7.206***	5.435***	4.265***	5.110***
	(3.46)	(2.71)	(2.83)	(3.55)
Size	-4.237***	-0.525*	-5.126***	-1.299***
	(-3.57)	(-1.79)	(-5.16)	(-4.20)
ROE	0.127***	0.099***	0.081***	0.068***
	(4.23)	(4.11)	(3.71)	(4.19)
Leverage	-0.076**	-0.046*	-0.006	-0.011
	(-2.13)	(-1.69)	(-0.23)	(-0.60)
Readability	-0.762	-0.073	0.056	0.251
	(-1.42)	(-0.17)	(0.13)	(0.73)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	No	Yes	No
Industry Fixed Effect	No	Yes	No	Yes
N	3,720	3,194	5,126	5,087
Adjusted R-Sq.	0.159	0.120	0.188	0.157

Table VIII: Annual Report Graphicity and Abnormal Returns, Conditional on Analyst Coverage

This table reports the results of panel regressions that examine whether the annual report graphicity predicts future stock returns, conditional on analyst coverage. Dependent variables are 6-month stock returns after the release of annual reports. The first two columns report the results for the subsample with low analyst coverage (below median), while the next two columns report the results for the subsample with high analyst coverage (above median). Standard errors are adjusted for heteroskedasticity and clustered by firm. Year and firm/industry fixed effects are included. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

	Low Analyst Following		High Analyst Following	
	Return [0,6]	Return [0,6]	Return [0,6]	Return [0,6]
Graphicity	5.787***	4.378**	5.124***	5.571***
	(2.94)	(2.34)	(3.06)	(3.61)
Size	-3.702***	-1.067***	-4.715***	-1.390***
	(-3.12)	(-2.66)	(-4.28)	(-5.08)
ROE	0.125***	0.105***	0.075***	0.057***
	(4.38)	(5.11)	(3.45)	(3.42)
Leverage	-0.066**	-0.044*	-0.027	-0.000
	(-2.10)	(-1.95)	(-0.93)	(-0.02)
Readability	0.181	0.750*	-0.332	-0.216
	(0.37)	(1.88)	(-0.68)	(-0.63)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	No	Yes	No
Industry Fixed Effect	No	Yes	No	Yes
N	4,189	3,811	4,528	4,470
Adjusted R-Sq.	0.178	0.133	0.194	0.154

Table IX: Annual Report Graphicity and Abnormal Returns, Conditional on Short Interests

This table reports the results of panel regressions that examine whether the annual report graphicity predicts future stock returns, conditional on average annual short interests ratio prior to the annual report release dates. Dependent variables are 6-month stock returns after the release of annual reports. The first two columns report the results for the subsample with low short interests ratio (below median), while the next two columns report the results for the subsample with high short interests ratio (above median). Standard errors are adjusted for heteroskedasticity and clustered by firm. Firm/Industry and year fixed effects are included. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

	Low Short Interests Ratio		High Short Interests Ratio	
	Return [0,6]	Return [0,6]	Return [0,6]	Return [0,6]
Graphicity	5.629***	3.940**	4.845***	6.014***
	(2.78)	(2.08)	(2.87)	(3.86)
Size	-4.102***	-0.567**	-4.703***	-0.852***
	(-3.13)	(-2.31)	(-4.32)	(-2.63)
ROE	0.103***	0.083***	0.098***	0.075***
	(3.53)	(3.77)	(4.32)	(4.66)
Leverage	-0.034	-0.016	-0.035	-0.023
	(-0.96)	(-0.68)	(-1.17)	(-1.18)
Readability	-0.522	-0.305	0.394	0.599
	(-1.00)	(-0.81)	(0.82)	(1.60)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	No	Yes	No
Industry Fixed Effect	No	Yes	No	Yes
N	4,082	3,617	5,059	4,927
Adjusted R-Sq.	0.376	0.240	0.332	0.197

Table X: Alternative Measures of Graphicity

This table reports the panel regression results, using two alternative measures of graphicity, namely $\Delta Pics$ and *Jump*. Dependent variables are 6-month stock returns after the release of annual reports. Standard errors are adjusted for heteroskedasticity and clustered by firm. Firm/Industry and year fixed effects are included. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

	(1) Return [0,6]	(2) Return [0,6]	(3) Return [0,6]	(4) Return [0,6]
ΔPics	0.818***	0.794***		
	(3.38)	(3.39)		
Jump			1.822***	1.815***
			(3.15)	(3.34)
Size	-3.898***	-0.795***	-3.703***	-0.737***
	(-5.87)	(-4.51)	(-5.15)	(-3.74)
ROE	0.099***	0.076***	0.093***	0.080***
	(5.85)	(6.10)	(5.22)	(6.15)
Leverage	-0.046**	-0.025*	-0.045**	-0.029**
	(-2.29)	(-1.87)	(-2.08)	(-2.02)
Readability	-0.008	0.218	0.002	0.228
	(-0.02)	(0.87)	(0.01)	(0.84)
Year Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	No	Yes	No
Industry Fixed Effect	No	Yes	No	Yes
N	9,446	8,825	8,321	7,789
Adjusted R-Sq.	0.161	0.128	0.170	0.134

Table XI: Short-run Abnormal Returns around Reporting Format Changes

This table reports the short-term cumulative abnormal returns (CARs) for the group of firms that newly release graphic annual reports. We compute the abnormal returns using the market model, within the event windows of 1 day before to 1 day after, 1 day after to 10 days after, and 1 day after to 20 days after the format changes. We report the *t*-statistic in parenthesis below each CAR estimate. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	[-1, 0]	[0, 1]	[-1, 1]	[1, 10]	[1, 20]
CAR	0.004	0.007	0.008	0.001	-0.007
	(0.86)	(1.15)	(1.22)	(0.24)	(-1.17)

Table XII: Annual Report Graphicity and Institutional Investing

This table reports the panel regression results that examine whether annual report *Graphicity* is linked with the increase in fundamental investment inflow. Dependent variables are the *Institutional Flow* for the period of one quarter (1Q), two quarters (2Q), and three quarters (3Q) after the release of annual reports. Standard errors are adjusted for heteroskedasticity and clustered by firm. Firm and year fixed effects are included. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

	(1) Institutional Flow (1Q)	(2) Institutional Flow (2Q)	(3) Institutional Flow (3Q)
Graphicity	0.890	1.416	4.070**
	(1.46)	(0.86)	(2.34)
Size	-0.525	-1.075	-2.096*
	(-1.24)	(-1.14)	(-1.86)
BtM	0.124	2.428	2.548
	(0.22)	(1.57)	(1.46)
ROE	-0.004	-0.008	-0.007
	(-0.37)	(-0.37)	(-0.29)
Leverage	0.014	0.030	0.009
	(1.09)	(1.11)	(0.28)
Year Fixed Effect	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
N	1,534	1,427	1,329
Adjusted R-Sq.	0.094	0.217	0.146

Note: Given that the institutional ownership data is available quarterly and the reporting dates are different from the annual report release dates, we limit our test sample by requiring the availability of institutional ownership data recorded around the annual earning announcement date. Specifically, we adopt the institutional ownership reported during the period from the earning announcement date to thirty calendar days afterwards, as the reference data. Dependent variables are constructed by subtracting the reference ownership from the future institutional ownership data reported on the first quarter, second quarter, and third quarter after the reference date.

Table XIII: Annual Report Graphicity and Corporate Investment

This table reports the panel regression results that examine the relationship between annual report graphicity and corporate investment activities. Table headings indicate dependent variables. The first three columns report the results with the full sample as the benchmark, while the next three columns report the results with the matched sample as the benchmark. Standard errors are adjusted for heteroskedasticity and clustered by firm. Both firm and year fixed effects are included. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

	Full Sample			Matched Sample		
	Asset Growth	Capex	R&D	Asset Growth	Capex	R&D
Treatment	0.517	-0.251	1.399***	1.129	-0.263	1.483**
	(0.55)	(-1.06)	(2.63)	(0.85)	(-0.86)	(2.04)
Size	-9.278***	-1.053***	-5.214***	-8.694***	-0.596**	-5.574***
	(-13.78)	(-6.12)	(-11.39)	(-8.93)	(-2.45)	(-8.63)
Cashflow	0.880***	0.078***	-0.178***	0.847***	0.074***	-0.200***
	(18.23)	(8.03)	(-5.63)	(12.05)	(5.29)	(-4.33)
ROE	-0.041**	0.004	0.020**	-0.050**	0.001	0.021
	(-2.48)	(1.22)	(2.10)	(-1.97)	(0.32)	(1.48)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	9,681	9,667	6,775	3,997	3,991	2,957
Adj. R-Sq.	0.336	0.712	0.853	0.314	0.720	0.838

Internet Appendix

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Appendix A. Regulation S-T Rule 304 on the Use of Graphics in Disclosures

As mentioned in Section I, publicly listed companies are required to submit various filings to the SEC and comply with Regulation S-T which outlines rules and procedures pertaining to the SEC's EDGAR system. Among others, Rule 304 of Regulation S-T provides the regulatory details regarding the use of graphic, image, audio or video material in firm disclosures.[24] In the following, we quote Rule 304 and discuss its implications for our study.

Rule 304(a) states that "*If a filer includes graphic, image, audio or video material in a document delivered to investors and others that is not reproduced in an electronic filing, the electronically filed version of that document must include a fair and accurate narrative description, tabular representation or transcript of the omitted material. Such descriptions, representations or transcripts may be included in the text of the electronic filing at the point where the graphic, image, audio or video material is presented in the delivered version, or they may be listed in an appendix to the electronic filing. Immaterial differences between the delivered and electronically filed versions, such as pagination, color, type size or style, or corporate logo need not be described.*" As a note, "*if the omitted graphic, image, audio or video material includes data, filers must include a tabular representation or other appropriate representation of that data in the electronically filed version of the document.*"

Rule 304(a) acknowledges the use of graphics in firms' documents distributed to investors. However, there should be no material differences between those documents (e.g., user-friendly annual reports) and their corresponding electronic filings with the SEC (e.g., plain 10-Ks). Thus, if the delivered version of firm annual report contains graphic content that is not reproduced in the electronic 10-K filing, the latter must simultaneously include a fair and accurate narrative description, tabular representation or transcript of the omitted (graphic) content. From the legal perspective, these two documents should be informationally equivalent.

Rule 304(b) states that "*(1) The graphic, image, audio and video material in the version of a document delivered to investors and others is deemed part of the electronic filing and subject to the civil liability and anti-fraud provisions of the federal securities laws. (2) Narrative descriptions, tabular representations or transcripts of graphic, image, audio and video material included in an electronic filing or appendix thereto also are deemed part of the filing. However, to the extent such descriptions, representations or transcripts represent a good faith effort to fairly and accurately describe omitted graphic, image, audio or video material, they are not subject to the civil liability and anti-fraud provisions of the federal*

[24] See the Code of Federal Regulations for Regulation S-T Rule 304 at https://www.ecfr.gov/current/title-17/chapter-II/part-232/subject-group-ECFRd7d61c154ee5265/section-232.304.

securities laws." By Rule 304(b), firms are legally accountable for the graphic content in documents they deliver to investors. The SEC expects "a good faith effort" by firms to disclose the extra graphic content in their electronic filings. This seem leave room for subtle differences between the graphic annual report and the plain 10-K filing.

Rule 304(c) states that "*An electronic filer must retain for a period of five years a copy of each publicly distributed document, in the format used, that contains graphic, image, audio or video material where such material is not included in the version filed with the Commission. The five-year period shall commence as of the filing date, or the date that appears on the document, whichever is later. Upon request, an electronic filer shall furnish to the Commission or its staff a copy of any or all of the documents contained in the file.*" By Rule 304(c), firms must keep records for 5 years of their distributed annual reports and make those accessible. This explains the abundance and continuity of our sample data.

Rule 304(d) states that "*For electronically filed ASCII documents, the performance graph that is to appear in registrant annual reports to security holders required by Exchange Act Rule 14a-3 or Exchange Act Rule 14c-3 to precede or accompany proxy statements or information statements relating to annual meetings of security holders at which directors are to be elected (or special meetings or written consents in lieu of such meetings), as required by Item 201(e) of Regulation S-K, and the line graph that is to appear in registrant annual reports to security holders, as required by paragraph (b)(7)(ii) of Item 27 of Form N-1A, must be furnished to the Commission by presenting the data in tabular or chart form within the electronic ASCII document, in compliance with paragraph (a) of this section and the formatting requirements of the EDGAR Filer Manual.*"[25]

Rule 304(e) states that "*Notwithstanding the provisions of paragraphs (a) through (d) of this section, electronically filed HTML documents must present the following information in an HTML graphic or image file within the electronic submission in compliance with the formatting requirements of the EDGAR Filer Manual: The performance graph that is to appear in registrant annual reports to security holders required by Exchange Act Rule 14a-3 or Exchange Act Rule 14c-3 to precede or accompany registrant proxy statements or information statements relating to annual meetings of security holders at which directors are to be elected (or special meetings or written consents in lieu of such meetings), as required by Item 201(e) of Regulation S-K; the line graph that is to appear in registrant annual reports to security holders, as required by paragraph (b)(7)(ii) of Item 27 of Form N-1A; and any other graphic material required by rule or form to be filed with the Commission. Filers may, but are not required to, submit any other graphic material in a HTML document by presenting the*

[25]See https://www.sec.gov/edgar/filer-information/current-edgar-filer-manual.

data in an HTML graphic or image file within the electronic filing, in compliance with the formatting requirements of the EDGAR Filer Manual. However, filers may not present in a graphic or image file information such as text or tables that users must be able to search and/or download into spreadsheet form (e.g., financial statements); filers must present such material as text in an ASCII document or as text or an HTML table in an HTML document."

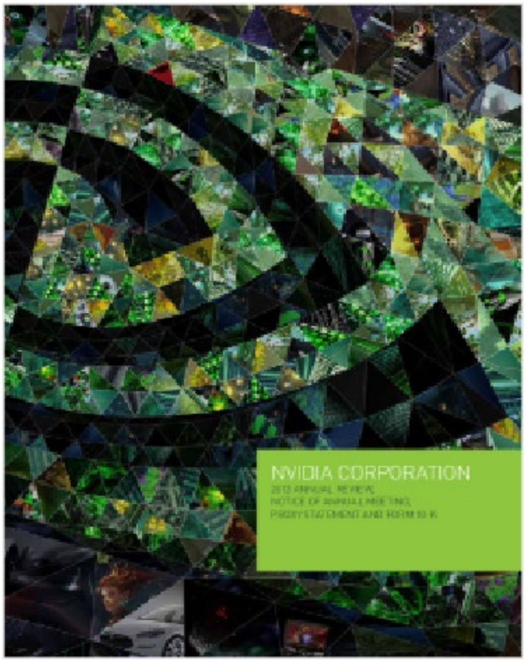
This paragraph (e) has been discussed and explained by the SEC.[26] In the SEC's view, "*'information such as text or tables that users must be able to search and/or download' consists of all information that the filer is required to include in the particular filing, such as disclosures in response to applicable form and Regulation S-K items and any additional information required to be included under Securities Act Rule 408 or Exchange Act Rule 12b-20."* The SEC does "*recognize that registrants may present information in Commission filings in formats such as bar graphs or other graphics that are not text-searchable but that they believe may be more useful to readers than tables or paragraphs that present the same information in searchable form. We welcome the use of graphic and image files to make information more accessible for users, provided that the filing complies with applicable EDGAR size and formatting requirements and the filer's use of graphics does not interfere with a user's ability to search required information. Therefore, with regard to required disclosures, a filer may present required information using graphics that are not text-searchable and still comply with Rule 304(e) if the filer also presents the same information as searchable text or in a searchable table within the filing. The searchable information could be included, for example, together with the related graphic in the filing or in an appendix to the filing. Any additional information that the filer chooses to include in the filing and that is not required to be disclosed may be presented graphically without a separate text-searchable presentation.*" By 304(f), "*electronic filers may not include animated graphics in any EDGAR document.*"

In summary, Rules 304(a)(b)(c) describe the legal environment when firms use graphics in documents they delivered to investors. Those delivered documents (e.g., graphic annual reports) should be substantially equivalent to their counterparts of electronic filings (e.g., plain 10-Ks). Nonetheless, there could be subtle informational differences between these two which can be overlooked by investors and regulators. Rules 304(d)(e)(f) set specific and stringent rules for the use of graphics in electronic filings. In general, the graphic presentation of information is discouraged in those filings (e.g., 10-Ks). On one hand, the presentation of required information (e.g., financial statements) within electronic filings must be searchable or downloadable in a spreadsheet format. On the other hand, cautious firms may want to avoid litigation risk and minimize the use of graphics in their electronic filings with the SEC.

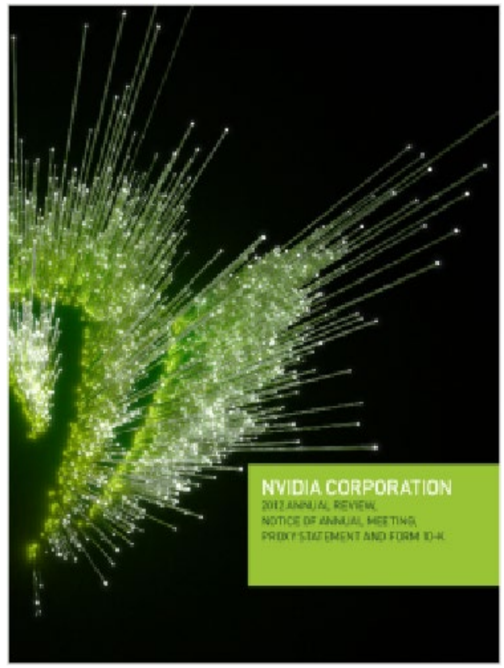
[26]See https://www.sec.gov/divisions/corpfin/guidance/regs-tinterp.htm.

Appendix B. Cover Pages of Nvidia's Annual Reports from 2010 to 2013

2013



2012



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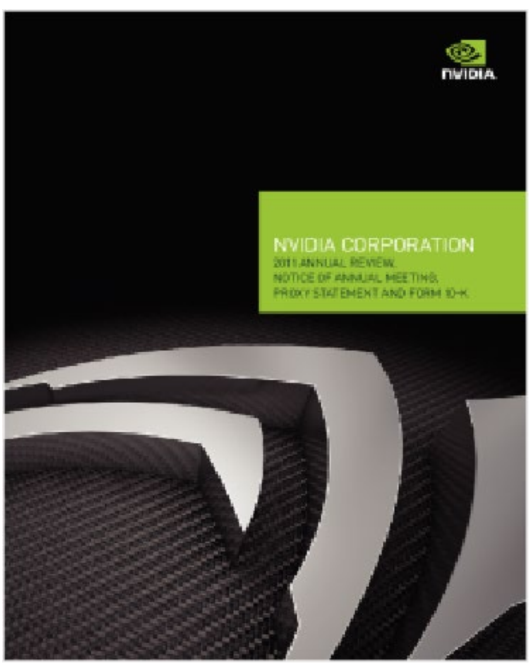
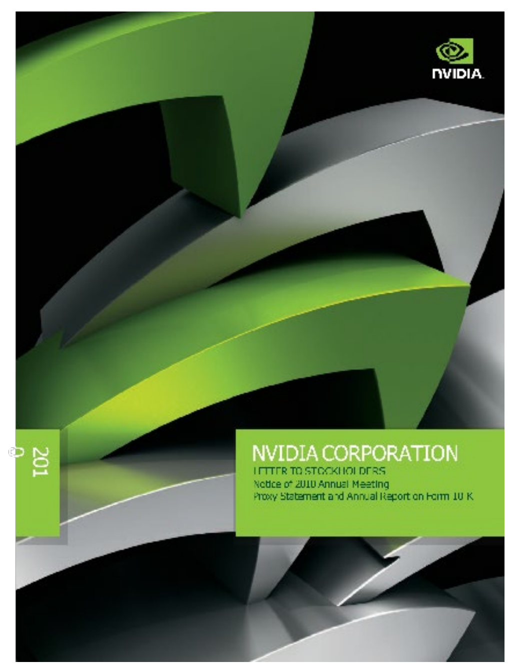


2010



Appendix C. Cover Page of Nvidia's Annual Report/10-K Issued in 2009

UNITED STATES
SECURITIES AND EXCHANGE COMMISSION
Washington, D.C. 20549

FORM 10-K

[x] **ANNUAL REPORT PURSUANT TO SECTION 13 OR 15(d) OF THE SECURITIES EXCHANGE ACT OF 1934**
For the fiscal year ended January 25, 2009

OR

[_] **TRANSITION REPORT PURSUANT TO SECTION 13 OR 15(d) OF THE SECURITIES EXCHANGE ACT OF 1934**

Commission file number: 0-23985

NVIDIA CORPORATION

(Exact name of registrant as specified in its charter)

Delaware	**94-3177549**
(State or other jurisdiction of Incorporation or Organization)	**(I.R.S. Employer Identification No.)**

2701 San Tomas Expressway
Santa Clara, California 95050
(408) 486-2000
(Address, including zip code, and telephone number, including area code, of principal executive offices)

Securities registered pursuant to Section 12(b) of the Act:

Title of each class	**Name of each exchange on which registered**
Common Stock, $0.001 par value per share	The NASDAQ Global Select Market

Securities registered pursuant to Section 12(g) of the Act:
None

Indicate by check mark if the registrant is a well-known seasoned issuer, as defined in Rule 405 of the Securities Act.
Yes ☒ No ☐

Indicate by check mark if the registrant is not required to file reports pursuant to Section 13 or Section 15(d) of the Act.
Yes ☐ No ☒

Indicate by check mark whether the registrant (1) has filed all reports required to be filed by Section 13 or 15(d) of the Securities Exchange Act of 1934 during the preceding 12 months (or for such shorter period that the registrant was required to file such reports), and (2) has been subject to such filing requirements for the past 90 days.
Yes ☒ No ☐

Indicate by check mark if disclosure of delinquent filers pursuant to Item 405 of Regulation S-K (§ 229.405 of this chapter) is not contained herein, and will not be contained, to the best of registrant's knowledge, in definitive proxy or information statements incorporated by reference in Part III of this Form 10-K or any amendment to this Form 10-K. ☒

Indicate by check mark whether the registrant is a large accelerated filer, an accelerated filer, a non-accelerated filer, or a smaller reporting company. See definitions of "large accelerated filer", "accelerated filer" and "smaller reporting company" in Rule 12b-2 of the Exchange Act. (Check one):

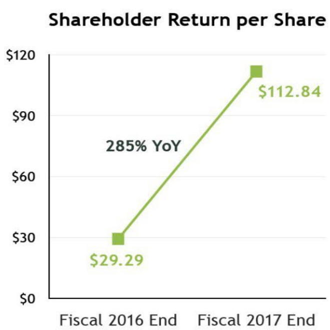
Large accelerated filer ☒ Accelerated filer ☐

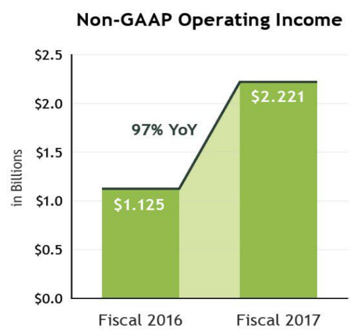
Non-accelerated filer ☐ (Do not check if a smaller reporting company) Smaller reporting company ☐

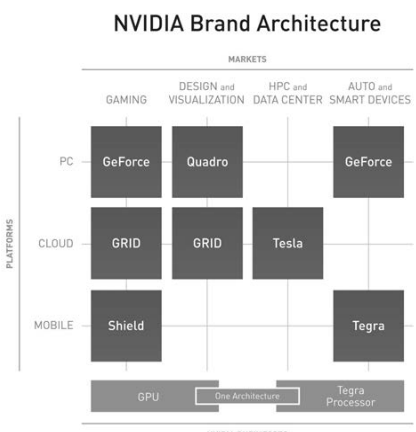
Indicate by check mark whether the registrant is a shell company (as defined in Rule 12b-2 of the Act).

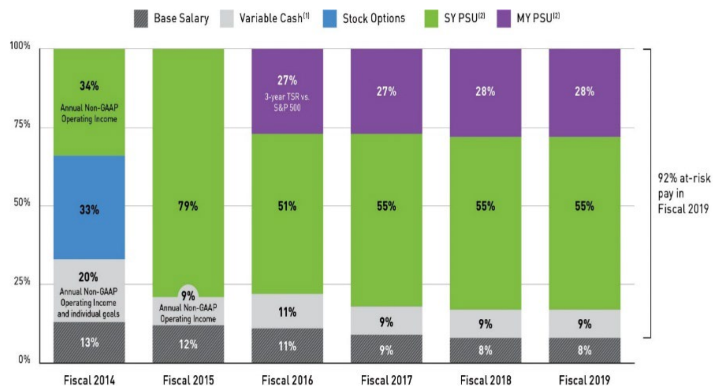

"Everyone in the deep learning business is using GPUs for training."
Yann LeCun, Director of AI Research at Facebook
Virtual Reality
nature
THE HIV-1 CAPSID
Atomic structure of the AIDS pathogen's protein coat

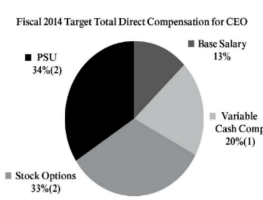
Appendix E. Selected Infographics about Performance and Compensations

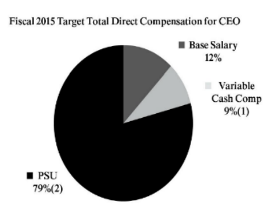


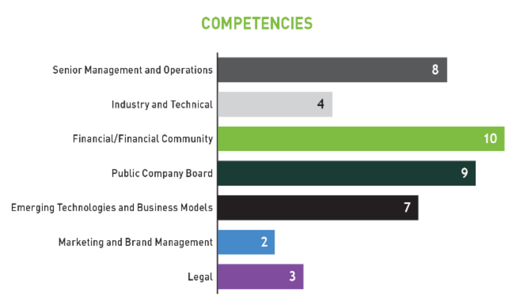


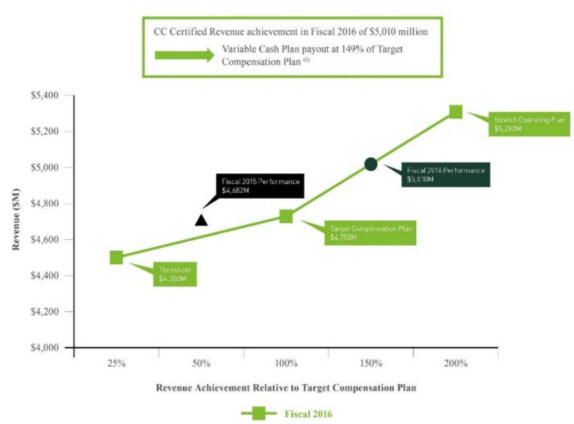












Appendix F. Proof of Proposition 1

First, we consider the ineffective case where $\mu = 0$, i.e., the manager's efforts have no impacts on any attentive traders. In this case, the manager will always choose $s = 0$ to save cost and all market participants will be ignorant of the component $\tilde{\alpha}$ until it is revealed. Given $s = 0$, the trading dynamics in our model is identical to a two-period special case of Holden and Subrahmanyam (1992) who characterize the subgame perfect linear equilibrium for the general multi-period case with multiple traders. Here, we provide analytical solution for the two-period case, following the general procedure of Proposition 1 in Holden and Subrahmanyam (1992). We use the same notation as theirs. Let $\Sigma_t := \text{Var}(\tilde{v}_0|\tilde{p}_t, \tilde{p}_{t-1}, ...\tilde{p}_0)$ represent the posterior variance of $\tilde{v}_0$ conditional on the price history up to time $t \in \{0, 1, 2\}$. In a linear equilibrium, market makers follow the linear pricing strategy (3), with

$$\lambda_1 = \frac{M\beta_1\Sigma_1}{\sigma_u^2}, \qquad \lambda_2 = \frac{M\beta_2\Sigma_2}{\sigma_u^2}, \tag{F-1}$$

where β_t is the trading intensity of each informed trader at time $t = 1, 2$. Let $\eta := \lambda_2/\lambda_1$. By backward induction, it is easy to derive that the optimal trading strategy for trader i is

$$X_{1,i}(\tilde{v}_0) = \beta_1 \cdot (\tilde{v}_0 - p_0) = \frac{\eta(M+1)^2 - 2}{\eta(M+1)^3 - 2M} \cdot \frac{\tilde{v}_0 - p_0}{\lambda_1} \tag{F-2}$$

$$X_{2,i}(\tilde{v}_0, \tilde{p}_1) = \beta_2 \cdot (\tilde{v}_0 - \tilde{p}_1) = \frac{\tilde{v}_0 - \tilde{p}_1}{\lambda_2(M+1)}. \tag{F-3}$$

The Bayesian update of the posterior variance about $\tilde{v}_0$ follows

$$\Sigma_2 = (1 - M\beta_2\lambda_2)\Sigma_1 = \frac{\Sigma_1}{M+1}, \qquad \Sigma_1 = (1 - M\beta_1\lambda_1)\Sigma_0 = \frac{\eta(M+1)^2\sigma_v^2}{\eta(M+1)^3 - 2M}. \tag{F-4}$$

Combining (F-1), (F-2), (F-3), and (F-4), we can derive the expressions (4) for λ_1 and λ_2. These allow us to write the ratio of lambdas which is equal to η by definition. We obtain

$$\frac{\lambda_2^2}{\lambda_1^2} = \frac{\eta(M+1)^3 - 2M}{\eta(M+1)^4 - 2(M+1)^2} = \eta^2 \tag{F-5}$$

This identity leads to the cubic equation (5). When there is a single informed trader ($M = 1$) as studied in Huddart et al. (2001), the cubic equation (5) becomes $8\eta^3 - 4\eta^2 - 4\eta + 1 = 0$ and the economic solution is the largest root $\eta \approx 0.901$.[27] Similarly, when $M > 1$, there exists a

[27] This cubic equation has three real roots at approximately -0.623, 0.223, and 0.901. only the largest root satisfies the second order conditions of Theorem 2 of Kyle (1985) and the requirement of $\lambda_t > 0$.

unique solution that meets the second order condition and the constraint $\lambda_t > 0$ for $t = 1, 2$. Note that stock prices are not efficient in this case, because market markers have overlooked a volatile component, $\tilde{\alpha}$, in the firm value. Traders in this case are only *partially* informed: none of them are aware of alpha as it cannot be effectively conveyed ($\mu = 0$). Nonetheless, stock prices are unpredictable based on the public information because all participants in financial markets have the common knowledge that the firm's liquidation value is drawn from the normal distribution $\mathcal{N}(1, \sigma_v^2)$. Therefore, the absence of abnormal returns is not indicative of market efficiency. It can result from ineffective disclosures (i.e., $\mu = 0$).

Now we consider the general, nontrivial case where $\mu \in (0, 1]$, i.e., the manager's extra efforts ($s = 1$) are effective to some extent. Note that if the manager chooses to make no efforts ($s = 0$) for whatever reason, traders cannot tell if it is due to no alpha ($\tilde{\alpha} = 0$), overly uncertain alpha ($\sigma_\alpha^2 \gg \overline{\alpha}$), or negative alpha ($\overline{\alpha} < 0$). For fundamental investors (as assumed in our model), they will not engage in speculative trading if they have not found any superior information. Thus, the trading equilibrium when firms choose $s = 0$ will be identical to the one under the ineffective communication ($\mu = 0$) as we have just discussed.

The difference occurs only when the manager makes extra efforts ($s = 1$). Even in this case, the rest of the market is unaware of $\tilde{\alpha}$ until the value of $\tilde{v} = \tilde{v}_0 + \tilde{\alpha}$ is publicly revealed. Therefore, market makers follow the same linear pricing strategy described by (3) and (4). Nonetheless, after observing $s = 1$, each attentive trader may discover the value of α with probability μ and fail to find it with probability $1 - \mu$. The potential impact of the manager's action on each attentive trader can be concisely written as $s\tilde{\alpha}\mathbf{1}_\mu$ which, conditional on the manager's efforts ($s = 1$), is exactly equal to $\tilde{\alpha}$ with probability μ and equal to zero with probability $1 - \mu$. Based on the assumption of fundamental investing, each attentive trader initiates an independent research after observing $s = 1$, which takes at least one period of time before he can find alpha. As fundamental traders, they only respond to the fundamental information they possess. Thus, each attentive trader's strategy at $t = 1$ is driven by his initial private information about $\tilde{v}_0$, independent of the manager's action $s = 1$ (as it is not directly informational). This implies that, in the subgame perfect linear equilibrium, the first-period optimal strategy $X_{i,1}$ is still given by Equation (F-2). However, the trading strategy $X_{i,2}$ at $t = 2$ may be affected by the manager's choice of $s = 1$ since traders may find alpha before $t = 2$. This indicates an extra informational term in their second-period trading strategy $X_{i,2}$. This extra term should be linearly proportional to the product $s\tilde{\alpha}\mathbf{1}_\mu$.

For any trader who has found alpha after one period, he is uncertain about how many other traders have discovered the same information of alpha. Due to the independence of $\tilde{v}_0$ and $\tilde{\alpha}$, the optimal strategy can be separated into two parts and written as $X_{i,2}(\tilde{v}_0, \tilde{p}_1, \tilde{s}) =$

$X^o_{i,2}(\tilde{v}_0, \tilde{p}_1) + Z_i(\tilde{s}\tilde{\alpha}\mathbf{1}_\mu)$. The first term is still given by Equation (F-3): $X^o_{i,2}(\tilde{v}_0, \tilde{p}_1) = \frac{\tilde{v}_0 - \tilde{p}_1}{\lambda_2(M+1)}$. The second term, $Z_i(\tilde{s}\tilde{\alpha}\mathbf{1}_\mu)$, is random as it depends on the discovery of alpha. Note that $\tilde{\alpha}$ is unexpected by market markers and the initial price change, $\tilde{p}_1 - p_0$, only reflects the market expectation of $\tilde{v}_0$ conditional on the total order flow $\tilde{y}_1$. Thus, before trading occurs at time $t = 2$, no information about alpha has been incorporated into the prices. Suppose trader i has found the value of alpha after his research, then we can write $Z_i(\tilde{s}\tilde{\alpha}\mathbf{1}_\mu) = z_i(\alpha)$ and the alpha-related part of trader i's objective function can be written as

$$\max_{z_i} \mathrm{E}\left[\left(\alpha - \lambda_2\left(z_i + \sum_{j=1}^{\tilde{M}_\alpha} z_j(\alpha) + \tilde{u}_2\right)\right) z_i\right], \tag{F-6}$$

where $\tilde{M}_\alpha$ represents the (random) number of other traders who have discovered the value of alpha after observing the manager's action $s = 1$. This is a binomial random variable, $\tilde{M}_\alpha \sim \mathcal{B}(M-1, \mu)$. From the perspective of trader i who has found alpha, there are at most $M - 1$ independent competitors and each of them has the same success rate μ. Equation (F-6) is essentially a one-period problem for a random number of informed traders who compete on the same alpha. Since we are considering a symmetric equilibrium where $z_i(\alpha) = z_j(\alpha) = z(\alpha)$, the first order condition of (F-6) leads to

$$\alpha - \lambda_2\left(2z_i + \mathrm{E}\left[\sum_{j=1}^{\tilde{M}_\alpha} z_j(\alpha)\right]\right) = \alpha - \lambda_2(2z(\alpha) + \mu(M-1)z(\alpha)) = 0, \tag{F-7}$$

which leads to the solution

$$z(\alpha) = \frac{\alpha}{\lambda_2(2 + \mu(M-1))}. \tag{F-8}$$

For $M = 1$, we obtain the simple monopolistic result $z(\alpha) = \frac{\alpha}{2\lambda_2}$ for the one-period problem. For $M > 1$, the uncertainty of the number of informed traders can reduce their competition. In summary, the optimal trading strategy for each attentive trader at $t = 2$ is given by

$$\begin{aligned} X_{i,2}(\tilde{v}_0, \tilde{p}_1, \tilde{s}) &= \frac{\tilde{v}_0 - \tilde{p}_1}{\lambda_2(M+1)} + \tilde{s}\mathbf{1}_\mu z(\tilde{\alpha}) \\ &= \frac{\tilde{v}_0 - \tilde{p}_1}{\lambda_2(M+1)} + \frac{\tilde{s}\tilde{\alpha}\mathbf{1}_\mu}{\lambda_2(2 + \mu(M-1))}, \end{aligned} \tag{F-9}$$

where the first term is driven by the information of $\tilde{v}_0$ and the second term is driven by $\tilde{s}\tilde{\alpha}\mathbf{1}_\mu$. Again, both terms are based on material private information about firm fundamentals. There is no speculative trading on the manager's choice of s at either $t = 1$ or $t = 2$. This complete our proof for Proposition 1.

Appendix G. Proof of Proposition 2

With rational expectations about the trading equilibrium in Proposition 1, the manager needs to evaluate the benefit from her choice of s against the associated cost. Although the manager anticipates how each trader may respond to her choice of $s \in \{0, 1\}$, she does not know exactly how many traders would find alpha following her action $s = 1$. Based on the result of subgame perfect linear equilibrium and the property that $\mathrm{E}[\tilde{v}_0 - p_0] = \mathrm{E}[\tilde{v}_0 - \tilde{p}_1] = 0$ (because the prices are efficient for $\tilde{v}_0$), the manager's objective (1) becomes

$$
\begin{aligned}
& \max_{s\in\{0,1\}} \mathrm{E}^{\mathcal{F}}[\tilde{p}_2 - p_0] - s \cdot c = \max_{s\in\{0,1\}} \mathrm{E}^{\mathcal{F}}[\lambda_1 \tilde{y}_1 + \lambda_2 \tilde{y}_2] - s \cdot c \\
= \quad & \max_{s\in\{0,1\}} \mathrm{E}^{\mathcal{F}}\left[\lambda_2 \sum_{i=1}^{M} \frac{s\tilde{\alpha}\mathbf{1}_\mu}{\lambda_2(2+\mu(M-1))}\right] - s \cdot c \\
= \quad & \max_{s\in\{0,1\}} \frac{s\mu M\overline{\alpha}}{2+\mu(M-1)} - s \cdot c
\end{aligned} \tag{G-10}
$$

This leads to her binary decision rule with the threshold, $K = \frac{2+\mu(M-1)}{\mu M}c$, as in Equation (7). When $\overline{\alpha} \geq K$, the manager chooses $s = 1$ and the stock will experience no abnormal return over the time window $[0, 1]$ but positive abnormal return $\mathrm{E}[\tilde{p}_2 - p_0] = \frac{\mu M\overline{\alpha}}{2+\mu(M-1)}$ afterwards. When $\overline{\alpha} < K$, the manager chooses $s = 0$ such that there will be no abnormal returns up to either $t = 1$ or $t = 2$. The result in Equation (9), $\mathrm{E}[\tilde{p}_1 - p_0|s = 0] = \mathrm{E}[\tilde{p}_2 - p_0|s = 0] = 0$, follows from the property that, in the subgame perfect linear equilibrium, market markers set efficient prices for $\tilde{v}_0$, i.e., $\tilde{p}_1 = \mathrm{E}[\tilde{v}_0|\tilde{y}_1]$ and $\tilde{p}_2 = E[\tilde{v}_0|\tilde{y}_1, \tilde{y}_2]$. Nonetheless, those prices are not efficient in any case because the market is ignorant of the volatile component $\tilde{\alpha}$.

As a note, we have assumed for simplicity that the manager's objective function is described by Equation (1). This is sufficient for the testable implications. There are different ways to describe the manager's utility. For example, a more complex specification can be

$$
\max_{s\in\{0,1\}} \mathrm{E}^{\mathcal{F}}[\delta \cdot (\tilde{p}_2(s) - p_0)] - s \cdot c - \gamma \mathrm{Var}^{\mathcal{F}}[\delta \cdot (\tilde{p}_2(s) - p_0)]. \tag{G-11}
$$

where the parameter δ reflects the strength of the manager's incentive to boost her firm's stock price and the parameter γ represents the manager's risk-aversion coefficient. This specification can make the expression of K complicated but not alter our main implications.

Our simple model can be extended or modified in many other ways. For example, the firm manager may be concerned about the time "integral" of price changes; the manager's choice variable s can be continuous over the interval $[0, 1]$. Those model variants do not change the key implications derived from the simple model in the main text.

Appendix H. Definitions of Variables

Variables	Definition
Return	Weekly stock returns for a given event window
Graph	Dummy variable equal to 1 if the firms use graphic annual reports in the fiscal year, and 0 otherwise
Graphicity	Dummy variable equal to 1 if a firm adds a graphic annual report on top of a plain 10-K in a fiscal year, and 0 otherwise
Δ Pics	Natural log of yearly change in total number of pictures and charts
Jump	Dummy variable equal to 1 if the total number of pictures in the financial report is 50% or higher than that in the previous year's report, and 0 otherwise
Readability	Fog Readability index
INST	Institutional ownership in percentage immediately before financial reports release date
Short Interest	Yearly average of short interests $\div$ volume immediately before financial reports release date
Analyst Coverage	Number of analysts following the company immediately before financial reports release date
Institutional Flow	Institutional net inflow in percentage, by taking the difference between the newly available institutional ownership and the reference institutional ownership
Treatment	Dummy variable equal to 1 if the company experiences any format change by newly issuing a graphic annual report, and its subsequent fiscal years during the period before the next format changes, and 0 otherwise
ROE	Return on equity
Leverage	Long term debt (DLTT) plus debt in current liabilities (DLC) scaled by the sum of long term debt, debt in current liabilities, and total stockholders' equity (SEQ) $\times$ 100
Size	Natural log of total assets at the beginning of a fiscal year
Capex	Capital expenditures (Compustat CAPX) scaled by end-of-year total assets (AT) $\times$ 100
R&D	Research and Development Expenses (XRD) scaled by end-of-year total assets (AT) $\times$ 100
Asset Growth	Total Assets (AT) divided by start-of-year Total Assets minus one $\times$ 100
Cash Flow	Net income before extraordinary items (IB) + depreciation and amortization expenses (DP) scaled by start-of-year total assets $\times$ 100
Accruals	Discretionary accruals (Dechow et al. 1995)

Appendix I. Firm Characteristics and Graphic Annual Reports

This table reports the results from estimating the following logistic regression, which identify the characteristics of firms that use graphic elements in their annual reports:

$$\begin{aligned} Logit(Graph_{i,t}) &= \beta_0 + \beta_1 \times Size_{i,t} + \beta_2 \times ROE_{i,t} + \beta_3 \times BtM_{i,t} \\ &\quad + \beta_4 \times Accruals_{i,t} + \beta_5 \times Readability_{i,t} + \epsilon_{i,t}. \end{aligned}$$

Columns (1) through (5) report the results of Size, ROE, Book-to-Market, Discretionary Accruals, and Readability Index as the independent variable without controlling for other firm characteristics. Column (6) reports the results by including all the above variables as the independent variables. We report the *t*-statistic in the parenthesis under each coefficient. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) Graph	(2) Graph	(3) Graph	(4) Graph	(5) Graph	(6) Graph
Size	0.257***					0.240***
	(16.99)					(13.77)
ROE		0.009***				0.002*
		(9.87)				(1.79)
BtM			-0.326***			-0.216***
			(-4.88)			(-2.90)
Discretionary-Accruals				-0.000		0.010
				(-0.03)		(0.63)
Readability					-0.025	-0.052*
					(-0.96)	(-1.93)
N	10,105	10,019	10,070	9,839	9,561	9,295
pseudo R^2	0.034	0.011	0.003	0.000	0.000	0.035

Appendix J. Annual Report Graphicity and Institutional Investing: Alternative Measures

This table reports the results of estimating the same regressions in Table XII, by replacing the main independent variable as one of the two alternative independent variables of *Graphicity*. The dependent variable is the *Institutional Flow* (IF) for the period of one quarter (1Q), two quarters (2Q), and three quarters (3Q) after the release of annual reports. Standard errors are adjusted for heteroskedasticity and clustered by firm. Firm and year fixed effects are included. We report the t-statistic in the parenthesis under each coefficient. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1) IF (1Q)	(2) IF (2Q)	(3) IF (3Q)	(4) IF (1Q)	(5) IF (2Q)	(6) IF (3Q)
ΔPics	0.183	0.287	0.690*			
	(1.02)	(0.94)	(1.68)			
Jump				0.435	0.712	1.482*
				(1.01)	(1.02)	(1.84)
Size	-0.503	-1.037	-1.998*	-1.045**	-2.040*	-2.615**
	(-1.20)	(-1.11)	(-1.78)	(-2.04)	(-1.87)	(-2.04)
BtM	0.131	2.419	2.565	0.344	3.683**	3.160
	(0.23)	(1.56)	(1.46)	(0.60)	(2.11)	(1.65)
ROE	-0.004	-0.008	-0.008	-0.005	0.000	0.003
	(-0.38)	(-0.36)	(-0.30)	(-0.52)	(0.01)	(0.13)
Leverage	0.013	0.028	0.006	0.024*	0.036	0.008
	(1.03)	(1.06)	(0.18)	(1.88)	(1.34)	(0.24)
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	1,534	1,427	1,329	1,326	1,230	1,148
Adjusted R-Sq.	0.094	0.217	0.144	0.135	0.256	0.178

Appendix K. Testing Pre-treatment Trends for Difference-in-Differences

This table reports the panel regression results that examine the real effects of *Graphicity* on corporate activities using a dynamic Difference-in-Differences setting. We expand the Treatment indicator to seven indicators for a few years before and after the release of annual reports. Table headings indicate different samples that the regressions are based on. The dependent variable is R&D expenses. Standard errors are adjusted for heteroskedasticity and clustered by firm. Firm and year fixed effects are included. *, **, *** indicate significance at the 10%, 5%, and 1% levels respectively.

	Full Sample	Matched Sample
	(1)	(2)
	R&D	R&D
Treatment(-3)	-0.578	-0.536
	(-0.87)	(-0.58)
Treatment(-2)	-0.241	-0.075
	(-0.35)	(-0.09)
Treatment(-1)	0.214	0.399
	(0.37)	(0.48)
Treatment(0)	-0.153	-0.193
	(-0.23)	(-0.20)
Treatment(1)	0.449	0.226
	(0.59)	(0.22)
Treatment(2)	1.252*	1.416
	(1.84)	(1.41)
Treatment(3+)	1.602**	2.061*
	(2.00)	(1.69)
Size	-5.368***	-5.865***
	(-11.78)	(-9.01)
Cashflow	-0.174***	-0.190***
	(-5.54)	(-4.14)
ROE	0.017*	0.018
	(1.75)	(1.14)
Year Fixed Effect	Yes	Yes
Firm Fixed Effect	Yes	Yes
N	7,021	3,137
Adjusted R-Sq.	0.851	0.835