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STRATEGIC USE OF NUMERIC VOLUME IN 10-K REPORTS

JIAJIA FU

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The Hong Kong Polytechnic University

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The Hong Kong Polytechnic University

School of Accounting and Finance

Strategic Use of Numeric Volume in 10-K Reports

Jiajia Fu

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______________________________ (Signed)

Jiajia Fu _______________(Name of Student)

Abstract

Managers have considerable discretion over choosing the degree of quantification with numbers in the 10-K. This paper provides the first large-sample evidence on whether and how managers structure the numeric volume of annual reports to hide adverse information from investors. Specifically, I investigate whether managers limit the numeric volume of the 10-K to obfuscate future firm performance, and how investors react to such volume management.

I view numeric volume as jointly determined by firm fundamentals and a discretionary component (referred to as *abnormal volume*) that could reflect manager's private information about future firm performance. I use *industry-adjusted volume* as a starting point to act as a proxy for *abnormal volume*. I also use (1) year-to-year change of numeric volume, and (2) the residual volume from the determinant model as alternatives to measure *abnormal volume*.

Two main findings follow. First I find that abnormal low volume predicts poor future earnings and cash flows. This relation is more pronounced in firms where the market has greater difficulty in detecting managerial intervention in the disclosure process. Second, I find that abnormal low volume strongly predicts negative future returns, suggesting that managers benefit from disclosing fewer numbers by delaying the incorporation of bad news into stock prices. The zero-investment portfolio for *abnormal volume* yields an annualized DGTW adjusted return of 8%. Further corroborating my main results, I find that numeric volume is abnormally low when there exist strong managerial incentives to withhold bad news and/or manipulate investors' perception upwardly, such as just meeting or beating earnings thresholds and the equity incentives from CEOs. Overall, the evidence is

consistent with my prediction that managers attempt to obfuscate future performance and inflate stock prices by disclosing fewer financial numbers in the 10-K.

It should be noted that this paper focuses on the volume of financial items that likely capture the whole information flow of the 10-Ks, as captured by Compustat. There are probably other ways in which managers attempt to inform or misinform investors by intervening the numeric volume in the 10-K. For example, do firms disclose more redundant numbers to increase investors' processing cost? Do firms disclose more good news items to distract investors' attention? Future research may explore these possibilities.

This paper makes several contributions. Assessing whether reported financial statements are intentionally intervened (misstated or manipulated) and detecting the signals for the deterioration of future firm performance are of considerable interests to regulators, investors and researchers. This study is the first to show that abnormal numeric volume in the 10-K reveals managerial opportunism and can be used as a red flag of future performance deterioration. The economic impact of abnormal volume seems to be fairly large (annualized DGTW-adjusted return of 8% based on the zero-investment strategy of abnormal volume). Also, my study contributes to the strategic disclosure literature by discovering a new mechanism – numeric volume, through which firms can control information flow to the market, and revealing whether and when managers engage in volume management.

Key words: Disclosure; Annual report data items; Profitability; Market efficiency; Compustat

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Chapter 1. Introduction

While the Securities and Exchange Commission (SEC) stipulates a basic framework and minimum standards for financial disclosures in the 10-K, considerable discretion remains in choosing what information is actually provided and how information is presented (Lang and Lundholm 1993).[1] Numeric volume, i.e., the number of numbers[2], in financial disclosures is a relatively new communication measure which represents a communication that is universally understood and often has more precision than a textual equivalent (Lundholm et al. 2014). Using a set of financial items that likely capture the whole information flow in the 10-K, I investigate whether firms choose to limit numeric volume in annual reports to obfuscate future firm performance, and whether and to what extent investors are misled by this volume management. My analysis rests on a simple premise: Managers have an information advantage, and they have incentives and the ability to be strategic in 10-K disclosures.

There is a growing interest in the recent accounting literature regarding how managers structure the features of financial disclosure to purposely communicate their view about firm performance to investors. Prior studies have examined the readability, tone or other linguistic features in various communication outlets, including 10-Ks/10-Qs (Loughran and McDonald 2014; Li 2008; Lehavy et al. 2011; Kravet and Muslu 2013), earnings press releases (Huang et al. 2013; Davis et al. 2012), and conference calls (Larcker and Zakolyukina 2012; Frankel et al. 2010).

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[1] For example, there is extensive evidence in the literature of earnings management and strategic disclosure that managers exert their direction in the 10-K to purposely influence investors' perception of firm value (McVay 2006; Koh and Reeb 2015; Riedl and Srinivasan 2010; Chen et al. 2015).

[2] I use the number of numbers, numeric volume, numeric quantity, and numeric disclosure interchangeably in this paper. Unless particular explanations are provided, volume in this paper is specifically referred to numeric volume.

One strand of this literature provides evidence that managers structure the disclosure to inform investors. For example, Li et al. (2013) develop a measure of competition by simply counting how many times a firm refers to competition in the 10-K. They find that this simple but novel measure of competition is very useful in assessing a firm's competition environment. Lundholm et al. (2014) count the number of financial numbers in the MD&A and earnings press releases, and consider this numeric volume as the part of disclosure quality in addition to readability. They find that foreign firms listed on US stock exchanges in general write clearer test and present more numerical data than their US counterparts. Their evidence suggests that foreign firms, with an attempt to lower U.S. investors' reluctance to own them, structure their disclosure in a way that would be earlier for investors to understand.

The other strand of the literature reveals managers' incentives and tactics to mislead investors. For example, in the examination of how 10-K readability relates to future firm performance, Li (2008) uses the both Fog Index and a simple count of words to access readability. He finds that firms with less readable 10-Ks (higher Fog Index and longer report length) have lower subsequent earnings. The evidence in Li (2008) suggests that managers try to hide poor future firm performance by increasing the textual volume of 10-Ks to bury earnings-relevant information in longer documents. Larcker and Zakolyukina (2012) analyze linguistic features in CEO and CFO statements during quarterly earnings conference calls and estimate a linguistics-based deceptiveness measure. They find deceptive CEOs use more references to general knowledge, fewer nonextreme positive emotion words and fewer shareholder value phrases.. Their deceptiveness measure predicts accounting manipulations better than a model based on discretionary accruals. Huang et al. (2013) focus on earnings press release and find that abnormal positive tone predicts poor future performance, suggesting managers exploit tone opportunistically to misinform investors.

My study explores a relatively new feature of 10-K reports – the numeric volume, namely, the number of financial numbers. I view the numeric volume as a disclosure decision and consider managers' opportunistic purposes in structuring the numeric volume of annual reports, so this study is similar in the spirit of the latter strand of the literature discussed above, such as Li (2008). In other words, the main purpose of this study is to examine whether managers, in the 10-K context, misinform investors through disclosing less financial numbers that likely affect investors' valuation. It is important to emphasize that instead of looking at the total number of numbers from the whole 10-K filings, I start from the quantity of financial items that likely captures the whole information flow of the 10-Ks, including both the financial statements items and the footnote items. I then estimate the *abnormal volume*, the main variable of interest, which I define as a component of numeric volume subject to managerial discretion.

The concept of "quantitative details" has been explored by researchers in several settings, including a segment reporting setting (Berger and Hann 2007; Bens et al. 2011), earnings press releases (D'Souza et al. 2010), MD&A of the 10-K (Lundholm et al. 2014) and management forecast (Hirst et al. 2007). However, the concept of quantities details of the mandated financial reports has received scant research attention. I am aware of only three papers, Blankespoor (2012), Chen et al. (2015) and Cheng et al. (2016) that explicitly address the quantitative details in the 10-K. While these three studies investigate the association between their numeric quantity measure and information quality, my study focuses on the "information content" of the numeric volume, and test whether managers limit the numeric volume in the 10-K to misinform investors.

Agency cost motive is one important driver for nondisclosure. Agency cost of disclosures may arise when disclosures provide information about value-reducing aspects of a firm (Bens et al. 2011). The accounting literature has long recognized that managers have incentives to delay bad news disclosure (Kothari et al. 2009; Kim; et al. 2015; Ge and Lennox 2011). In a survey study by Graham et al. (2005), several interviewed CFO argue that they withhold bad news in hopes that the firm's situation will get better before the next information release.

I hypothesize that managers choose a lower level of numeric volume in the 10-K to hide bad news. Concurrent summary performance measures may not fully reflect firms' economic fundamentals. When disaggregated financial items contain unfavorable information about future performance, managers may choose to withhold those numbers to influence investors' expectation opportunistically. It is difficult for investors to detect this type of manipulation because large volume and high degree of complexity in the 10-K increase investors' processing cost. Bloomfield (2002) posits that information more costly to extract from public disclosure is less completely revealed in market prices (hereafter referred to as the "incomplete revelation hypothesis").

I lean on the Compustat template to estimate a firm's numeric volume in the 10-K. Following Cheng et al. (2016), I construct the volume measure through a count of nonmissing Compustat data items (*NFID*).[3] The maintained assumption is that the

[3] A financial item in COMPUSTAT is coded to be missing when (1) the firm has the item but does not disclose it, or (2) the firm does not have such item. My goal is to capture the variation in the numeric disclosure where managers are able to exert direction. Missing data from the second scenario will bring about measurement errors. Cheng et al. (2016) account for the second scenario when calculating

template that Compustat employs is well structured and thus can represent a complete set of financial items that have relatively high impact on investors' perception of firm value. It should be noted that Compustat collects financial numbers in both the financial statements and footnotes. I also decompose *NFID* into income statement-based volume (*NFID_IS*) and balance sheet-based volume (*NFID_BS*) to investigate whether managers manage distinct types of numeric volume differently.

The main variable of interest in my study is the abnormal component of numeric quantity, i.e., abnormal volume (*ABVOL*), which captures managers' discretion over choosing the degree of quantification with numbers in the 10-K. I expect that various economic factors mechanically relate to the numeric volume in the 10-K, and therefore I first use a benchmark model to visualize how a firm's numeric quantity is explained by the proposed economic factors, industry effect and year effect. My determinant model shows that more than 70% of the variation of *NFID* is explained by *NFID* at the industry-year level. The incremental increase in the adjusted R-square is less than 5% when adding a variety of firm characteristics that determine *NFID*. Therefore, I use industry-adjusted *NFID* as a starting point to act as a proxy for abnormal volume.[4] I also consider the robustness of results using (1) the change in *NFID*, and (2) the residual from the determinant model as alternatives to measure abnormal volume.

NFID to capture the variation in the disclosure. Details of how this measure is constructed are discussed in Section 3.2 Variable Measurements.

[4] Industry-adjusted numeric quantity is a powerful and straightforward benchmark. It helps to visualize the economic impact of abnormal numeric disclosure in my later tests. Although it contains large measurement error that may bias my main results down to zero, all my results remain strong. I control for a variety of firm characteristics identified in the determinant model in my later empirical tests so as to better capture the numeric volume that is more subject to managers' intervention.

I first examine the relation between abnormal volume and future firm accounting performance. I find that abnormal low volume is associated with poor future earnings and operating cash flows. The power of abnormal volume to predict future accounting performance is incremental to the effect of various valuation metrics and firm characteristics that have been shown to predict future firm performance in prior studies. This result is consistent with the agency cost motive for nondisclosure, as it implies that managers suppress financial numbers that contain information about subsequent profitability deterioration. I then repeat the analysis using abnormal volume related to the Balance Sheet and Income Statement, separately, and find that the income statement-based abnormal volume drives this relation. I interpret this finding to mean that managers choose to hide adverse information by deliberately disclosing less income statement-related items, which is consistent with the conventional notion that income statement items provide the most value-relevant information that is more likely to affect investors' perception of firm value.

Next, I examine whether stock prices rationally reflect the implication of abnormal volume for one-year-ahead earnings. A large amount of information and a high degree of complexity in the 10-K make it quite challenging for investors to see through managerial opportunism that is driving the discretionary volume of financial items. If managers succeed in delaying the incorporation of bad news into stock prices by disclosing fewer numbers in the 10-K, there should be a return reversal when information about poor firm performance arrives subsequently, either in firms' disclosure, analysts' reports or the business press. Consistent with this conjecture, I find that abnormal low volume in the 10-K predicts lower future returns with a fairly large economic magnitude. This result holds after controlling for accrual management, real earnings management and other return predictors. The zero-investment strategy based on the magnitude of income statement-based abnormal volume yields an annualized DGTW-adjusted return of 8%.

To reinforce my finding that the power of abnormal volume to predict future earnings and return manifests managers' attempt to obfuscate future firm performance, I examine cross-sectional settings where volume management is more likely or less likely to be constrained by the market's ability to assess managers' intervention in the disclosure process. Disclosure literature suggests that the benefit of hiding bad news would be amplified if investors have difficulty in determining whether nondisclosure is due to non-existence of information or due to its adverse contents (Jung and Kwon 1988; Dye 1985). First, I predict and find that the positive relation between abnormal volume and future earnings/returns is more pronounced for firms with high information uncertainty (e.g., loss firm, or firms with high earnings volatility, high return volatility, or high dispersion in analysts' forecasts). Second, I predict that the power of abnormal volume to predict future earnings/returns is reduced in firms with more sophisticated investors. Using the number of analyst following and the institutional holdings as measures of the processing ability of investors, I find that the positive relation between abnormal volume and future performance is largely attenuated for firms with more sophisticated investors. These results corroborate my finding that managers opportunistically manage the numeric volume of the 10-K to obfuscate firms' future performance.

Finally, I present evidence that volume management is used in settings where managers have strong incentives to withhold adverse information and bias investors' perceptions upwardly. I find that abnormal low volume increases the likelihood of just meeting or beating past earnings. I also find a robust negative relation between CEOs' compensation-based equity incentives and abnormal volume in the 10-K. These results further demonstrate that managers adjust the numeric volume of the 10-K for opportunistic purposes.

This paper makes several contributions. First, this paper speaks to a long-standing but still unresolved question: how do managers "hide" bad earnings news? Assessing whether corporate documents/disclosures are intentionally intervened and detecting the signals for the deterioration of future firm performance is of considerable interests to regulators, investors and researchers. This study is the first to show that abnormal numeric volume in the 10-K reveals managerial opportunism and can be used as a red flag of future performance deterioration. Evidence in this paper suggests that managers limit the disclosure of financial items in the 10-K to hide unfavorable forthcoming news, or to prevent the revelation of their opportunism. The economic impact of abnormal volume seems to be large. I find that a trading strategy based on income statement-based abnormal volume yields an annualized DGTW-adjusted return of 8% or more. Abnormal volume remains to be a strong return predictor after controlling for a variety of firm characteristics and other return predictors. The result of abnormal volume as a return predictor contributes to the market efficiency literature.

Second, my study extends the strategic disclosure literature that discovers how managers use disclosure choice for opportunistic purposes. For example, Li (2008) finds that managers provide less readable 10-K reports to obfuscate firm performance. Huang et al. (2013) document that an abnormal positive tone in the earnings release is indicative of poor future performance. My study is in the spirit of Li (2008) and Huang et al. (2013). While tools differ, such disclosure choices deviate from the truthfulness of disclosure and reflect managerial incentives to temporarily mislead investors. My study contributes to this line of literature by discovering a new mechanism-numeric volume, through which firms can control information flow to the market, and revealing whether and when managers engage in volume management.

This paper proceeds as follows. Section 2 discusses the related literature. Section 3 develops hypotheses. Section 4 describes the sample and variable measurement, and discusses the descriptive statistics. Section 5 presents research design and results on the relation between abnormal numeric volume and future fundamentals. Section 6 presents additional analyses and robustness checks. Section 7 concludes.

Chapter 2. Literature Review

2.1 Cost of Nondisclosure

Early theoretical studies in disclosure literature consider disclosure a signal or mechanism to overcome aversion section (Grossman and Hart 1980; Grossman 1981; Milgrom 1981). Their models, relying on the following assumptions, predict that managers fully disclose information relevant to firm value. These assumptions, as summarized in Beyer et al. (2010), include: (1) disclosures are costless; (2) investors know that managers have private information; (3) investors react to firms' disclosure in a uniform fashion and firms could anticipate how investors would interpret their disclosures; (4) managers seek to maximize their firm value; (5) firms can credibly signal their private information; (6) firms cannot commit ex-ante to a specific disclose policy.[5] In their models, if firms withhold any information, rational investors would infer that such "non-disclosure" signal the worst possible outcome. Firms anticipate such investors' reaction and thus respond through disclosing full of information to avoid price decline, i.e., the cost of non-disclose.

In the real world, however, we do not observe full disclosure because one or more of the six assumptions listed above do not hold. Subsequent analytical studies investigate constraints to full disclosure.[6] Proprietary cost is the traditional motive in the literature to explain nondisclosure in general (Verrecchia 1983; Hayes and Lundholm 1996; Verrecchia 2001; Dye 1985). Empirical papers generally find

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[5] See Dye and Sunder (2001).

[6] Another important line of the literature addresses the association between disclosure and capital market benefit. Both analytical and empirical work suggests that higher disclosure results in a variety of capital market benefits. The primary benefit is the reduction of information asymmetry between managers and investors . Lower information asymmetry is associated with higher liquidity, lower cost of capital, and better information environment which in turn attract more traders, analysts and institutional investors. Other benefits include the avoidance of litigation (Skinner 1994) and the signaling of managerial ability.

evidence consistent with the theory that disclosure is constrained by proprietary costs in various settings of disclosure or corporate activities, such as segment disclosures (Berger and Hann 2007; Botosan and Mary 2005), material contract disclosures (Verrecchia and Weber 2006), and patent filings (Arundel 2001).

Agency cost motive is another important driver for non-disclosure. Agency cost motive arises when managerial interests revealed by the disclosure are not aligned with those of shareholders. For example, managers are reluctant to disseminate their private information when it comes to their career concerns, external reputation and compensation. Nagar et al. (2003) provide evidence that stock price-based incentive contracts effectively encourage disclosure. Berger and Hann (2007) examine the segment disclosure and provide evidence consistent with "agency cost motive" hypothesis that that managers dominated by agency cost motive tend to withhold the segments with relatively low abnormal profits. Agency cost motive, in various circumstances, explains managers' tendency to withhold bad news which has been long recognized in the accounting literature (Kothari et al. 2009; Kim; et al. 2015; Ge and Lennox 2011). I provide more discussion on why and how managers withhold bad news in section 2.2.

To sum up, disclosure literature documents that proprietary cost and agency cost are two main motives for managers' nondisclosure. Managers attempting to maximize firm valuation will choose not to disclose news if they obtain higher payoff by avoiding the cost associated with a disclosure.

2.2 Agency Conflict and Bad News Withholding

Graham et al. (2005) conduct a comprehensive survey that invites CFOs to describe their choices related to financial reporting and voluntary disclosures. Some CFOs argue that they delay bad news disclosure in hopes that they can bury the bad news if firms' statuses improve before the next information release. Managers' tendency to hide bad news can stem from the traditional agency problem where managerial interests are not well aligned with those of shareholders, (agency cost motive).[7] Kothari et al. (2009) discuss that career-related cost and compensation concerns are two main reasons that drives managers' agency cost motive. Career concerns refer to the impact of bad news disclosure on managers' career, such as performance evaluation, promotion, employment opportunities inside and outside the firm, potential termination, potential loss of postretirement benefits and so forth (Nagar 1999). In addition to career concerns, managers withhold bad news to avoid a loss in wealth. Negative market reaction to bad news may shrink managers' compensation package, including lower bonus payments, less stock option awards, etc.

Consistent with the agency cost motive, a voluminous body of literature on voluntary disclosure decision reveals opportunistic managerial disclosure choices. For example, Schrand and Walther (2000) provide evidence that managers strategically select the prior-period earnings as a benchmark to evaluate current-period earnings in quarterly earnings announcements. deHaan et al. (2015) find that managers announce earnings during periods of low attention to hide bad news. Non-GAAP information is also a widespread form of voluntary disclosure. While corporate managers often claim non-GAAP earnings helps to communicate permanent earnings and thus informative to investors, it has long been criticized that managers use non-GAAP earnings to opportunistically portray firm performance

[7] Another line of studies show that managers accelerate bad news disclosure under certain circumstance. For example, Skinner (1994) first documents that litigation risk concerns motivate managers to voluntarily disclose bad news. Aboody and Kasznik (2000) show that managers strategically manage the timing of voluntary disclosers around the stock option award dates. They find CEOs accelerate bad news and/or withhold good news prior to scheduled option grant dates to lower the exercise price of options and thus maximize their option compensation.

and mislead investors. For example, some studies document that non-GAAP exclusions negatively predict future performance, suggesting that these items are excluded for opportunistic purposes (Doyle et al. 2013; Doyle et al. 2003; Kolev et al. 2008). Doyle et al. (2013) find that managers opportunistically define non-GAAP earnings to meet or beat analyst forecast. In addition to various financial disclose choices, there is an emerging literature that examines how managers structure qualitative information in disclosures. I discuss more in section 2.3.

2.3 Disclosure Features in the 10-K

The 10-K reports are one of the most comprehensive and credible channels through which managers communicate their superior information to outside investors. There is growing research that explores the information content of the properties of financial disclosure in the 10-K or in a particular section of the 10-K. These papers vary by measures of disclosure features, managerial incentives and capital market outcomes investigated. Disclosure features of the 10-K examined in prior literature include readability (Li 2008), file size (Loughran and McDonald 2014), tone (Feldman et al. 2010; Li 2010), lexical characteristics such as the use of causation words (Li et al. 2013; Loughran and McDonald 2011; Nelson and Pritchard 2007), and the level of disaggregation of financial items (Chen et al. 2015).

With regard to managerial incentives, prior studies examine whether managers influence annual report features for informative or strategic purposes. For example, Li (2008) finds that firms with poor current earnings have less readable annual reports. He concludes that this result suggests managers' intervention in the reports' readability with an incentive to obfuscate poor firm performance. Loughran and McDonald (2014) report that the file size of the 10-K document provides a simple readability proxy that outperforms the traditional Fog Index. In contrast to these studies that reveal managers' strategic use of 10-K features, other studies find evidence consistent with informative purposes. Li (2010) documents that the average tone of the forward-looking statement in the MD&A section of 10-K and 10-Q filings predicts future earnings even after controlling for various future performance determinants documented in prior literature. Li et al. (2013) find that the qualitative information in the 10-K is very useful for assessing a firm's competition environment. Chen et al. (2015) find that firms with a greater level of disaggregation of financial items are associated with lower bid-ask spreads, cost of equity and dispersion in analysts' forecasts, and higher accuracy in analysts' forecasts. Collectively, these studies suggest that managers influence distinct features of the 10-K differently to communicate firms' overall performance that they would like investors to perceive.

Numeric volume reflects the amount of quantitative details in the disclosure**.** Only a few papers examine numeric volume as a disclosure feature in financial disclosures. Several studies investigate the variation of numeric volume in voluntary disclosure settings, including earnings press releases and management forecasts.[8] Hirst et al. (2007) find that disaggregation of management forecast works to counteract the effect of agency-problem-induced incentives and thus increases forecast credibility. D'Souza et al. (2010) focus on earnings releases and report that managers choose to disclose less GAAP line items in earnings releases to mask their intervention in the financial reporting process. Lundholm et al. (2014) use total number of numbers in earnings press releases and the MD&A as one dimension of

[8] While MD&A section in the 10-K is mandated, it is more similar to voluntary disclosures such as earnings repress releases than to the rest part of the 10-K, in terms of managerial discretion and the disclosure volume, which are two key words in my study. Therefore, I review Lundholm et al. (2014) that examines total number of numbers in earnings releases and the MD&A in the section of voluntary disclosures, rather than in the section of the 10-K.

disclosure quality in addition to readability. They find that in an effort to reduce U.S. investors' information disadvantage and home bias, foreign firms present relatively more numerical data than their U.S. counterparts.

Voluntary disclosure and mandated reports are distinct in many ways, such as regulations, managerial incentives, investors' reaction to the news, disclosure content, the textual and numeric volume and so forth. For example, while earnings press releases or management forecasts are salient to investors, the filing of 10-K are often viewed as a formality by investors and the information content in the 10-K is largely underestimated. The complexity of the 10-K, as reflected by the large volume of the report relative to voluntary disclosures, makes investors more difficult to exploit the 10-K information. Prior research suggests that market tends to process information in earnings press releases more efficiently than information in 10-K filings (You and Zhang 2009; Levi 2008; Louis et al. 2008). Furthermore, the format or content of voluntary disclosure is much less than that of SEC filings, providing managers the significant flexibility to exert their discretion. As such, one cannot simply generalize research findings from the voluntary disclosure setting to the 10-K contexts.

To the best of my knowledge, the few papers investigate the nature and the role of numeric quantities in the 10-K. As these papers are closely related to my study, I first discuss in details on their research questions, measures of numeric volume and findings. I then provide a discussion on how my study is different from others.

Blankespoor (2012) use Perl to identify and count financial numbers for financial statements and footnotes. She considers the numeric volume in 10-K findings a disclosure choice that reflects the amount of firm-specific information managers choose to disclose to investors. Using the eXtensible Business Reporting

Language (XBRL) regulation as an exogenous shock that reduces investor processing costs for quantitative footnote disclosures, she predicts and finds that firms increase the numeric volume after the adoption of XBRL. Her conclusion is that firms choose to disclose more information after investor processing cost decreases.

The use of numeric volume in my paper differs from that in Blankespoor (2012) in the following ways. The maintained assumption in Blankespoor (2012) is that more financial numbers, better disclosure quality. While this assumption is more likely to be held in voluntary disclosure settings due to relatively low textual and numeric volumes. It may not be held in many ways in the context of the 10-K. In other words, one can imagine many exceptions that make the relation to be insignificant or even inverse. For example, firms trying to obscure current or future poor performance can discuss more redundant numbers, either irrelevant or repetitive, so as to distract investors' attention. As in Chen et al. (2015) and Cheng et al. (2016) discussed below, I view numeric volume as jointly determined by firm fundamentals and a discretionary component that could reflect manager's private information about future fundamentals or managerial incentives, if any. One may expect the information content of the normal and discretionary volume to be different. If the determinant model to isolate normal volume from discretionary volume works well, normal volume should capture truthful disclosures whereas discretionary volume captures strategic disclosure. Therefore, instead of using the total number of numbers, the first step in my research design is to measure the discretionary component, which is consistent with my research purpose – the strategic use of numeric volume.

Also, Blankespoor (2012) suffers measurement error in coding the volume measure. For example, page numbers are counted as financial items in Blankespoor

(2012) as she did not have an effective way to remove page numbers. She also did not differentiate new numbers (financial items specifically for current fiscal year) and old numbers (financial items disclosed in the past). It is likely that managers structure the volume of new and old information in a different way. Old numbers are not as informative as new numbers to investors. For example, if managers tend to misinform investors, they may choose to limit the volume of new numbers but discuss more old numbers so as to bury the unfavorable news in an overwhelming amount of uninformative text and data (Loughran and McDonald 2014). In my paper, I follow Cheng et al. (2016) and rest on Compustat to construct my volume measure. While measurement error is still an issue as Compustat does not include all financial items in the 10-K, my volume measures mainly capture the volume of new numbers and thus attenuate the confounding effect from old numbers.

Two papers construct measures of numeric volume using Compustat template. Chen et al. (2015) (CMS) construct a disaggregation quality measure (DQ) that, as they claim, captures the level of disaggregation of accounting data and reflects the extent of quantitative details in the 10-K. The concept of disaggregation is the essence of their measure. They develop a three-level nesting structure (subaccount, parent account, and group account) to measure disaggregation using Compustat data items. Take INVT (Inventory –Total) as an example. As illustrated in their paper, INVT is classified as a parent account. Four subaccounts, which should add to the parent account, are nested to INVT: raw material inventory (INVRM), work-in-progress inventory (INVWIP), finished goods inventory (INVFG) and inventory-other (INVO). Meanwhile, INVT is nested to the group account ACT (Current Assets –Total), the sum account of in total eight current asset parent accounts.

With the disaggregation framework, CMS then construct their DQ measure through counting the number of non-missing financial items in Compustat. A higher value of DQ represents higher disaggregation details. They offer a battery of validation tests by examining the association between DQ and a set of variables documented to be associated with disclosure quality in prior literature. Specifically, they find DQ is negatively (positively) associated with analyst forecast dispersion (accuracy), bid-ask spreads and cost of equity. Therefore, they conclude that DQ can be used as a new measure of disclosure quality.

Unlike CMS that emphasize on the disaggregation feature, Cheng et al. (2016) are more interested in the amount firm-specific information captured by the financial numbers in the 10-K. They are motivated by the unsolved question in the literature: Does large volume of the 10-K represent more information? They use price asynchronicity (i.e., the inverse of price synchronicity) to measure the amount of firm-specific information reflected in stock prices. They find that a disclosure volume measure based on the number of financial items in 10-K (NFID) as captured by Compustat wins over the other quantity and quality measures (file size, number of words, DQ from CMS) in explaining price asynchronicity. They promote their NFID measure can be used as a simple and direct measure of the amount of firm-specific information provided by a firm.

This paper differs from CMS and Cheng et al. (2016) in the following ways. First, research questions in these two studies address the disclosure quality. My study, however, explores the information value of numeric volume to investors. As a result, unlike the above two studies that investigate the association between the volume and information asymmetry, I'm interested in investigating whether the numeric volume conveys new information. Specifically, is numeric volume useful in predicting future accounting performance? Does the market properly incorporate the information content of disclosure volume into stock prices?

Chapter 3. Hypothesis Development

3.1 Abnormal Volume and Future Accounting Performance

The "management obfuscation hypothesis" argues that managers have more incentive to obfuscate information when firm performance is poor because the market may react in a delayed fashion to fully incorporate information that is more costly to extract from the disclosure (Bloomfield 2002). In other words, because the information obscure to investors is less completely revealed in stock prices, managers may want to strategically hide adverse information through less transparent disclosures (agency cost motive).

Prior studies investigate various disclosure choices and provide evidence consistent with this "obfuscation hypothesis" (Lang and Lundholm 1993; Schrand and Walther 2000; Miller 2002; Li 2008). For example, managers strategically choose to make the annual report less readable to when firm performance is poor, making it difficult for investors to process information (Li 2008). I test the "obfuscation hypothesis" by investigating whether managers strategically adjust the numeric volume of the 10-K.[9] The overall numeric volume of the 10-K is jointly determined by economic fundamentals and managerial incentives. In other words, both truthful and strategic disclosures co-exist. It should be noted that the main variable of interest in this paper is the discretionary component of the 10-K volume that is driven by managerial incentives. I develop my determinant model in the later section that decomposes the overall volume into normal and abnormal components.

I argue that managers have incentives and considerable capability to engage in volume management. First, agency cost of disclosure may arise when detailed

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[9] My study is similar in spirit to Li (2008) that tests the "management obfuscation hypothesis" using readability as a communication tool.

financial numbers provide clues about value-reducing aspects of a firm. The large information details in the 10-K allow investors to verify information released in earlier voluntary disclosures. Because of this feedback role of annual reports, managers who are hiding adverse news elsewhere may also provide less concrete information to prevent investors from getting any clues of their opportunism (Kim; et al. 2015; Bloomfield 2002). Second, the deception by omission (i.e., withholding bad news about future earnings) commonly incurs low litigation cost because it is difficult for a plaintiff to prove that managers deliberately withheld the news from the market (Ge and Lennox 2011). Third, managers have large latitude in determining what to provide and how to present when preparing the 10-K (Lang and Lundholm 1993; Chen et al. 2015). Finally, the long length and the complexity of the 10-K filings lower the disclosure cost for managers' bad new withholding, because these features make it difficult for investors to detect managers' intervention in volume disclosure. Therefore, consistent with the obfuscation hypothesis, I predict a positive relation between abnormal volume and future earnings and state the hypothesis as follows.

P1: Abnormal numeric volume positively predicts future accounting performance.

3.2 Market Reactions to Abnormal Volume in the 10-K

If managers engage in volume management to mask poor future performance to mislead investors, then a natural question is whether managers succeed in delaying bad news into stock prices. A large amount of information and a high degree of complexity in the 10-K make it quite challenging for investors to see through managerial opportunism that is driving the discretionary volume of financial items. If investors fail to see through managers' incentives to engage in volume management, there should be contemporaneous overpricing for stocks with abnormal low volume. When information about poor firm performance arrives subsequently, I expect stock prices for firms with abnormal low volume in the 10-K to converge to fundamental values (i.e. price correction process). Given investors' ignorance and the complexity of 10-K filings, I make the hypothesis as follows.

P2: Abnormal numeric volume positively predicts future abnormal returns.

3.3 Cross-Sectional Predictions: Variations in Investors' Ability to Assess Volume Management

The first two hypotheses establish two main relations examined in this paper; the remaining hypotheses are about variation in these two relations to reinforce my argument that managers engage in volume management to obfuscate future firm performance. Managers make a trade-off between benefits and costs when making disclosure decisions. Volume management is not cost free. Firms are likely to face different levels of constraints to use this strategy. For example, Rogers and Stocken (2005) document that managers are more willing to misrepresent their forward-looking information when the market has greater difficulty to detect their intervention. In this vein, if the positive relation between abnormal volume and future performance is driven by managers' bad news-withholding behavior, then I expect this relation to be more pronounced in firms where investors' ability to assess managers' disclosure bias is low.

In the first set of cross-sectional tests, I examine the effect of information uncertainty on managers' volume management. Firms with high information uncertainty are inherently more costly for investors to process. Seminal theoretical work regarding discretionary disclosure policy addresses the role of uncertainty in discretionary disclosure model (Dye 1985; Verrecchia 1983; Jovanovic). Their work suggests that the disclosure cost is minimal for managers to withhold bad news when investors are unable to distinguish non-existence of information from managers' deliberate withholding. Specifically, I identify high uncertainty firms as those with losses, those with highly volatile earnings, those with highly volatile returns, and those with more disperse analysts' earnings forecasts. I predict the following:

P3: The relations in P1 and P2 are more pronounced in firms with high uncertainty.

In the second set of cross-sectional tests, I examine the effect of investor sophistication on managers' volume management. Sophisticated investors have more expertise, resources and ability to process detailed financial information at lower cost than other investors. Prior literature has widely addressed the notion that sophisticated market participants (e.g., financial analysts, institutional investors) improve firms' information environment by their price discovery role and monitoring role (Yu 2008; Cheng et al. 2010; McInnis and Collins 2011). In addition, Jung and Kwon (1988) extend the Dye model (Dye 1985) to allow outside investors to revise, in the absence of disclosure, their probabilities that managers have received no private information. Their model demonstrates the possibility that investors' information acquisition from independent sources (e.g., financial analysts, financial press) may trigger the release of information that would otherwise be withheld by managers. Therefore, I predict that managers are less likely to withhold bad news by exerting discretion over the numeric volume of 10-K when firms are largely followed by sophisticated investors, as shown by firms' analyst following and institutional holdings.

P4: The relations in P1 and P2 are attenuated in firms with more sophisticated investors.

Chapter 4. Sample Selection and Variable Measurement

4.1 Sample and Data

I obtain financial data from the Compustat annual database, stock price and return data from CRSP, analyst following and forecasts from I/B/E/S, and institutional ownership data from Thomson Reuters. The 10-K Fog index used in robustness checks is obtained from the website of Feng Li.[10] I also download the data on 10-K file size from the website of Bill McDonald.[11]

My initial sample covers all U.S. domestic listed firms included in Compustat and CRSP from 1976 to 2011.[12] I then exclude Fama-French industries identified by numbers 44-47 (finance firms) and 48 (representing "almost nothing"). To obtain the final sample, I also eliminate observations without sufficient data for return calculation and for control variables in main regression analyses. The final sample in my main tests consists of 106,823 firm-year observations. All continuous financial variables except returns are winsorized at the one percent level. Sample sizes vary across different tests and are noted in the tables.

4.2 Variable Measurements

4.2.1 Construction of Numeric Volume

I follow Cheng et al. (2016) to construct measures of numeric volume in the 10-K (labeled as *NFID*), which rests on a count of nonmissing data items in firms' annual reports as captured by Compustat. After excluding financial data items that are unique to financial and utility firms, I am able to identify 440 financial items that

[10] Source: http://webuser.bus.umich.edu/feng/
[11] Source: http://www3.nd.edu/~mcdonald/Word_Lists.html
[12] I use one-year-ahead earnings, cash flows and risk-adjusted returns in my main tests. Data used for tests on future accounting performance covers until 2012. Note that I start to calculate cumulative returns 4 months after the fiscal year end. Therefore, data used for return tests extends to 2013.

are applicable to industrial firms, including 178 balance sheet-related items, 157 income statement-related items, 44 cash flow items, and 61 miscellaneous items.[13]

The next step is to determine the total number of items that are "applicable" to an industry in a particular year. An item is not "applicable" if its value is missing for all firms in a two-digit SIC industry in a year. Compustat uses the same data collection model to all firms in the cross-section. The purpose of this adjustment is to minimize the impact of items that are irrelevant to a firm's operations. The overall numeric volume measure, *NFID*, is defined as the percentage of non-missing financial items in Compustat for each firm-year, calculated using the number of non-missing items divided by the total number of "applicable" items. A higher *NFID* indicates that more financial numbers could be derived from a firm's annual report. Compustat classifies all financial items into four categories: balance sheet items, income statement items, cash flow items, and miscellaneous items. According to this classification scheme, I also construct two sub-measures: *NFID_BS* for balance sheet-related items and *NFID_IS* for income statement-related items. I leave the sub-measures of the other two categories for future research. I provide an example of how I compute NFID_IS in Appendix B.

It should be noted that numeric volume measures constructed from the Compustat Annual contain the normal component that varies in economic fundamentals and the abnormal component that is subject to managerial discretion. Using the overall volume as a starting point, I construct the abnormal volume, the focus of this study, in section 4.2.4.

[13] The classification of financial items mostly follows the Compustat classification. The few of reclassifications implemented follows Cheng et al. (2016).

4.2.2 Future Returns

I measure buy-and-hold abnormal returns, for firm *i* over 12 months starting four months after the fiscal year end, as follows:

$$BHAR_{t+1} = \prod_{s}(1+r_{is}) - \prod_{s}(1+r_{ps}) \tag{1}$$

where r_{is} and r_{ps} are monthly returns for firm *i* and benchmark portfolio *p*, respectively. I estimate expected returns, i.e., returns for the benchmark portfolio, with characteristics-based risk-adjustment of DGTW (1997). In DGTW's characteristics-based portfolio matching procedure, a stock is matched with the benchmark portfolio on size, book-to-market ratio, and the previous 12-month return momentum. The benchmark portfolios are formed each month by sorting stocks into five size quintiles. Each size quintile is then further divided into five quantiles according to the book-to-market ratio. Each of the 25 groups is further divided into five quintiles on the basis of return momentum. If a firm is delisted during the return accumulation window, I compute the remaining return by using the CRSP daily delisting return and reinvesting remaining proceeds in the appropriate benchmark portfolio (Beaver et al. 2007). I follow Beaver et al. (2007) to set delisting return at the delisting month.[14] Because the size-adjusted return is common in prior research on the mispricing of accounting information, I also use size-adjusted returns in sensitivity tests.

4.2.3 Control Variables

The regression analyses on future performance include controls that relate to disclosure volume and earnings performance. I control for non-strategic determinants of the numeric volume in the 10-K to isolate the effect of the normal volume. I

[14] My main inferences are not affected by the exclusion of delisting returns.

discuss these variables in section 4.2.4. I also control for a variety of known determinants of future earnings or cash flows, including size, book-to-market, contemporaneous returns, earnings volatility, and return volatility (Huang et al. 2013; Li 2010). I include accruals to control for the impact of differential persistence of accruals and cash flows on future earnings, as documented in Sloan (1996). Regarding the analysis on future returns, I control for common return predictors, including size, book-to-market, return momentum, and total accruals (Huang et al. 2013; Sloan 1996; Jung et al. 2015). Because prior studies document the significant negative effect of real earnings management on future firm performance (Gunny 2005), I include a proxy for real earnings management (REM_t) as another control. As in Zang (2011), I estimate REM_t as the sum of abnormal production cost ($PROD_t$) and abnormal discretionary expenditures ($DISX_t$). A higher value of REM_t indicates a larger increase in earnings by overproduction and the cutting of discretionary expenditures. Following Roychowdhury (2006), I estimate $PROD_t$ and $DISX_t$ as the estimated residuals from Equations (2) and (3), respectively. Equations (2) and (3) are estimated cross-sectionally for each industry-year with at least 15 observations, where industry is defined using two-digit SIC code.

$$PROD_t / A_{t-1} = \alpha_0 + \alpha_1(1/A_{t-1}) + \alpha_2(S_t / A_{t-1}) + \alpha_3(\Delta S_t / A_{t-1}) + \alpha_4(\Delta S_{t-1} / A_{t-1}) + \varepsilon_t \quad (2)$$

where $PROD_t$ is the sum of the cost of goods sold in year t and the change in inventory from year t-1 to year t. Other variables are defined in Appendix A.

$$DISX_t / A_{t-1} = \alpha_0 + \alpha_1(1/A_{t-1}) + \alpha_2(S_{t-1} / A_{t-1}) + \varepsilon_t \quad (3)$$

where $DISX_t$ is the discretionary expenditures, measured as the sum of R&D, advertising, and SG&A expenditures. Abnormal $DISX_t$ are residuals from Equation (3) multiplied by -1, so that higher values indicate larger cuts in discretionary expenditures to increase reported earnings.

4.2.4 Abnormal Volume Measure in the 10-K

I construct the abnormal volume measure based on the determinant model results, which present explanatory evidence on the extent to which non-strategic factors (i.e., firm fundamentals) explain the overall volume (*NFID*). Because I focus on the managerial discretion over the volume disclosure, it is important to empirically document the determinants and isolate their effects in my later empirical tests. Following Chen et al. (2015) and Cheng et al. (2016), I identify ten variables in my determinant models which capture firm fundamentals that might impact the numeric volume in the 10-K. These determinants are measures for special or unusual firm events (DRCP, M&A, SEO, ABSSPI), volatility of business or operations (STD_EARN, STD_RET), complexity of operations (BUSSEG, SIZE, AGE), and growth opportunities (BTM). I expect the cross-sectional numeric disclosure volume to center around the mean volume at the industry-year level. Therefore, I also examine how industry mean of *NFID* determines firms' quantification level with numbers in the 10-K. All variables are defined in Appendix A. I cluster standard errors by year and industry.

$$NFID_{i,t} = f\,(DRCP_{i,t}, M\,\&\,A_{i,t}, SEO_{i,t}, ABSSPI_{i,t}, STD\_RET_{i,t}, STD\_EARN_{i,t}, SIZE_{i,t}, AGE_{i,t}, BUSSEG_{i,t}, BTM_{i,t}, IND\_NFID_{i,t}) \quad (4)$$

Table 1 reports the estimation results of Equation (4). The mean of *NFID* at the industry-year level explains the substantial amount of variations in *NFID* (adj. R-square = 0.726), while the rest of firm fundamental variables only explains *NFID* for 7.3%. The incremental increase in adjusted R-square is only 1.1% from column 2 to column 3. I obtain a similar pattern on the adjusted R-square for the determinant models of *NFID_BS* and *NFID_IS*. Results in Table 1 indicate that the most powerful factor driving *NFID* (*NFID_BS*, *NFID_IS*) is the mean of *NFID* (*NFID_BS*, *NFID_IS*) at the industry-year level. Therefore, I use demeaned value of the numeric volume, i.e., *DM_NFID_IS*, *DM_NFID_BS*, and *DM_NFID_IS*, as the main measure of abnormal volume. I control for other determinants in my later tests.

[Insert Table 1]

4.2.5 Summary Statistics

Table 2 presents descriptive statistics on the main variables used in my later analyses. The average percentage of the overall non-missing financial items (*NFID*) is 77.91%, with a mean of 81.73% for balance sheet items (*NFID_BS*) and 71.78% for income statement items (*NFID_IS*). These statistics are comparable to those in Cheng et al. (2016). High percentages of non-missing items are expected because 10-K reports, as one of the most important mandatory filings, are heavily regulated by the SEC. Summary statistics for other variables are similar to those from previous literature.

[Insert Table 2]

Chapter 5. Research Design and Results

5.1 Abnormal Numeric Volume and Future Firm Performance

H1 states that all else equal, firms with lower numeric volume have less favorable one-year-ahead financial performance, as measured by either earnings or cash flows from operations. To test H1, I estimate the following OLS regression. All variables are defined in Appendix A:

$$EARN_{t+1}\ or\ CFO_{t+1} = \alpha_0 + \beta_1 DM\_NFID_t + \beta_2 EARN_t + \sum \beta_k CONTROLS_t + \varepsilon_{t+1} \quad (5)$$

Note that the demeaned value of the numeric volume, i.e., *DM_NFID_IS*, *DM_NFID_BS*, and *DM_NFID_IS*, is used as the main measure of abnormal volume. (See discussion in section 4.2.4). Table 3 presents the results. In all the regressions, the firm fundamental variables used in the determinant model (i.e. Equation 4) are included as control variables. The results without these control variables are not reported but are of similar economic magnitude and statistical significance. I include year and industry fixed effects in all the regressions. All the standard errors are clustered by industry and year, as implemented in related studies (Chen et al. 2015; Li 2008).

I find evidence consistent with H1. In Table 3, Panel A, the positive coefficient on *DM_NFID* (coefficient = 0.043, t-value = 3.05) indicates that firms with numeric volume below the industry mean have lower earnings subsequently. To gauge the economic size of effects, I perform the following calculation. A decrease of one standard deviation (0.0508) in *DM_NFID* implies a decrease of 0.22% (0.0508*0.043) in the one-year-ahead earnings. For comparison, a 0.22% decline amounts to about 5.4% (0.22%/4.06%) of the median earnings, which is 4.06% in my sample.

I repeat this analysis using *NFID_IS* in column (2) and *NFID_BS* in column (3), and find that the relation between abnormal volume and future earnings is driven by abnormal volume related to the income statement. In column (4), I include both *DM_NFID_IS* and *DM_NFID_BS* into the regression. While t-statistics for the coefficient on *DM_NFID_BS* in column (4) decrease largely, from 1.56 in column (3) to 0.11 in column (4), the coefficient on *DM_NFID_IS* remains similar in terms of the magnitude and the significance (coefficient = 0.044, t-value = 3.42).

The economic impact of volume management is likely to be under-estimated when using future earnings as a proxy for future firm performance, because earnings are considerably subject to managerial discretion. Table 3, Panel B reports the results using future cash flow to measure firm performance. For CFO regressions, the coefficients on *DM_NFID*, *DM_NFID_IS*, and *DM_NFID_BS* are 0.042 (with t-value = 2.19), 0.035 (with t-value = 2.59), and 0.017 (with t-value = 1.31), respectively. A decrease of one standard deviation in *DM_NFID* translates, therefore, to a decrease in asset-scaled CFO of 0.68% (0.042*0.1626). The 0.68% decline amounts to 8.88% of the median CFO (0.0765).

To summarize, I find that firms with abnormal low volume in the 10-K tend to have poor future performance. This effect is both economically and statistically significant. This result suggests that managers choose a lower level of numeric disclosure to obfuscate poor future performance.

[Insert Table 3]

5.2 Abnormal Numeric Volume and Future Stock Returns

5.2.1 Return Analysis

If volume management is used to withhold bad news, the ultimate goal of such action is to inflate stock valuation. I run the following regression to formally test whether investors are misled by managers' volume management.

$$BHAR_{t+1} = \alpha_0 + \beta_1 DM\_NFID_t + \sum \beta_k CONTROLS_t + \varepsilon_{t+1} \quad (6)$$

To gauge economic magnitude more easily, I rank measures of abnormal volume (i.e., *DM_NFID*, *DM_NFID_IS*, *DM_NFID_BS*) into deciles in the range of 0 to 1. This allows the coefficient to represent the hedge return on the corresponding zero-investment portfolio.

Results in Table 4 show that *RNFID* and *RNFID_IS* strongly predict future returns whereas *RNFID_BS* does not. This result is consistent with the result in testing H1 that the relation between abnormal volume and future earnings is driven by *NFID_IS*. The magnitudes of the coefficients on *RDM_NFID* and *RDM_NFID_IS* are economically significant and comparable to and even larger than the magnitudes of mispricing on accruals, cash flows and real earnings management. Column (3), Panel B indicates that the one-year-ahead abnormal return for firms in the lowest decile rank of *DM_NFID_IS* is 11% lower than that for firms in the highest decile rank, after including all the controls into the regression.

[Insert Table 4]

5.2.2 Portfolio Analysis

To provide insight from the trading perspective, I form a zero-investment portfolio based on the deciles of the abnormal volume. I measure *abnormal volume* using the residuals from the determinant model with *NFID_IS* as the explanatory variable (i.e., *Residual Volume*).[15] The hedge return on the portfolio for abnormal volume would indicate the economic impact of the opportunistic volume management. Table 5 reports equal-weighted portfolio results based on raw cumulative returns and DGTW buy-hold-returns. I show that the zero-investment trading strategy long on firms with the highest decile rank of *abnormal volume* and short on firms with the lowest decile rank produces economically and statistically positive returns in the following year, with an annualized raw return of 9.3% and a DGTW return of 8.1%. Hedge returns diminish gradually in the following two years, consistent with the notion that investors correct the pricing error on the abnormal volume when new information arrives subsequently.

I also investigate the time-series pattern of my portfolio results to check (1) whether large hedge returns in Table 5 are driven by only a few years, and (2) whether the time-series pattern of portfolio returns is more consistent with mispricing or risk. Annual DGTW returns from the zero-investment trading strategy based on *abnormal volume* are plotted in Figure 1. I report hedge returns from the *accruals* strategy for comparison purpose. Over the sample period from 1976 to 2011, *abnormal volume* strategy generates positive hedge returns in 28 out of 36 years, similar to the *accruals* strategy that yields positive portfolio return in 30 out of 36 years.

To sum up, a close comparison of annual hedge returns from the two trading strategies reveals that (1) hedge returns from the volume strategy are more consistent

[15] A critical assumption underlying the portfolio is that other effects are randomized across groups. If this assumption is violated, the results of the portfolio tests would not be consistent with those of the regression analysis. Residuals from the determinant model for NFID_IS are orthogonal to the effects of identified economic factors. I select to focus on NFID_IS because tests on the relation between volume management and future earnings/future returns show that the strong predictive power of overall abnormal volume is driven by abnormal volume related to income statement.

with the mispricing story; (2) the economic impact of the volume strategy is fairly large and is comparable to that of the accruals strategy.

[Insert Table 5]

5.3 Cross-sectional Tests

To further determine whether the relation between abnormal volume and future earnings or future abnormal returns is consistent with the management obfuscation explanation, I examine two cross-sectional settings where the cost of withholding bad news to managers varies with the market's difficulty in processing information.

5.3.1 Information Uncertainty

I use information uncertainty as one measure for the market's difficulty in processing information. The proxies for information uncertainty include loss/profit indicator, earnings volatility, return volatility and dispersion in analysts' forecasts. Higher values of these measures indicate higher information uncertainty. Control variables used in this test follow those used in the main tests (i.e., Table 3 and Table 4). I expect the coefficient on *DM_NFID_IS * Uncertainty Measure* to be consistently positive across all regressions in Table 6.

Table 6 reports the results of the analysis of information uncertainty. I find that the coefficient on *DM_NFID_IS * Uncertainty Measure* is consistently positive, lending support to my conjecture that managers engage in volume management for opportunistic purposes.

[Insert Table 6]

5.3.2 Investor Sophistication

I estimate the interactive effect of investor sophistication on the relation between abnormal volume and future earnings or future abnormal returns. Prior studies show that analysts and institutions are associated with more disclosure (Lang and Lundholm 1996; Ajinkya et al. 2005). I augment Equations (5) and (6) with two variables: *Sophistication Measure* and *NFID_IS * Sophistication Measure*. I use two variables as proxies for investor sophistication: analyst following and institutional holdings.

Table 7 provides the results of the investor sophistication model for both analyst following and institutional holdings. Consistent with my prediction that firms engage less in the volume management when largely followed by sophisticated investors, the coefficient on *NFID_IS * Sophistication Measures* is significantly negative across all columns in both Panel A and Panel B.

[Insert Table 7]

Chapter 6. Additional Tests and Robustness Analyses

Results above indicate that the predictive power of abnormal volume is driven by income statement items. Therefore, I use abnormal volume related to the income statement as the key variable in the following tests so as to increase the test power.

6.1 Volume Management and Managerial Opportunism

The evidence that abnormal numeric quantity in 10-K reports is positively associated with future earnings and future returns is consistent with the management obfuscation hypothesis. To corroborate this finding, I investigate whether abnormal numeric quantity is associated with the presence of strong managerial incentives to conceal bad news and opportunistically bias investors' perceptions. Specifically, I consider whether numeric quantity is abnormally low in firms just meeting or beating earnings benchmarks and in firms where CEOs' equity incentives are high.

I run the following OLS regressions to examine whether abnormal volume is negatively associated with the likelihood of just meeting or beating earnings benchmarks and CEOs' equity incentives, respectively.

$$\begin{aligned} DM\_NFID\_IS_t = {} & \alpha_0 + \beta_1 JMBE_t + \beta_2 DUM\Delta EPS_t + \beta_3 EARN_t \\ & + \sum \beta_k CONTROLS_t + \varepsilon_{t+1} \end{aligned} \tag{7}$$

$$DM\_NFID\_IS_t = \alpha_0 + \beta_1 Equity\ Incentive_t + \sum \beta_k CONTROLS_t + \varepsilon_{t+1} \tag{8}$$

Table 8, Panel A presents the estimation results of *JMBE* regression. I add *DUMΔEPS* and *EARN* to control for the effect of current performance on the choice of disclosure volume. Other controls include the full sets of firm fundamental variables used in the determinant model for *NFID_IS* (see Equation 4). The coefficient on *JMBE* across three columns is consistently negative and significant at the 1% level. This result suggests that firms that just meet or beat previous earnings disclose fewer income statement-related numbers in the 10-K, attempting to mask managers' opportunistic intervention in the financial reporting process.

To test Equation (8), I use four measures as the proxies for CEOs' compensation-based equity incentives: *Delta* (Core and Guay 2002), *Equity Wealth* (Daniel et al. 2013), *Scaled Incentives* (Edmans et al. 2009), and *Scaled Equity Wealth*.[16] Detailed variable definitions are provided in Appendix A. Table 8, Panel B presents the estimation results of the *Equity Incentive* regression. The robust negative relation between CEOs' equity incentives and abnormal numeric volume across the four columns is consistent with managers' opportunistic use of the numeric volume in the 10-K.

[Insert Table 8]

6.2 Market's Perception of the Implication of Abnormal Volume for Future Earnings

To provide an intuitive description of how investors exploit the information content of abnormal volume to forecast future performance, I follow Ali et al. (2012) and use a methodology similar to the Mishkin (1983) test.

$$\begin{aligned} EARN_{t+1} &= b_0 + b_1 EARN_t + b_2 DM\_NFID\_IS_t \\ &\quad + \sum b_k CONTROL\_1_t + \sum b_k CONTROL\_2_t + \varepsilon_{t+1} \end{aligned} \tag{9}$$

$$\begin{aligned} BHAR_{t+1} &= \alpha_0 + \lambda_0 EARN_{t+1} + \lambda_1 EARN_t + \lambda_2 DM\_NFID\_IS_t \\ &\quad + \sum \lambda_k CONTROL\_1_t + \sum \lambda_k CONTROL\_2_t + v_{t+1} \end{aligned} \tag{10}$$

Equation (9) is the earnings prediction model, and Equation (10) is the return prediction model. The market's perception regarding the implication of current

[16] Measures are downloaded from Lalitha Naveen's website: http://sites.temple.edu/lnaveen/data/.

abnormal volume to future earnings can be derived as $b_2^* = -\lambda_2 / \lambda_0$.[17] Equations (9) and (10) are estimated annually using OLS.

I include two sets of controls in both Equations (9) and (10). Kraft et al. (2007) argue that correlated omitted variables from forecasting and pricing equations may lead to incorrect conclusions about efficient pricing of a certain signal, if the omitted variables are not rationally priced. Therefore, my first set of controls includes all the control variables that Kraft et al. (2007) consider, including *BHAR*, Δ*CAPX*, Δ*SALE*, *CAPX*, *SALE*, *NOA*, and *WACC*. The second set of controls consists of all the determinants in the determinant model for *NFID_IS*.

Results are reported in Table 9. Abnormal volume represented by *DM_NFID_IS* positively predicts future earnings (b_2 = 0.0262, t-value = 2.86). However, results of the return prediction model show that the market perceives firms with lower abnormal volume to have better future performance (b_2^* = –0.2146, with t-value = –3.7). The difference between b_2 and b_2^* is significantly positive. Evidence in this test suggests that managers succeed in misleading investors by engaging in volume management.

[Insert Table 9]

6.3 Alternative Research Design: Change Analysis

The abnormal disclosure of financial items could be driven by unobservable firm heterogeneity that also predicts future performance. To address this endogeneity issue, I conduct change analysis. The positive relation between the abnormal volume and future firm performance (future returns) in the 10-K holds in a change

[17] Kraft et al. (2007) raise a concern with regard to the use of a system of non-linear equations, such as Mishkin (1983), because such estimation requires an iterative procedure which can be unreliable. Ali et al. (2012) provide details on how to use the OLS framework to estimate the relation between the variable of interest and future earnings that is implicit in market prices.

specification in all regressions in Panel A (Panel B), Table 10. It is noted that effect of the volume management in the change analysis, as indicated by the coefficient on Δ*NFID_IS*, is weaker than that in the level analysis in terms of both economic and statistical significance. It is likely due to the absence of a large year-to-year change in *NFID_IS*. All firms filing with the SEC are required to present comparative financial statements from year to year so numeric volume in the 10-K is expected to be sticky, leading to low test power in the change analysis.

[Insert Table 10]

6.4 Inclusion of Normal Numeric Volume in Main Regression Analyses

I add normal volume to earlier test regressions to examine whether normal volume and abnormal volume affect dependent variables differently, i.e., future earnings, future cash flows, and future abnormal returns. If the power of abnormal volume to predict future returns arises from managerial withholding of bad news, and if the way I isolate the normal from abnormal components of the volume is effective, I then expect the normal component of numeric volume not to be associated with future abnormal returns. Table 11 presents results for two sets of normal vs. abnormal measures. In the regression with future abnormal returns as the dependent variable, neither *IND_NFID_IS* nor *Predicted Volume* turns to be significant. Normal volume conceptually should be orthogonal to abnormal volume, and therefore adding the normal component into the regressions should not affect the coefficient estimate on abnormal volume if measure for normal and abnormal volumes are valid. Consistent with my prediction, the power of *DM_NFID_IS* and *Residual Volume* to predict future returns remains. For the regression of future performance, it appears that both *IND_NFID_IS* and *Predicted Volume* predict future performance. This is not surprising because normal volume is a function of fundamental variables that are determinants of future performance.

[Insert Table 11]

6.5 Main Regression Analyses Conditional on Forthcoming News

A positive relation between performance and abnormal volume is certainly consistent with the managerial obfuscation story. However, one may be concerned that this relation could also be driven by managerial signaling incentives. Managers who have confidence in future firm performance may choose to disclose more information for investors to evaluate firm valuation more easily. These two managerial motives are not mutually exclusive and may co-exist, jointly driving the positive relation between abnormal volume and future firm performance. To provide insight into this relation, I investigate whether managers are more likely to adjust numeric volume downwardly when they foresee upcoming performance deterioration. If this is the case, then I expect that the power of abnormal volume to predict future earnings and returns is concentrated in firms with subsequent earnings decline. Assuming that managers have private information about future firm performance, I use the realized earnings and the change in earnings at year *t*+1 as two proxies to indicate managers' anticipation of future earnings. In Table 12, I find that the relations between *DM_NFID_IS* and future earnings, future cash flows, and future abnormal returns are consistently driven by firms with negative earnings change and by firms with loss in the immediately preceding year. This result is more consistent with the bad news-withholding argument.

[Insert Table 12]

Chapter 7. Conclusion

Managers have considerable discretion over choosing the degree of quantification with numbers in the 10-K. This paper provides the first large-sample evidence on whether and how managers structure the numeric volume of annual reports to hide adverse information from investors. Putting a particular focus on future firm performance, I investigate whether managers limit the numeric volume of the 10-K to obfuscate future firm performance, and how investors react to such volume management.

Two main findings follow. First, I find that abnormal volume positively predicts future earnings and cash flows, and the effect is economically significant. Second, I find that abnormal volume has strong power to positively predict one-year-head abnormal returns. The zero-investment portfolio based on decile rankings of abnormal volume yields an annualized DGTW return of 8.1%. My evidence suggests that managers disclose fewer financial numbers in the 10-K to obfuscate unfavorable future firm performance and investors fail to see through such opportunistic volume management.

Further corroborating the “management obfuscation hypothesis” in Bloomfield (2002), I find that the relation between abnormal volume and future firm performance, or future abnormal returns, is more pronounced in firms where the market has difficulty in detecting managerial intervention in the disclosure process. Abnormal volume is also negatively associated with opportunistic managerial incentives, such as the likelihood of just meeting or beating earnings thresholds and the equity incentives from CEOs. Overall, my evidence indicates that abnormally low volume contains negative information about future firm fundamentals, and that investors are misinformed by managers’ volume management.

It should be emphasized that this paper focuses on the volume of financial items that likely capture the whole information flow of the 10-Ks. There are probably many other ways in which firms seek to inform or mislead investors by playing with the numbers in the 10-K. For example, do firms use redundant numbers in the 10-K to increase investors' processing cost? Do firms disclose more good news items to distract investors' attention? Future research may explore these possibilities.

As with any studies investigating managers' strategic tactics in formal disclosures such as 10-Ks and 10-Qs, the findings in this study are subject to some limitations. First, formal disclosures are carefully scripted, and their volumes or even the contents do not change much over time. As a result, disclosure property measures, such as readability (e.g., measured as file size, reporting length, fog index) and numeric quantity (e.g., NFID in my study), exhibit high persistence. This property weakens the test power of using year-to –year disclosure changes as the variable of interests. Second, I'm not completely certain that the management, mostly CEO and/or CFO, influence the numeric volume in the 10-K in a significant way. 10-Ks are the product of collaborative efforts. The different parts of the reports are written and edited by different individuals who are unlikely to be executives (Larcker and Zakolyukina 2012). Third, simply counting the missing items ignores important context, background knowledge, and narrative explanations for specific disclosure decisions, such as R&D disclosure (Merkley 2014) and segment disclosure (Berger and Hann 2007). Finally, I rely on the Compustat items to construct the measure of numeric volume, which may not be completely appropriate for capturing the whole information flow in 10-Ks. For example, Compustat items do not include financial numbers discussed in MD&A section and exclude non-GAAP numbers as well.

Further researchers interested in using NFID to proxy for the numeric quantity in 10-Ks should take these limitations into consideration.

Tables

Table 1
Expected Numeric Quantity Model

Panel A: Determinant model of NFID

	Dependent Variable = NFID		
	(1)	(2)	(3)
Intercept	0.848***	0.002	-0.023***
	(27.93)	(0.64)	(-2.96)
IND_MEAN		0.999***	1.018***
		(264.28)	(168.42)
DRCP	0.034**		0.019***
	(2.27)		(10.78)
M&A	-0.015		-0.001
	(-1.19)		(-0.88)
SEO	-0.020		-0.006***
	(-1.31)		(-5.47)
BTM	0.003		-0.000
	(0.38)		(-0.29)
AGE	-0.009		0.001
	(-0.96)		(1.25)
BUSSEG	0.017*		-0.005**
	(1.84)		(-2.52)
SIZE	-0.007**		0.003***
	(-2.46)		(3.07)
ABSSPI	-0.041*		0.035***
	(-1.74)		(5.28)
STD_EARN	-0.147***		-0.031***
	(-3.65)		(-4.94)
STD_RET	-0.106**		-0.009**
	(-2.12)		(-2.34)
Adj. R^2	0.073	0.726	0.737
N	106823	106823	106823

Table 1 Continued

Panel B: Determinant model of NFID_IS

	Dependent Variable = NFID_IS		
	(1)	(2)	(3)
Intercept	0.810***	0.006***	-0.096***
	(20.23)	(3.09)	(-7.79)
IND_MEAN (Income Statement)		0.994***	1.060***
		(390.15)	(98.32)
DRCP	-0.009		0.044***
	(-0.53)		(9.86)
M&A	-0.025**		0.001
	(-2.27)		(0.53)
SEO	-0.028**		-0.009***
	(-2.42)		(-6.17)
BTM	0.010		0.004***
	(1.36)		(3.41)
AGE	-0.004		0.005***
	(-0.52)		(3.07)
BUSSEG	0.018		-0.007***
	(1.51)		(-2.90)
SIZE	-0.010***		0.009***
	(-4.03)		(5.27)
ABSSPI	0.026		0.103***
	(0.82)		(7.95)
STD_EARN	-0.311***		-0.035***
	(-7.17)		(-4.58)
STD_RET	-0.210***		0.007
	(-3.97)		(1.05)
Adj. R^2	0.113	0.767	0.798
N	106823	106823	106823

Table 1 Continued

Panel C: Determinant model of NFID_BS			
	Dependent Variable = NFID_BS		
	(1)	(2)	(3)
Intercept	0.857***	-0.001	0.005
.	(24.26)	(-0.62)	(0.90)
IND_MEAN (Balance Sheet)		1.003***	1.007***
.		(418.36)	(271.16)
DRCP	0.080***		-0.000
.	(4.09)		(-0.23)
M&A	-0.009		-0.003**
.	(-0.56)		(-1.99)
SEO	-0.011		-0.002*
.	(-0.48)		(-1.70)
BTM	-0.002		-0.004**
.	(-0.28)		(-2.07)
AGE	-0.012		0.001
.	(-0.89)		(0.46)
BUSSEG	0.014		-0.005*
.	(1.60)		(-1.72)
SIZE	-0.004		0.000
.	(-1.00)		(0.20)
ABSSPI	-0.087***		-0.003
.	(-3.31)		(-0.37)
STD_EARN	0.005		-0.018*
.	(0.10)		(-1.83)
STD_RET	-0.024		-0.015***
.	(-0.39)		(-3.19)
Adj. R^2	**0.044**	**0.652**	**0.653**
N	106823	106823	106823

This table presents the determinant models of numeric volumes. The sample consists of 106823 firm-year observations from 1976 to 2011. NFID is number of non-missing values divided by the total number of items that are applicable to industry. NFID_IS and NFID_BS are NFID constructed on the basis of income statement items and balance sheet items, respectively. Industry Mean is the mean value of NFID, NFID_IS or NFID_BS at the industry-year level. Other variables are firm fundamental determinants. Definitions of other variables are provided in Appendix A. Panel A, B and C reports the estimation results of the determinant model for NFID, NFID_IS and NFID_BS, respectively. Column (1) models include only firm fundamentals as determinants, whereas column (2) models include only the industry mean of numeric volume as the determinant. Column (3) models combine firm fundamentals and industry mean values of numeric volume.

T-statistics shown in brackets are based on two-way clustering at the industry and year levels. *, **, and *** indicate significance levels at 10%, 5% and 1%, respectively.

Table 2
Descriptive Statistics

Variable	N	Mean	Std Dev	25th Pctl	Median	75th Pctl
NFID	106823	0.7791	0.0971	0.7181	0.7827	0.8561
NFID_IS	106823	0.7178	0.1377	0.6066	0.7347	0.8382
NFID_BS	106823	0.8173	0.1160	0.7445	0.8471	0.9108
DM_NFID	106823	0.0012	0.0508	-0.0293	0.0014	0.0324
DM_NFID_IS	106823	0.0018	0.0665	-0.0386	0.0011	0.0394
DM_NFID_BS	106823	0.0011	0.0684	-0.0371	0.0042	0.0397
ABNFID	106823	0.0000	0.0656	-0.0396	0.0009	0.0397
NNFID	106823	0.7178	0.1211	0.6019	0.7299	0.8293
EARN	106786	0.0029	0.1688	-0.0069	0.0406	0.0799
BHAR	106823	0.0172	0.6668	-0.3023	-0.0637	0.1897
WACC	102575	-0.0376	0.0948	-0.0798	-0.0367	0.0057
SIZE	106823	4.8783	2.2281	3.2281	4.7822	6.4571
BTM	106823	0.8185	0.6859	0.3666	0.6314	1.0437
STD_RET	106823	0.1392	0.1030	0.0797	0.1156	0.1685
STD_EARN	106823	0.0640	0.0787	0.0167	0.0352	0.0779
ABSSPI	106823	0.0176	0.0493	0.0000	0.0000	0.0103
BUSSEG	106823	0.9895	0.3912	0.6931	0.6931	1.3863
DRCP	106823	0.0885	0.2841	0.0000	0.0000	0.0000
AGE	106823	2.5709	0.6551	2.0794	2.5649	3.0910
M&A	106823	0.2402	0.4272	0.0000	0.0000	0.0000
SEO	106823	0.0902	0.2865	0.0000	0.0000	0.0000
CFO	74793	0.0507	0.1626	0.0129	0.0765	0.1330
TACC	74792	-0.0637	0.1163	-0.1012	-0.0515	-0.0107
RM	55896	-0.0195	0.3956	-0.1967	0.0234	0.2113
ABTACC	60801	-0.0022	0.0917	-0.0445	-0.0014	0.0413

This table presents the sample statistics. The initial sample includes all firm-year observations included in Compustat from 1976 to 2011. After merging the initial sample with the CRSP database to obtain necessary return data, I further impose the following sample selection criteria: (1) I exclude Fama-French Industries identified by numbers 44-47 (representing "finance firms") and 48 (representing "almost nothing"); I require firms to have sufficient financial data to construct the firm fundamentals determinants of numeric quantity disclosure. The final sample consists of 106,823 observations from 1976 to 2011. Variable definitions are provided in Appendix A.

Table 3
Regressions of Future Financial Performance on Abnormal Numeric Volume Measures

Panel A: Future Earnings and Abnormal Numeric Disclosure

	Dependent Variable = One-year-ahead Earnings (*EARN* $_{t+1}$)			
Variables	(1)	(2)	(3)	(4)
Intercept	-0.014	-0.011	-0.015	-0.011
	(-1.30)	(-1.03)	(-1.43)	(-1.05)
DM_NFID	**0.043*****			
	(3.05)			
DM_NFID_IS		**0.044*****		**0.044*****
		(3.59)		**(3.42)**
DM_NFID_BS			**0.012**	**0.001**
			(1.56)	**(0.11)**
BHAR	0.027***	0.027***	0.027***	0.027***
.	(9.29)	(9.30)	(9.29)	(9.30)
BTM	-0.008***	-0.008***	-0.008***	-0.008***
.	(-5.56)	(-5.74)	(-5.49)	(-5.71)
EARN	0.718***	0.718***	0.718***	0.718***
.	(27.55)	(27.71)	(27.48)	(27.68)
WACC	-0.109***	-0.109***	-0.109***	-0.109***
.	(-6.72)	(-6.78)	(-6.73)	(-6.76)
M&A	-0.002	-0.002	-0.002	-0.002
.	(-1.40)	(-1.41)	(-1.44)	(-1.43)
SEO	-0.015***	-0.015***	-0.015***	-0.015***
.	(-4.18)	(-4.18)	(-4.23)	(-4.18)
STD_EARN	-0.160***	-0.160***	-0.161***	-0.160***
.	(-7.73)	(-7.75)	(-7.75)	(-7.75)
STD_RET	-0.128***	-0.128***	-0.128***	-0.128***
.	(-6.39)	(-6.42)	(-6.38)	(-6.42)
ABSSPI	0.400***	0.397***	0.401***	0.397***
.	(6.72)	(6.66)	(6.73)	(6.66)
DRCP	0.004	0.002	0.005	0.002
.	(0.98)	(0.62)	(1.27)	(0.64)
AGE	0.006***	0.006***	0.006***	0.006***
.	(4.74)	(4.68)	(4.80)	(4.70)
BUSSEG	-0.001	-0.001	-0.001	-0.001
.	(-0.54)	(-0.50)	(-0.65)	(-0.51)
SIZE	0.002***	0.002**	0.002***	0.002**
.	(2.69)	(2.20)	(2.89)	(2.20)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.566	0.566	0.566	0.566
N	106823	106823	106823	106823

Table 3 Continued

Panel B: Future Cash Flow and Abnormal Numeric Disclosure

Variables	(1)	(2)	(3)	(4)
	Dependent Variable = One-year-ahead Cash Flow from Operations (*CFO* $_{t+1}$)			
Intercept	0.039***	0.042***	0.037***	0.042***
	(5.33)	(6.01)	(4.93)	(5.99)
DM_NFID	**0.042****			
	(2.19)			
DM_NFID_IS		**0.035*****		**0.032****
		(2.59)		**(2.42)**
DM_NFID_BS			**0.017**	**0.009**
			(1.31)	**(0.72)**
BHAR	0.006***	0.006***	0.006***	0.006***
	(2.74)	(2.75)	(2.74)	(2.74)
BTM	0.006***	0.006***	0.006***	0.006***
	(4.39)	(4.41)	(4.39)	(4.46)
CFO	0.711***	0.712***	0.711***	0.711***
	(32.16)	(32.38)	(32.03)	(32.13)
TACC	0.259***	0.259***	0.258***	0.259***
	(11.05)	(11.07)	(11.05)	(11.06)
M&A	-0.001	-0.001	-0.001	-0.001
	(-0.43)	(-0.44)	(-0.46)	(-0.43)
SEO	-0.010***	-0.010***	-0.010***	-0.010***
	(-5.65)	(-5.65)	(-5.61)	(-5.63)
STD_EARN	-0.094***	-0.093***	-0.094***	-0.093***
	(-5.65)	(-5.70)	(-5.65)	(-5.69)
STD_RET	-0.050***	-0.051***	-0.050***	-0.051***
	(-3.88)	(-3.93)	(-3.85)	(-3.89)
ABSSPI	0.189***	0.187***	0.191***	0.187***
	(6.17)	(6.09)	(6.16)	(6.08)
DRCP	0.007***	0.006***	0.008***	0.006***
	(3.52)	(3.71)	(3.87)	(3.99)
AGE	0.001	0.001	0.001	0.001
	(1.23)	(1.08)	(1.36)	(1.09)
BUSSEG	-0.003	-0.004*	-0.004	-0.004*
	(-1.58)	(-1.71)	(-1.62)	(-1.68)
SIZE	0.003***	0.003***	0.003***	0.003***
	(6.57)	(5.87)	(6.55)	(5.78)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.598	0.599	0.598	0.599
N	74291	74291	74291	74291

Table 3 Continued

This table reports the results of regressing the future accounting performance on abnormal numeric volume and control variables. The dependent variables are one-year-ahead earnings (EARN $_{t+1}$) in Panel A and one-year-ahead operating cash flow (CFO $_{t+1}$) in Panel B. Sample in Panel A consists of 106,823 observations from 1976 to 2011. As financial data from cash flow statements is available since 1988, the sample in Panel B reduces to 74291 with the sample period from 1988 to 2011..
Industry (Fama-French 48 industries) and year fixed effects are included in the regressions.
T-statistics shown in brackets are based on two-way clustering at both the industry level and the year level. *, **, and *** indicate significance levels at 10%, 5% and 1%, respectively.

Variables not shown below are defined in Appendix A.

EARN $_{t+1}$ = one-year-ahead earnings, measured as income before extraordinary items at t+1, divided by average total assets at t+1;

CFO $_{t+1}$ = one-year-ahead cash flow from operations, measured as cash flow from operation at t+1, divided by average total assets at t+1; cash flow statement data is available since 1988;

DM_NFID = abnormal volume, measured as the difference between NFID and industry mean of NFID based on Fama-French 48 industry classifications;

DM_NFID_IS = income statement abnormal volume, measured as the difference between NFID_IS and industry mean of NFID_IS based on Fama-French industry classifications;

DM_NFID_BS = balance sheet abnormal volume, measured as the difference between NFID_BS and industry mean of NFID_BS based on Fama-French industry classifications;

Table 4
Market Delayed Reactions to Abnormal Numeric Volume

Panel A: Regressions of Future Abnormal Returns on Abnormal Numeric Volume

	Dependent Variable = *BHAR* $_{t+1}$		
Variables	(1)	(2)	(3)
RDM_NFID	**0.067******	**0.062******	**0.089******
	(4.39)	**(4.16)**	**(4.40)**
RCFO			0.070***
			(2.62)
RTACC			-0.052*
			(-1.95)
RREM			-0.060**
			(-2.18)
BHAR	-0.008	-0.005	-0.019**
	(-1.44)	(-0.58)	(-2.47)
BTM	0.033**	0.032**	0.046***
	(2.36)	(2.12)	(2.67)
SIZE	-0.011***	-0.010***	-0.014***
	(-4.03)	(-3.60)	(-4.88)
ABSSPI		0.389**	0.387**
		(2.08)	(1.97)
DRCP		-0.002	-0.016
		(-0.14)	(-0.91)
AGE		-0.003	-0.018***
		(-0.55)	(-3.59)
BUSSEG		0.003	0.021***
		(0.42)	(2.86)
M&A		-0.017***	-0.017**
		(-2.92)	(-2.45)
SEO		-0.053***	-0.046***
		(-4.25)	(-3.99)
STD_EARN		-0.021	0.082
		(-0.24)	(0.89)
STD_RET		-0.068	-0.072
		(-0.58)	(-0.73)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Adj. R2	0.010	0.012	0.018
N	106823	106823	55895

Table 4 Continued

Panel B: Regressions of Future Abnormal Returns on Abnormal Numeric Volume Estimated Using Financial Items in Income Statement Classification

	Dependent Variable = *BHAR* $_{t+1}$		
Variables	(1)	(2)	(3)
RDM_NFID_IS	**0.077*** **	**0.073*** **	**0.110*** **
	(4.09)	**(3.90)**	**(4.05)**
RCFO			0.076***
			(2.90)
RTACC			-0.049*
			(-1.85)
RREM			-0.059**
			(-2.12)
BHAR	-0.008	-0.005	-0.020**
	(-1.42)	(-0.57)	(-2.49)
BTM	0.031**	0.030**	0.043**
	(2.26)	(2.03)	(2.55)
SIZE	-0.013***	-0.011***	-0.016***
	(-4.55)	(-4.39)	(-7.29)
ABSSPI		0.370**	0.358*
		(1.99)	(1.86)
DRCP		-0.010	-0.029
		(-0.65)	(-1.44)
AGE		-0.004	-0.020***
		(-0.73)	(-3.74)
BUSSEG		0.003	0.018**
		(0.45)	(2.37)
M&A		-0.016***	-0.016**
		(-2.83)	(-2.43)
SEO		-0.053***	-0.046***
		(-4.24)	(-3.98)
STD_EARN		-0.021	0.087
		(-0.25)	(0.93)
STD_RET		-0.071	-0.076
		(-0.61)	(-0.78)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Adj. R2	0.011	0.012	0.019
N	106823	106823	55895

Table 4 Continued

Panel C: Regressions of Future Abnormal Returns on Abnormal Numeric Volume Estimated Using Financial Items in Balance Sheet Classification

	Dependent Variable = *BHAR* $_{t+1}$		
Variables	(1)	(2)	(3)
RDM_NFID_BS	**0.026*** **	**0.025** **	**0.027***
	(2.67)	**(2.41)**	**(1.94)**
RCFO			0.071***
			(2.65)
RTACC			-0.053*
			(-1.96)
RREM			-0.062**
			(-2.21)
BHAR	-0.008	-0.005	-0.019**
	(-1.43)	(-0.56)	(-2.42)
BTM	0.035**	0.033**	0.049***
	(2.43)	(2.15)	(2.75)
SIZE	-0.009***	-0.008***	-0.010***
	(-3.15)	(-2.70)	(-2.63)
ABSSPI		0.405**	0.412**
		(2.14)	(2.07)
DRCP		0.012	0.003
		(0.78)	(0.18)
AGE		-0.002	-0.016***
		(-0.40)	(-3.28)
BUSSEG		0.001	0.020***
		(0.20)	(2.70)
M&A		-0.017***	-0.018**
		(-2.93)	(-2.57)
SEO		-0.055***	-0.048***
		(-4.33)	(-4.16)
STD_EARN		-0.029	0.074
		(-0.34)	(0.81)
STD_RET		-0.070	-0.074
		(-0.59)	(-0.75)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Adj. R2	0.009	0.011	0.017
N	106823	106823	55895

Table 4 Continued

This table reports regression results of the market's delayed reactions to abnormal numeric disclosure. Sample in Panel A, B and C consists of 106,823 observations from 1976 to 2011. *RDM_NFID*, *RDM_NFID_IS*, and *RDM_NFID_BS* are annual decile ranks so as to gauge economic significance more easily. The decile rankings (1 to 10) are reduced by 1 and then divided by 9 so as to range between 0 to 1. *RCFO*, *RTACC*, and *RREM* are annual decile ranks as well, and are included as control variables in column (3) to test whether mispricing on earnings management affects the mispricing on *abnormal volume*. As cash flow statement data is available since 1988 and estimating the degree of real earnings management and accrual management imposes additional data requirements, observations in column (3) of all the three panels are reduced to 55,895.
Industry (Fama-French 48 industries) and year fixed effects are included in all regressions. T-statistics shown in brackets are based on two-way clustering at both the industry level and the year level. *, **, and *** indicate significance levels at 10%, 5% and 1%, respectively.

Variables not shown below are defined in Appendix A.

BHAR $_{t+1}$ = DGTW returns, calculated over 12 months starting 4 months after the end of fiscal year t; DGTW (Daniel et al. 1997) subtracts from each stock return the return on a portfolio of firms matched on market equity, market-book, and prior one-year return quintiles;

RDM_NFID = annual decile ranks of *abnormal volume*; *abnormal volume* is measured as the difference between NFID and industry mean of NFID based on Fama-French 48 industry classifications;

RDM_NFID_IS = annual decile ranks of *income-statement-related abnormal volume*, measured as the difference between NFID_IS and industry mean of NFID_IS based on Fama-French industry classifications;

RDM_NFID_BS = annual decile ranks of *balance-sheet-related abnormal volume*, measured as the difference between NFID_BS and industry mean of NFID_BS based on Fama-French industry classifications;

RTACC = annual decile ranks of total accruals; total accruals are measured as (income before extraordinary items – cash flow from operations), divided by average total assets; cash flow statement data is available since 1988;

RREM = annual decile ranks of real earnings management proxy; the proxy of real earnings management is estimated as a sum of abnormal production cost and abnormal discretionary expenditures (Zang 2011). See section 4.1.3 for more details.

Table 5
Time-series Means of Buy-and-Hold Stock Return for Portfolios Formed on Abnormal Numeric Volume

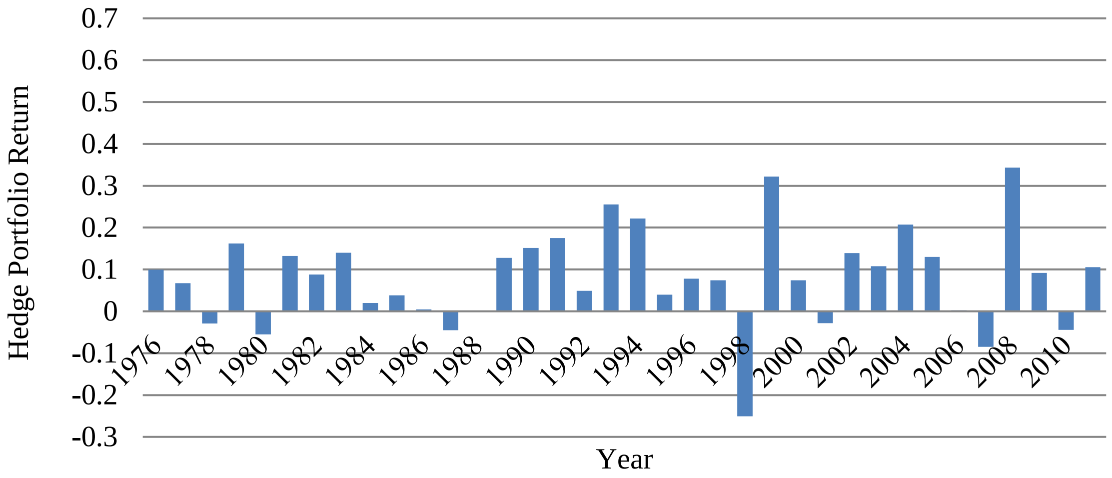
	***Raw Buy-hold Return* (*BHRET*)**			***DGTW Adjusted Return* (*BHAR)***		
Sorted by *Abnormal Volume*	t+1	t+2	t+3	t+1	t+2	t+3
Lowest (short)	0.133	0.148	0.164	-0.014	0.001	0.009
	(4.12)	(4.39)	(4.32)	(-1.18)	(0.05)	(0.69)
1	0.151	0.150	0.153	-0.003	0.004	0.002
	(4.21)	(3.98)	(4.11)	(-0.28)	(0.27)	(0.15)
2	0.159	0.162	0.161	0.004	0.008	0.012
	(4.38)	(4.18)	(4.26)	(0.36)	(0.74)	(1.00)
3	0.156	0.155	0.176	-0.002	0.009	0.025
	(4.05)	(4.10)	(4.37)	(-0.18)	(0.85)	(1.69)
4	0.163	0.155	0.161	0.010	0.011	0.017
	(4.17)	(4.44)	(4.31)	(1.02)	(1.36)	(1.54)
5	0.174	0.158	0.149	0.019	0.015	0.009
	(4.48)	(4.16)	(3.94)	(1.89)	(1.12)	(0.95)
6	0.176	0.182	0.170	0.025	0.037	0.032
	(4.63)	(5.00)	(4.54)	(2.34)	(4.29)	(2.70)
7	0.189	0.179	0.181	0.034	0.034	0.043
	(4.93)	(4.98)	(4.68)	(3.07)	(3.12)	(3.78)
8	0.188	0.190	0.188	0.031	0.048	0.049
	(4.59)	(4.79)	(4.85)	(3.02)	(3.70)	(4.92)
Highest (long)	0.225	0.200	0.191	0.067	0.063	0.053
	(5.15)	(4.96)	(5.14)	(3.93)	(4.46)	(4.54)
Hedge	**0.093*** (3.49)**	**0.052** (2.24)**	**0.027 (1.19)**	**0.081*** (4.18)**	**0.062*** (3.64)**	**0.043*** (2.86)**

Table 5 Continued

This table reports results of the zero-investment portfolios. Sample consists of 106,823 observations from 1976 to 2011. Portfolios are formed annually by assigning firms into deciles according to the magnitude of *abnormal volume* in fiscal year t.
Abnormal volume in this table is measured by residuals from the determinant model for *NFID_IS* with all economic factors and industry-year mean included as determinants (See Table 1, Panel B, Column 3). Portfolio returns are calculated using raw returns (*BHRET*) and DGTW adjusted returns (*BHAR*). For firms that delist during the return window, the remaining return is calculated by using the delisting return from the CRSP database, and then reinvesting remaining proceeds in the appropriate benchmark portfolio (Beaver et al. 2007).
The hedge portfolio takes a long position in the highest *abnormal volume* portfolio and a short position in the lowest *abnormal volume* portfolio.
T-statistics are reported in the parentheses based on the time-series of annual portfolio abnormal stock returns. *, **, and *** indicate significance levels at 10%, 5% and 1%, respectively.

Variable Definitions:
BHAR = DGTW returns, calculated over 12 months starting 4 months after the end of fiscal year t; DGTW (Daniel et al. 1997) subtracts from each stock return the return on a portfolio of firms matched on market equity, market-book, and prior one-year return quintiles;
BHRET = raw buy-hold return, computed over 12 months, starting four months after the fiscal year end.

Graph A: Hedge Return for *Abnormal Volume* Strategy



Graph B: Hedge Return for *Accrual* strategy (for Comparison Use)

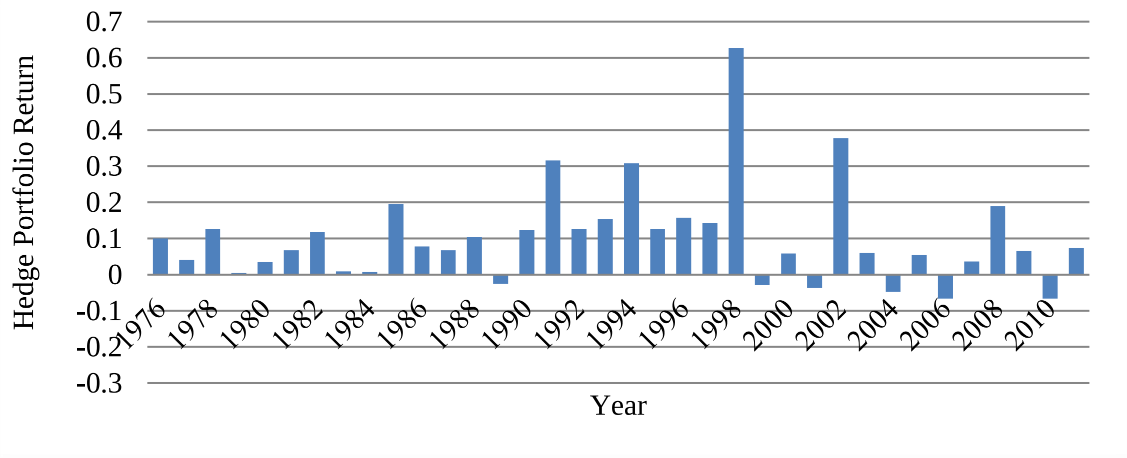


Figure 1 Hedge Return for Abnormal Volume Strategy

Graph A present hedge returns from 1976 to 2011 for the *abnormal volume* strategy and the *accrual* strategy, respectively. As in Table 5, abnormal volume is measured by residuals from the determinant model for NFID_IS with all economic factors and the industry-year mean for NFID_IS (see Table 1, Panel B, Column 3). WACC is the working capital accruals, calculated as: (∆current asset–∆cash)–(∆current liabilities–∆debt included in current liabilities–∆income taxes)–depreciation and amortization expense. The hedge portfolio for *abnormal volume* takes a long position in the highest decile of *abnormal volume* and a short position in the lowest decile of *abnormal volume*. Similarly, the hedge portfolio for WACC takes a long position in the highest decile of WACC and a short position in the lowest decile of WACC. Abnormal returns are measured using DGTW adjusted returns (BHAR), cumulated over one-year period beginning four months after the fiscal year end.

Table 6
Investors' Ability to Detect Misrepresentation and Managers' Strategic Use of Numeric Quantity

Panel A: Impact of Information Uncertainty on the Relation between Abnormal Volume and Future Performance

	Dependent Variable = *EARN* $_{t+1}$			
	(1)	(2)	(3)	(4)
Variables	*LOSS*	*STD_EARN*	*STD_RET*	*AF_DISP*
Intercept	0.019**	0.025***	0.020***	0.030**
	(2.42)	(3.09)	(3.00)	(2.40)
DM_NFID_IS	0.005	-0.050***	-0.035***	-0.017
	(0.50)	(-3.38)	(-2.79)	(-1.08)
DM_NFID_IS * Uncertainty Measure	**0.177*** **	**0.215*** **	**0.182*** **	**0.088*** **
	(5.31)	**(5.25)**	**(5.08)**	**(4.21)**
Uncertainty Measure	-0.005**	-0.027***	-0.029***	-0.015***
	(-2.34)	(-5.55)	(-7.30)	(-4.43)
EARN	0.708***	0.729***	0.725***	0.711***
	(25.68)	(29.25)	(30.20)	(22.74)
WACC	-0.109***	-0.111***	-0.105***	-0.093***
	(-6.73)	(-6.66)	(-6.53)	(-4.65)
BHAR	0.027***	0.027***	0.025***	0.034***
	(9.32)	(9.36)	(8.21)	(7.94)
BTM	-0.007***	-0.007***	-0.008***	-0.014***
	(-5.25)	(-4.75)	(-6.19)	(-3.60)
SIZE	0.002**	0.001*	0.002**	0.002
	(2.24)	(1.85)	(2.13)	(1.49)
STD_EARN	-0.158***		-0.163***	-0.125***
	(-7.65)		(-7.69)	(-6.91)
STD_RET	-0.126***	-0.132***		-0.137***
	(-6.54)	(-6.56)		(-4.03)
Other Firm Fundamental Controls	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adj. R2	0.567	0.565	0.565	0.580
N	106823	106823	106823	51801

Table 6 Continued

Panel B: Impact of Information Uncertainty on the Relation between Abnormal Volume and Future Abnormal Return

	Dependent Variable = *BHAR* $_{t+1}$			
	(1)	(2)	(3)	(4)
Variables	*LOSS*	*STD_EARN*	*STD_RET*	*AF_DISP*
Intercept	-0.029	-0.018	-0.048	0.024
	(-0.88)	(-0.52)	(-1.39)	(0.59)
DM_NFID_IS	0.357***	0.252***	0.113**	0.224**
	(4.18)	(3.70)	(2.17)	(2.44)
DM_NFID_IS * Uncertainty Measure	**0.259****	**0.352*****	**0.666*****	**0.385*****
	(2.51)	**(2.65)**	**(5.31)**	**(2.90)**
Uncertainty Measure	-0.033***	-0.020	0.001	-0.053***
	(-2.88)	(-1.48)	(0.03)	(-2.90)
WACC	-0.288***	-0.262***	-0.257***	-0.256***
	(-5.51)	(-4.63)	(-4.51)	(-2.82)
BHAR	-0.007	-0.004	-0.007	-0.008
	(-0.89)	(-0.53)	(-1.02)	(-0.80)
BTM	0.027*	0.024*	0.024*	0.030
	(1.87)	(1.70)	(1.66)	(1.33)
SIZE	-0.014***	-0.014***	-0.012***	-0.015***
	(-5.47)	(-5.37)	(-4.62)	(-4.44)
STD_EARN	0.012		-0.043	-0.013
	(0.15)		(-0.48)	(-0.20)
STD_RET	-0.057	-0.070		0.062
	(-0.55)	(-0.63)		(0.29)
Other Firm Fundamental Controls	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adj. R2	0.014	0.014	0.014	0.018
N	106823	106823	106823	51801

This table examines whether the relation between abnormal volume and future performance (Panel A) / future abnormal returns (Panel B) is related to empirical proxies for information uncertainty. *DM_NFID_IS* measures abnormal volume. Information uncertainty reflects investors' difficulty in detecting managerial intervention in the disclosure process. Proxies for information uncertainty include loss (*LOSS*), earnings volatility (*STD_EARN*), return volatility (*STD_RET*), and dispersion in analysts' forecasts (*AF_DISP*). Tabulated control variables are predictors for either future earnings or future returns. Other firm fundamental controls (not tabulated) include *ABSSPI*, *DRCP*, *BUSSEG*, *AGE*, *M&A and SEO,* which are firm fundamental determinants for *NFID_IS*., as shown in Table 1, Panel B, Column 3.

Table 6 Continued

Industry (Fama-French 48 industries) and year fixed effects are included in all regressions. T-statistics shown in brackets are based on two-way clustering at both the industry level and the year level. *, **, and *** indicate significance levels at 10%, 5% and 1%, respectively.

Variables not shown below are defined in Appendix A.

DM_NFID_IS = *abnormal volume* measure estimated using financial items in the Income Statement classification, calculated as the difference between NFID_IS and industry mean of NFID_IS based on Fama-French industry classifications;

EARN $_{t+1}$ = one-year-ahead earnings, measured as income before extraordinary items at t+1, divided by average total assets at t+1;

BHAR $_{t+1}$ = DGTW returns, calculated over 12 months starting 4 months after the end of fiscal year t; DGTW (Daniel et al. 1997) subtracts from each stock return the return on a portfolio of firms matched on market equity, market-book, and prior one-year return quintiles;

LOSS = one if income before extraordinary items (IB) is less than zero, and zero otherwise;

STD_EARN = standard deviation of ROA calculated over the last five years, with at least three years of data required; ROA is calculated as earnings divided by average total assets;

STD_RET = standard deviation of monthly return over the 12-month return cumulation period for fiscal year t, starting four months after the fiscal year end of year t-1;

AF_DISP = analyst forecast dispersion, measured as the average standard deviation of analysts' forecasts of year t+1 earnings at each month over year t;

Table 7

The Sophistication of Investor Base and Managers' Strategic Use of Numeric Quantity

Panel A: Impact of Investor Sophistication on the Relation between Abnormal Volume and Future Performance

	Dependent Variable = *EARN* $_{t+1}$	
	(1)	(2)
Variables	*# Analyst Following*	*Inst. Ownership*
Intercept	0.007	-0.009
	(0.81)	(-0.80)
DM_NFID_IS	0.053***	0.083***
	(3.54)	(4.21)
DM_NFID_IS* Sophistication Measure	**-0.050*** **	**-0.079*** **
	(-5.58)	**(-4.09)**
Sophistication Measure	0.005***	-0.008***
	(2.62)	(-3.35)
WACC	-0.117***	-0.113***
	(-6.80)	(-7.06)
BHAR	0.028***	0.027***
	(8.50)	(8.91)
BTM	-0.008***	-0.008***
	(-4.42)	(-5.00)
SIZE	0.002*	0.002**
	(1.91)	(2.47)
EARN	0.716***	0.717***
	(27.76)	(27.73)
STD_EARN	-0.158***	-0.161***
	(-7.66)	(-7.62)
STD_RET	-0.128***	-0.131***
	(-6.04)	(-6.46)
Other Firm Fundamental Controls	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Adj. R^2	0.561	0.562
N	88764	96336

Table 7 Continued

Panel B: Impact of Investor Sophistication on the Relation between Abnormal Volume and Future Abnormal Return

	Dependent Variable = *BHAR* $_{t+1}$	
	(1)	(2)
Variables	*# Analyst Following*	*Inst. Ownership*
Intercept	-0.040	0.204***
	(-1.05)	(4.93)
DM_NFID_IS	0.533***	0.582***
	(4.68)	(4.11)
DM_NFID_IS* Sophistication Measure	**-0.278****	**-0.304****
	(-2.47)	**(-2.55)**
Sophistication Measure	0.053***	-0.195***
	(4.38)	(-9.00)
WACC	-0.257***	-0.249***
	(-4.07)	(-4.31)
BHAR	-0.004	-0.009
	(-0.45)	(-1.11)
BTM	0.041**	0.035**
	(2.54)	(2.25)
SIZE	-0.019***	-0.011***
	(-5.34)	(-4.25)
EARN		
STD_EARN	-0.011	-0.091
	(-0.13)	(-1.19)
STD_RET	-0.087	-0.122
	(-0.79)	(-1.12)
Other Firm Fundamental Controls	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Adj. R^2	0.016	0.024
N	88764	96336

This table examines whether the sophistication of investor base affects the relation between abnormal numeric volume and future performance (Panel A) / future abnormal return (Panel B). Empirical proxies for the sophistication of investor base include the number of analyst following and institutional ownership. *Abnormal Volume* is measured by *DM_NFID_IS*.
Other firm fundamental controls (not tabulated) include *ABSSPI*, *DRCP*, *AGE*, *BUSSEG*, *M&A* and *SEO*, which are firm fundamental determinants for *NFID_IS*, as shown in Table 1, Panel B, Column 3.
Industry (Fama-French 48 industries) and year fixed effects are included.
T-statistics shown in brackets are based on two-way clustering at both the industry level and the year level. *, **, and *** indicate significance levels at 10%, 5% and 1%, respectively.

Table 7 Continued

Variables not shown below are defined in Appendix A.

DM_NFID_IS = *abnormal volume* measure estimated using financial items in the Income Statement classification, calculated as the difference between NFID_IS and industry mean of NFID_IS based on Fama-French industry classifications;

$EARN_{t+1}$ = one-year-ahead earnings, measured as income before extraordinary items at t+1, divided by average total assets at t+1;

$BHAR_{t+1}$ = DGTW returns, calculated over 12 months starting 4 months after the end of fiscal year t; DGTW (Daniel et al. 1997) subtracts from each stock return the return on a portfolio of firms matched on market equity, market-book, and prior one-year return quintiles;

#Analyst following = the number of analyst following for firm *i* during fiscal year *t*, constructed on the basis of I/B/E/S starting from 1983.

Inst. Ownership = aggregated institutional holdings at the firm-year level; Institutional holding data is available since 1980;

Table 8
Abnormal Numeric Disclosure and Managers' Opportunistic Incentives

Panel A: Abnormal Volume and Just Meet or Beat Prior Year's Earnings

	Dependent Variable = *DM_NFID_IS*		
Variables	*JMBE=1 when ΔEPS ∈ [0,0.4%]* (1)	*JMBE=1 when ΔEPS ∈ [0,0.5%]* (2)	*JMBE=1 when ΔEPS ∈ [0,0.6%]* (3)
Intercept	-0.093***	-0.093***	-0.093***
	(-5.83)	(-5.83)	(-5.83)
JMBE	**-0.004*** **	**-0.004*** **	**-0.004*** **
	(-3.75)	**(-4.95)**	**(-4.23)**
DUMΔEPS	0.003***	0.003***	0.003***
	(4.70)	(5.06)	(4.84)
EARN	-0.005	-0.005	-0.005
	(-1.06)	(-1.09)	(-1.11)
Controls for firm fundamentals	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Adj. R^2	0.174	0.174	0.174
Observations with MBE=1	6802	8366	9861
N	106660	106660	106660

Panel B: Abnormal Volume and CEOs' Equity Incentives

	Dependent Variable = *DM_NFID_IS*			
Variables	*Delta* (1)	*Equity Wealth* (2)	*Scaled Incentives* (3)	*Scaled EquityWealth* (4)
Intercept	-0.131***	-0.123***	-0.129***	-0.128***
	(-12.48)	(-11.05)	(-12.24)	(-12.27)
Equity Incentive	-0.003**	-0.002*	-0.004***	-0.004***
	(-2.29)	(-1.84)	(-3.90)	(-4.23)
Controls for firm fundamentals	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.446	0.444	0.444	0.445
N	20564	20512	20512	20504

Table 8 Continued

This table tests whether firms facing incentives to mask unfavorable news disclose fewer numbers in the 10-K. Panel A reports the results of regressing abnormal volume, measured as *DM_NFID_IS,* on just meeting or beating prior year's earnings (*JMBE*) and control variables.
Dummy_△EARN and EARN are used to control for the effect of current earnings performance on abnormal volume. Panel B reports results regarding the relation between abnormal volume and CEOs' equity incentives.
Firm fundamental controls (not tabulated) are included in all regressions, including *ABSSPI, DRCP, AGE, BUSSEG, M&A, SEO, BHAR, BTM, SIZE, STD_EARN,* and *STD_RET*.
Data used to compute equity incentive variables in Panel B is from Execucomp database with the coverage starting from 1994.
Industry (Fama-French 48 industries) and year fixed effects are included in all regressions.
T-statistics shown in brackets are based on two-way clustering at both the industry level and the year level. *, **, and *** indicate significance levels at 10%, 5% and 1%, respectively.

Variables not shown below are defined in Appendix A.
DM_NFID_IS = abnormal volume measure estimated using financial items in the Income Statement classification, calculated as the difference between NFID_IS and industry mean of NFID_IS based on Fama-French industry classifications.
DUM⊿EPS = indicator that equals one if △*EPS* is positive and zero otherwise; △*EPS* is measured as change in income before extraordinary items from year t-1 to t, scaled by the beginning market value of equity.
JMBE = one if △*EPS* falls in the neighborhood from zero to a small positive numbers that is defined in each test, and zero otherwise.
Delta = log of 1 plus dollar change in wealth associated with a 1% change in the firm's stock price;
Equity Wealth = log of value of the CEO's stock and option portfolio (in $000s);
Scaled Incentives = log of (dollar change in wealth associated with a 1% change in the firm's stock price *100 / total annual compensation); total annual compensation is TDC1 in Execucomp;
Scaled Equity Wealth = log of (value of the CEO's stock and option portfolio / total annual compensation)

Table 9
Actual versus the Market's Assessment of the Association between Abnormal Numeric Disclosure and One-Year-Ahead Earnings

Earnings Prediction Model: $EARN_{t+1} = b_0 + b_1 EARN_t + b_2 DM\_NFID\_IS_t + \sum b_k CONTROL\_1_t + \sum b_k CONTROL\_2_t + \varepsilon_{t+1}$

Returns Model: $BHAR_{t+1} = a_0 + \lambda_0 EARN_{t+1} + \lambda_1 EARN_t + \lambda_2 DM\_NFID\_IS_t + \sum \lambda_k CONTROL\_1_t + \sum \lambda_k CONTROL\_2_t + \nu_{t+1}$

Variables	b_i	t (bi)	λi	t (λi)	$b_i^* = -\lambda_i / \lambda_0$	t (b_i^*)	Difference (bi-bi*)	t(dif)
EARN $_{t+1}$			1.1456	12.13				
EARN	0.5775	38.72	-0.6886	-9.63	0.4847	16.46	0.0927	3.20
DM_NFID_IS	**0.0262**	**2.86**	**0.2238**	**3.75**	**-0.2146**	**-3.70**	**0.2408**	**3.87**
Controls of Future Earnings								
BHAR	0.0365	14.12	-0.0755	-4.47	0.0543	4.27	-0.0178	-1.56
CHGCAPX	-0.0015	-0.11	0.0190	0.35	-0.0215	-0.45	0.0200	0.37
CHGSALE	0.0189	6.39	0.0177	1.60	-0.0103	-1.16	0.0292	2.93
CAPX	-0.0551	-5.04	-0.0828	-1.63	0.0846	1.54	-0.1397	-2.50
SALE	0.0090	7.98	0.0134	1.52	-0.0121	-1.89	0.0210	3.10
NOA	-0.0029	-0.99	-0.0986	-5.34	0.0653	4.85	-0.0682	-5.52
WACC	-0.1028	-14.37	-0.1271	-3.88	0.1128	3.72	-0.2155	-6.86
Control for firm fundamentals	Yes		Yes					
Industry Fixed Effects	Yes		Yes					
Year Fixed Effects	Yes		Yes					
Adj. R^2	0.5629		0.1236					
N	92535		92535					

Table 9 Continued

This table presents the results from estimating the earnings prediction model and returns model using OLS. Regressions are estimated annually. This table follows Kraft et al. (2007) to transform OLS estimates to Mishkin estimates. b_i represents the persistence of current financial variable to future earnings. b_i^* indicates the market's perception of b_i. The time-series average of the annual coefficients are reported. Sample mean t-statistics are computed for bi=bi*.

Abnormal Volume is measured as DM_NFID_IS. BHAR $_{t+1}$ is DGTW returns, calculated over 12 months starting 4 months after the end of fiscal year t. Two sets of control variables are included. The first set (CONTROL_1) includes controls for future earnings, and the second set (CONTROL_2) include firm fundamental determinants for NFID_IS, as shown in Table 1, Panel B, Column 3, including *ABSSPI*, *BTM*, *DRCP*, *AGE*, *BUSSEG*, *SIZE M&A*, *SEO STD_EARN*, *STD_RET*. All variables are defined in Appendix A.

Industry (Fama-French 48 industries) fixed effects are included in the regressions.

*, **, and *** indicate significance levels at 10%, 5% and 1%, respectively.

Table 10
Results for Regressions of Future Performance/ Delayed Market Reaction to Abnormal Numeric Volume: Change Analysis

Panel A: Change Analysis on Future Earnings

Dependent Variable =	*EARN* $_{t+1}$	*CFO* $_{t+1}$
Variable	(1)	(2)
Intercept	-0.048***	0.016
	(-3.47)	(1.34)
ΔNFID_IS $_{t}$	**0.047*** **	0.027**
	(2.72)	(2.06)
NFID_IS $_{t-1}$	0.056***	0.037***
	(4.07)	(3.18)
WACC	-0.107***	
	(-6.96)	
EARN	0.720***	
	(26.42)	
CFO		0.714***
		(30.95)
TACC		0.261***
		(11.09)
BHAR	0.027***	0.006***
	(9.36)	(2.75)
BTM	-0.008***	0.006***
	(-5.62)	(4.35)
SIZE	0.002**	0.003***
	(-4.18)	(-5.89)
STD_EARN	-0.155***	-0.092***
	(-7.46)	(-5.72)
STD_RET	-0.129***	-0.049***
	(-6.16)	(-3.64)
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Adj. R^2	0.565	0.596
N	106222	73819

Table 10 Continued

Panel B: Change Analysis on Future Returns

	Dependent Variable = $BHAR_{t+1}$		
Variable	(1)	(2)	(3)
Intercept	0.039	0.067*	-0.021**
	(0.88)	(1.83)	(-2.07)
$D\_\Delta NFID\_IS_t$	**0.034****	**0.035****	**0.055****
	(2.11)	**(2.10)**	**(2.14)**
$D\_NFID\_IS_{t-1}$	0.083***	0.082***	0.120***
	(4.07)	(4.05)	(3.80)
DWACC		-0.077***	
		(-5.72)	
DCFO			0.074***
			(2.80)
DTACC			-0.049*
			(-1.83)
DREM			-0.059**
			(-2.07)
BHAR	-0.005	-0.004	-0.020**
	(-0.58)	(-0.55)	(-2.47)
BTM	0.031**	0.026*	0.043**
	(2.04)	(1.80)	(2.47)
SIZE	-0.011***	-0.011***	-0.015***
	(-3.42)	(-3.77)	(-4.24)
STD_EARN	-0.017	-0.029	0.089
	(-0.19)	(-0.34)	(0.92)
STD_RET	-0.068	-0.083	-0.071
	(-0.57)	(-0.76)	(-0.72)
Industry Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Adj. R^2	0.012	0.013	0.019
N	106222	106222	73819

This table presents results in change analysis. Panel A (Panel B) reports the results of regressing future performance (delayed market reaction) to change in numeric volume of the 10-K in year t. In Panel B, mispricing factors, including *$\Delta NFID\_IS_t$, $NFID\_IS_{t-1}$, WACC, CFO, TACC, and REM*, are ranked into deciles in order to gauge economic significance of market mispricing more easily. Other firm fundamental contros (not tabulated) include *ABSSPI, DRCP, BUSSEG, AGE, M&A and SEO*. All variables are defined in Appendix A. Industry (Fama-French 48 industries) and year fixed effects are included in all regressions. T-statistics shown in brackets are based on two-way clustering at both the industry level and the year level. *, **, and *** indicate significance levels at 10%, 5% and 1%, respectively.

Table 11
Regression Results Summary of Including Normal Numeric Quantity

	Abnormal Volume=Demeaned value of NFID_IS; Normal Volume=Industry mean of NFID_IS			*Abnormal Volume = Residual Volume; Normal Volume=Predicted Volume*		
	Dependent Variable =			Dependent Variable =		
	$EARN_{t+1}$	CFO_{t+1}	$BHAR_{t+1}$	$EARN_{t+1}$	CFO_{t+1}	$BHAR_{t+1}$
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal Volume	**0.038*** **	**0.039** **	**0.072*** **	**0.051*** **	**0.036*** **	**0.059*** **
	(2.80)	**(2.58)**	**(3.87)**	**(3.67)**	**(2.76)**	**(3.43)**
Normal Volume	0.108***	0.051**	-0.221	0.007	0.088***	0.038
	(4.42)	(2.37)	(-0.36)	(0.16)	(2.66)	(1.21)
Controls Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.580	0.609	0.013	0.580	0.609	0.013
N	106823	74291	106823	106823	74291	106823

This table presents regression results when expected numeric volume is included as an additional repressor in predicting future earnings, cash flows, and abnormal returns. Two sets of measures of normal and abnormal volume are employed. In column (1) to (3), *Normal Volume* is measured as the mean of NFID_IS at the industry-year level whereas *Abnormal Volume* is measured as the demeaned value of NFID_IS. In column (4) to (6), *Normal Volume* is measured as the predictive value from the determinant model for NFID_IS whereas *Abnormal Volume* is measured as the residual accordingly. The determinant model for NFID_IS is shown in Table 1, Panel B, Column (3).

Control Variables follow the design in Table 3 and Table 4.

In return regressions, i.e., column (3) and column (6), *Abnormal Volume* and *Normal Volume* are ranked into deciles for ease of coefficient interpretation.
Industry (Fama-French 48 industries) and year fixed effects are included in all regressions.
T-statistics shown in brackets are based on two-way clustering at both the industry level and the year level. *, **, and *** indicate significance levels at 10%, 5% and 1%, respectively.

Table 12

Which side drives the results? Downside or Upside?

Positive Future News =	***DUM△EARN* t+1**			***DUMPROFIT* t+1**		
	Dependent Variable =			Dependent Variable =		
Variable	*EARN t+1* (1)	*CFO t+1* (2)	*BHARt+1* (3)	*EARN t+1* (4)	*CFO t+1* (5)	*BHARt+1* (6)
Intercept	-0.053***	0.018**	0.012	-0.118***	-0.001	-0.115***
	(-4.71)	(2.16)	(0.32)	(-10.07)	(-0.14)	(-2.87)
DM_NFID_IS	**0.122*** **	**0.082*** **	**0.588*** **	**0.200*** **	**0.122*** **	**0.714*** **
	(4.65)	**(3.76)**	**(6.14)**	**(6.03)**	**(3.74)**	**(5.12)**
Positive Future News	0.111***	0.063***	0.281***	0.155***	0.063***	0.309***
	(8.86)	(7.81)	(15.22)	(16.41)	(11.04)	(18.35)
DM_NFID_IS * Positive Future News	**-0.215*** **	**-0.131*** **	**-0.486*** **	**-0.229*** **	**-0.125*** **	**-0.440*** **
	(-4.95)	**(-4.42)**	**(-6.37)**	**(-6.11)**	**(-3.35)**	**(-3.31)**
Controls Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.639	0.608	0.055	0.671	0.620	0.044
N	106823	74291	106823	106823	74291	106823

This table tests whether the relation between abnormal numeric volume and future performance is driven by the downside, i.e., firms with unfavorable forthcoming performance. Determinants for NFID_IS identified in Table 1 are controlled for but not reported for brevity, including *BHAR*, *BTM*, *ABSSPI*, *SIZE*, *STD_EARN*, *STD_RET*, *M&A*, *SEO*, *BUSSEG*, *DRCP* and *AGE*. *Positive Future News* reflects managers' anticipation of future news. *Positive Future News* is an indicator that equals one if future news is positive and zero otherwise. ΔEARN $_{t+1}$ and EARN $_{t+1}$ are used to measure future news. *DUM△EARN* $_{t+1}$ (*DUMPROFIT* $_{t+1}$) equals one if ΔEARN $_{t+1}$ (EARN $_{t+1}$) is positive, and zero otherwise. Other variables are defined in Appendix A.

Control Variables in each regression follow the design in Table 3 and Table 4.

Industry (Fama-French 48 industries) and year fixed effects are included in all regressions.

T-statistics shown in brackets are based on two-way clustering at both the industry level and the year level. *, **, and *** indicate significance levels at 10%, 5% and 1%, respectively.

Appendix A: Variable Definitions

Degree of Quantification Using Numbers

NFID	number of all Compustat items with non-missing values divided by the total number of items that are applicable to an industry;
NFID_BS	number of all Compustat balance sheet items with non-missing values divided by the total number of items that are applicable to an industry;
NFID_IS	number of all Compustat income statement items with non-missing values divided by the total number of items that are applicable to an industry;

Abnormal Degree of Quantification Using Numbers (*abnormal volume*)

DM_NFID	abnormal volume, measured as the difference between NFID and industry mean of NFID based on Fama-French 48 industry classifications;
DM_NFID_BS	balance sheet abnormal volume, measured as the difference between NFID_BS and industry mean of NFID_BS based on Fama-French industry classifications;
DM_NFID_IS	income statement abnormal volume, measured as the difference between NFID_IS and industry mean of NFID_IS based on Fama-French industry classifications;
Residual Volume	residual estimated from the determinant model of NFID_IS;
Predicted Volume	predicted value estimated from the determinant model of NFID_IS;

Accounting Performance and Abnormal Returns

$EARN_{t+1}$	one-year-ahead earnings, measured as income before extraordinary items at t+1, divided by average total assets at t+1;
CFO_{t+1}	one-year-ahead cash flow from operations, measured as cash flow from operation at t+1, divided by average total assets at t+1; cash flow statement data is available since 1988;
$BHAR_{t+1}$	one-year-ahead DGTW returns, calculated over 12 months starting 4 months after the fiscal year end; DGTW subtracts from each stock return the return on a portfolio of firms matched on size, market-book, and return momentum (i.e., prior one-year return) quintiles;

Control Variables in Regression Analysis

DRCP	an indicator variable for asset restructuring, which equals one if Restructuring Cost Pretax (RCP) is nonzero;
M&A	an indicator variable for mergers and acquisitions, which is set to one if the firm engaged in M&A during the current fiscal year according to SDC database, and zero otherwise;
SEO	an indicator variable for seasoned equity offering, which is set to one if the firm has a seasoned equity offering in the current fiscal year according to the SDC database, and zero otherwise;
STD_RET	standard deviation of monthly return over the 12-month return cumulation period for fiscal year t, starting four months after the fiscal year end of year t-1;
STD_ROA	standard deviation of ROA calculated over the last five years, with at least three years of data required;
ABSSPI	the absolute value of special items (SPI), divided by average total assets; SPI is set to zero if special item data is missing in Compustat;
BUSSEG	natural logarithm of (1+number of business segments). The number of business segments is set to one if data is missing in Compustat;
AGE	natural logarithm of (1+the number of years from the first year the firm entered the CRSP database);
SIZE	natural logarithm of market capitalization (in billions);
BTM	the ratio of book value of equity to market value of equity at the end of fiscal year t;
BHAR	DGTW returns, calculated over 12 months starting 4 months after the end of fiscal year t; DGTW subtracts from each stock return the return on a portfolio of firms matched on market equity, market-book, and prior one-year return quintiles;
WACC	working capital accruals, measured as (△current asset – △cash) – (△current liabilities – △debt included in current liabilities – △income taxes) – depreciation and amortization expense;
TACC	total accruals, measured as (income before extraordinary items – cash flow from operations), divided by average total assets; cash flow statement data is available since 1988;
REM	the proxy of real earnings management, estimated as a sum of abnormal production cost and abnormal discretionary expenditures (Zang 2011). See section 4.1.3 for more details.

Other Variables in Cross Sectional Tests

AF_DISP	forecast dispersion, measured as the average standard

	deviation of analysts' forecasts of year t+1 earnings at each month over year t;
# Analyst Following	total number of analysts following firm i at year t;
Inst.Ownership	institutional holdings for firm i at year t according to 13F;
Readability Measures	
FOG	Fog Index of the 10-K for fiscal year t, calculated as (words per sentence + percent of complex words) * 0.4. A higher Fog Index means that the report is more difficult to read;
FILESIZE	natural logarithm of the file size of the 10-K for fiscal year t;
CEO Equity Incentives	
Delta	log of 1 plus dollar change in wealth associated with a 1% change in the firm's stock price;
Equity Wealth	log of value of the CEO's stock and option portfolio (in $000s);
Scaled Incentives	log of (dollar change in wealth associated with a 1% change in the firm's stock price *100 / total annual compensation); total annual compensation is TDC1 in Execucomp;
Scaled Equity Wealth	log of (value of the CEO's stock and option portfolio / total annual compensation)

Appendix B: Example of the Computation of NFID_IS

I use Apple Inc's (GVKEY=001690) annual report in the fiscal year of 2011 as an example to explain how I compute numeric NFID_IS. NFID and NFID_BS are constructed in a similar way based on financial items from the corresponding categories.

I began by downloading data from the Compustat. I selected data items in the Income Statement Classification. I then code those data items with non-missing (missing) values as equal to 1 (0) (Column 3). Next, I selected all firms that operate in the same two-digit SIC industry (two-digit SIC=35) in the same fiscal year. I count the number of reported firms for each data item (Industry Count, column 4). If it turns out that one data item receives zero count (empty value in column 4), this item is defined as not applicable to the corresponding two-digit SIC industry (value =0 in column 5). In the case below, I find that for in the industry of two-digit SIC=35, the total number of applicable items in the income statement category is 149. Apple Inc. discloses 96 items as captured by Compustat. Therefore, NFID_IS for Apple Inc in 2011 is 96/149, i.e., 64.43%.

Compustat Financial Item	**Value**	**1=non-missing**	**Industry count**	**1= applicable to ind**
(1)	(2)	(3)	(4)	(5)
Accounting Changes - Cumulative Effect	0	1	283	1
Amortization of Intangibles	222	1	264	1
Acquisition/Merger After-tax		0	81	1
Acquisition/Merger Diluted EPS Effect		0	81	1
Acquisition/Merger Basic EPS Effect		0	81	1
Acquisitions - Income Contribution	0	1	80	1
Acquisition/Merger Pretax		0	82	1
Acquisitions - Sales Contribution	0	1	80	1
As Reported Core - After-tax		0		0

As Reported Core - Diluted EPS Effect		0		0
As Reported Core - Basic EPS Effect		0		0
Comprehensive Income - Total	26411	1	282	1
Comp Inc - Beginning Net Income	25922	1	282	1
Comp Inc - Currency Trans Adj	-12	1	281	1
Comp Inc - Derivative Gains/Losses	542	1	280	1
Comprehensive Income - Noncontrolling Interest	0	1	282	1
Comp Inc - Other Adj	0	1	282	1
Comp Inc - Minimum Pension Adj	0	1	282	1
Comp Inc - Securities Gains/Losses	-41	1	280	1
Comprehensive Income - Parent	26411	1	282	1
Cost of Goods Sold	62609	1	283	1
Common Stock Equivalents - Dollar Savings	0	1	283	1
Depreciation of Tangible Fixed Assets		0		0
Dilution Adjustment	0	1	282	1
Dilution applicable - Excluding Extraordinary Items	25922	1	282	1
Discontinued Operations	0	1	283	1
Nonrecurring Disc Operations	0	1	265	1
Depreciation and Amortization	1822	1	282	1
Extinguishment of Debt After-tax		0	34	1
Extinguishment of Debt Diluted EPS Effect		0	34	1
Extinguishment of Debt Basic EPS Effect		0	34	1
Extinguishment of Debt Pretax		0	35	1
Dividends Common/Ordinary	0	1	282	1
Dividends - Preferred/Preference	0	1	283	1
Dividends - Total	0	1	282	1
Earnings Before Interest and Taxes	33790	1	283	1
Earnings Before Interest	35612	1	282	1
Earnings Per Share (Diluted) - Including Extraordinary Items	27.68	1	282	1
Earnings Per Share (Diluted) - Excluding Extraordinary Items	27.68	1	282	1
Earnings Per Share (Basic) - Including Extraordinary Items	28.05	1	282	1
Earnings Per Share (Basic) - Excluding Extraordinary Items	28.05	1	282	1
Equity in Earnings - Unconsolidated Subsidiaries	0	1	266	1
Foreign Exchange Income (Loss)		0	152	1
Goodwill Amortization		0		0
Impairments of Goodwill After-tax		0	17	1
Impairments of Goodwill Diluted EPS Effect		0	17	1
Impairments of Goodwill Basic EPS Effect		0	17	1
Impairments of Goodwill Pretax		0	17	1
Gain/Loss After-tax		0	46	1

Gain/Loss on Sale (Core Earnings Adjusted) After-tax	71.5	1	113	1
Gain/Loss on Sale (Core Earnings Adjusted) Diluted EPS	0.08	1	113	1
Gain/Loss on Sale (Core Earnings Adjusted) Basic EPS Effect	0.08	1	113	1
Gain/Loss on Sale (Core Earnings Adjusted) Pretax	110	1	114	1
Gain/Loss Diluted EPS Effect		0	46	1
Gain/Loss Basic EPS Effect		0	46	1
Gain/Loss Pretax		0	46	1
Gross Profit (Loss)	45640	1	283	1
Gain/Loss on Ineffective Hedges		0	64	1
Income Before Extraordinary Items	25922	1	283	1
Income Before Extraordinary Items - Adjusted for Common Stock Equivalents	25922	1	283	1
Income Before Extraordinary Items - applicable for Common	25922	1	283	1
Income before Extraordinary Items and Noncontrolling Interests	25922	1	283	1
Interest and Related Income - Total		0	192	1
Interest Capitalized	0	1	274	1
Rental Income		0	27	1
Investment Tax Credit (Income Account)	167	1	187	1
Noncontrolling Interest (Income Account)	0	1	265	1
Net Income (Loss)	25922	1	283	1
Net Income Adjusted for Common/Ordinary Stock (Capital) Equivalents	25922	1	283	1
Net Income Effect Capitalized Interest		0		0
Nonoperating Income (Expense)	415	1	283	1
Nonoperating Income (Expense) - Other	415	1	283	1
Nonrecurring Income Taxes After-tax		0	35	1
Nonrecurring Income Tax Diluted EPS Effect		0	35	1
Nonrecurring Income Tax Basic EPS Effect		0	35	1
Order Backlog		0	130	1
Operating Income After Depreciation	33790	1	283	1
Operating Income Before Depreciation	35612	1	282	1
Earnings Per Share from Operations	28.05	1	282	1
Earnings Per Share - Diluted - from Operations	27.68	1	282	1
Pretax Income	34205	1	283	1
Pretax Income - Domestic	10205	1	177	1
Pretax Income - Foreign	24000	1	177	1
Core Pension Adjustment	0	1	281	1
Core Pension Adjustment Diluted EPS Effect	0	1	279	1
Core Pension Adjustment Basic EPS Effect	0	1	279	1
Core Pension Interest Adjustment After-tax		0	92	1

Core Pension Interest Adjustment Diluted EPS Effect		0	91	1
Core Pension Interest Adjustment Basic EPS Effect		0	91	1
Core Pension Interest Adjustment Pretax		0	92	1
Core Pension w/o Interest Adjustment After-tax		0	95	1
Core Pension w/o Interest Adjustment Diluted EPS Effect		0	94	1
Core Pension w/o Interest Adjustment Basic EPS Effect		0	94	1
Core Pension w/o Interest Adjustment Pretax		0	95	1
Core Post Retirement Adjustment	0	1	280	1
Core Post Retirement Adjustment Diluted EPS Effect	0	1	279	1
Core Post Retirement Adjustment Basic EPS Effect	0	1	279	1
Restructuring Costs After-tax		0	106	1
Restructuring Costs Diluted EPS Effect		0	105	1
Restructuring Costs Basic EPS Effect		0	105	1
Restructuring Costs Pretax		0	106	1
In Process R&D Expense	0	1	283	1
In Process R&D Expense After-tax	0	1	283	1
In Process R&D Expense Diluted EPS Effect	0	1	282	1
In Process R&D Expense Basic EPS Effect	0	1	282	1
Revenue - Total	108249	1	283	1
Reversal - Restructruring/Acquisition Aftertax		0	24	1
Reversal - Restructuring/Acq Diluted EPS Effect		0	24	1
Reversal - Restructuring/Acq Basic EPS Effect		0	24	1
Reversal - Restructruring/Acquisition Pretax		0	25	1
Sales/Turnover (Net)	108249	1	283	1
Settlement (Litigation/Insurance) After-tax		0	43	1
Settlement (Litigation/Insurance) Diluted EPS Effect		0	43	1
Settlement (Litigation/Insurance) Basic EPS Effect		0	43	1
Settlement (Litigation/Insurance) Pretax		0	43	1
S&P Core Earnings	25850.5	1	280	1
S&P Core Earnings EPS Diluted	27.6	1	279	1
S&P Core Earnings EPS Basic	27.97	1	279	1
Special Items	0	1	279	1
Other Special Items Diluted EPS Effect		0	49	1
Other Special Items Basic EPS Effect		0	49	1
Other Special Items After-tax		0	49	1
Other Special Items Pretax		0	49	1
Stock Compensation Expense	1168	1	264	1

After-tax stock compensation	701	1	123	1
Income Taxes - Current	5415	1	216	1
Deferred Taxes-Federal	2998	1	202	1
Deferred Taxes-Foreign	-167	1	224	1
Income Taxes - Deferred	2868	1	270	1
Deferred Taxes-State	37	1	202	1
Income Taxes - Federal	3884	1	216	1
Income Taxes - Foreign	769	1	238	1
Income Taxes - Other	0	1	268	1
Income Taxes - State	762	1	215	1
Income Taxes - Total	8283	1	283	1
Interest & Penalties Reconized - I/S	14	1	110	1
Excise Taxes	0	1	282	1
Writedowns After-tax		0	43	1
Writedowns Diluted EPS Effect		0	43	1
Writedowns Basic EPS Effect		0	43	1
Writedowns Pretax		0	44	1
Advertising Expense	933	1	114	1
Depletion Expense (Schedule VI)		0		0
Depreciation Expense (Schedule VI)		0		0
Extraordinary Items	0	1	283	1
Extraordinary Items and Discontinued Operations	0	1	283	1
Interest and Related Expense - Total	0	1	264	1
Interest Expense - Long-Term Debt	0	1	91	1
Implied Option Expense	0	1	270	1
Staff Expense - Total		0	29	1
Operating Expenses - Total	72637	1	283	1
Implied Option EPS Diluted	0	1	270	1
Implied Option EPS Basic	0	1	270	1
Pension and Retirement Expense	90	1	204	1
Research and Development Expense	2429	1	241	1
Rental Expense	338	1	242	1
Selling, General and Administrative Expense	10028	1	280	1
Total non-missing item		**96**		**149**
NFID_IS		**64.43%**		

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