THE ACCOUNTING REVIEW
Vol. 85, No. 6
2010
pp. 2107–2143

American Accounting Association
DOI: 10.2308/accr.00000001

The Effects of Reporting Complexity on Small and Large Investor Trading

Brian P. Miller
Indiana University

ABSTRACT: This study examines the effects of financial reporting complexity on investors' trading behavior. I find that more complex (longer and less readable) filings are associated with lower overall trading, and that this relationship appears due to a reduction in small investors' trading activity. Additional evidence suggests that the association between report complexity and lower abnormal trading is driven by both cross-sectional variation in firms' disclosure attributes and variations in disclosure complexity over time. Given regulatory concerns over plain English disclosures and the trend toward more disclosure, my investigation into the effects of reporting complexity on small and large investors should be of interest to regulators concerned with reporting clarity and leveling the playing field across classes of investors.

Keywords: *disclosure; readability; plain English; trading volume; small and large investors*.

JEL Classifications: *G30; G12; M41; M48*.

I. INTRODUCTION

The securities industry has historically been driven by the fundamental concept that "all investors, whether large institutions or private individuals, should have access to certain basic facts about an investment prior to buying it, and so long as they hold it" (SEC 2010, under "Introduction"). Consistent with this philosophy, investors are increasingly able to access

This study is based on my dissertation, completed at The Pennsylvania State University. I am grateful for the guidance and assistance of my dissertation committee: Paul Fischer (co-chair), Andy Leone, Karl Muller (co-chair), and Arun Upneja. Useful comments and discussions have also been provided by Walid Al-Issa, Orie Barron, Daniel Beneish, Neil Bhattacharya, Christine Cheng, Mark Evans, Bob Jennings, Dan Givoly, Karen Hennes, Max Hewitt, Steven Huddart, Steven Kachelmeier (senior editor), Ben Lansford, Feng Li, Laureen Maines, Jim Vincent, Teri Lombardi Yohn, Hal White, two anonymous referees and seminar participants at Carnegie Mellon University, Duke University, Indiana University, Michigan State University, The Ohio State University, The Pennsylvania State University, Purdue University, Southern Methodist University, University of Michigan, The University of North Carolina at Chapel Hill, University of Notre Dame, University of Rochester, University of Toronto, and Washington University in St. Louis. I also express gratitude to Justin Patterson and StyleWriter software engineers for programming assistance. Finally, I acknowledge financial support from the Smeal Dissertation Research Award.

Editor's note: Accepted by Steven Kachelmeier.

Submitted: December 2008
Accepted: May 2010
Published Online: November 2010

more data from longer public filings.[1] However, this trend may not necessarily aid investors if it is more costly to extract useful information from larger and more complex disclosures (Bloomfield 2002).

Although there is evidence regarding the effects of reporting length on long-term market prices (You and Zhang 2009), the effects on individual market participants and aggregate trading volume remain unexamined. As such, I investigate the effects of reporting complexity (length and readability) on small and large investors' trading behavior (volume and consensus) around 10-K filings. This investigation should interest regulators concerned with both reporting clarity and leveling the playing field across classes of investors.[2]

I first consider the effect of more complex reports on abnormal trading around the 10-K filing. I hypothesize that, faced with more complex reports, investors may elect not to process the report because doing so is too costly. Consequently, these investors will not initiate trades in response to the report (Grossman and Stiglitz 1980; Bloomfield 2002). After controlling for information content, I predict that more complex filings will lead to lower trading volume, and these effects will be most pronounced among smaller investors (due to their limited processing capabilities and expertise). Although theory predicts that higher processing costs affect investor trading behavior, *a priori* it is unclear whether the trend toward more complex filings will affect overall investor trading behavior. First, contemporaneous advances in technology are likely to dampen overall processing costs, making it easier for all investors to process more complex reports. Second, the increased availability of other information sources (e.g., media and analyst reports) could mitigate the effects of these attributes on investor trading behavior.[3]

I examine approximately 13,000 10-K reports filed between 1995 and 2006 and find evidence consistent with more complex reports affecting trade behavior around the filing. Specifically, I find that (1) more complex reports are associated with lower levels of aggregate trading volume; and (2) the relationship between report complexity and trade activity appears to be driven by a reduction in small investor trade volume. These results are robust to controlling for the information content of the report and factors such as profitability and persistence that have been shown to vary with reporting complexity. Overall, the evidence is consistent with more complex reports being more costly to process, with the effects being most pronounced among small traders.

In addition to trading volume, I also investigate whether more complex reports lead to more dispersion in the inferences drawn by those investors who do elect to trade. Based on prior experimental evidence (Barron et al. 2004), I predict that when reports are more complex, small investors will interpret the information in a more diverse manner. Consistent with this prediction, I find that more complex reports are associated with a decrease in consensus among small investors, but not among large investors.

Admittedly, reporting complexity is a broad notion that captures both differences in relative report complexity across firms as well as variations in disclosure attributes over time. I attempt to isolate these potentially different effects by performing both within-year and within-firm analyses.

---

[1] Radin (2007) points out that increases in report length can be traced to new disclosures devoted to risk, compensation, pension accounting, and stock options. It is also plausible that firms have voluntarily increased disclosure over time. Bloomfield (2008) provides an excellent review of the potential theories why managers may alter their reporting in certain settings. The focus of this study is how report complexity affects different investors' trade behavior and not necessarily the causes of increased disclosure over time.

[2] SEC concerns over report clarity are highlighted in the Plain English Handbook (SEC 1998), while concerns over a level playing field are the focus of recent regulatory initiatives (e.g., limit disclosure practices that discriminate across classes of investors (SEC 2000a) and regulate the fair execution of trades (SEC 2000b).

[3] Advances in technology are likely to assist all investors with accessing and processing more complex reports. However, large investors may be more likely to take advantage of new parsing tools (e.g., Perl) to analyze reports, whereas less sophisticated investors may rely more on public information from sources such as Yahoo! Finance. These differences could further exacerbate the processing differential between small and large investors.

The results show the association between more complex reports and lower abnormal trading appears to be associated with both cross-sectional variation in firms' disclosure attributes (e.g., operational complexity) in a given year as well as variations in disclosure length over time (e.g., increased disclosure due to regulation) for a given firm.

While the evidence in this study substantiates some regulatory concerns regarding the length and the readability of mandatory filings (SEC 1998), it is unclear *a priori* which of these complexity attributes have a larger effect on investors. Hence, in addition to investigating the effects of length and readability separately, I also investigate the effects of both measures when included in the same model. I find that when both measures are analyzed simultaneously, the effects of longer reports remain significant, while the readability measures become insignificant. This finding suggests the measures are substitutes, but the effects of longer reports dominate the readability of the filings.

The evidence in this study is generally consistent with the theory of more complex filings being too costly for small investors to process in the short window surrounding the filing date. This evidence should prove useful to both academics and regulators. The findings specifically challenge some long-standing regulatory assumptions that requiring more disclosure will not only aid investors in their trading decisions, but also help level the playing field between small and large investors. Thus, although the SEC has made progress in assisting the small investor in gaining electronic access to financial information (Asthana et al. 2004), simply making more data available may not benefit small investors if the reports are too long and complex to process.

Section II provides additional background and hypothesis development. Section III outlines the research design. Sample selection and descriptive data are provided in Section IV. Empirical results are summarized in Section V. Section VI provides additional analyses, and Section VII concludes.

II. BACKGROUND AND HYPOTHESIS DEVELPMENT

Efforts by the SEC to make financial data more readable and understandable date back to the Securities Act of 1933 (Firtel 1999). In 1969, the SEC released the *Wheat Report*, which indicated that the length and complexity of prospectuses prevented the average investor from readily understanding them. The report went on to recommend against unnecessarily long, complex and/or verbose writing. These concerns over lengthy reports were reiterated by Arthur Levitt in his 1997 remarks to the Securities Regulation Institute, when he asserted that "[i]n many cases, the problem is not a lack of information; quite the opposite. Too much information can be as much a problem as too little. More disclosure does not always mean better disclosure" (Levitt 1997, under "More Timely and Useful Disclosure for Investors").

Under Levitt's leadership, the SEC adopted the 1998 plain English regulation, SEC Rule 421(d), which required issuers to use plain English principles in the design of prospectuses (SEC 1998). Despite this regulation and concerns that financial reports have simply become too long for investors to process (Paredes 2003), there has been a substantial increase in report length over the past decade (Li 2008). Whether this additional data is beneficial to investors is unclear. In fact, some accounting practitioners argue that the useful information disclosed in annual filings is now hidden among a plethora of boilerplate, redundant, immaterial, or even irrelevant data, making disclosures increasingly difficult to process (Radin 2007).

Related Literature

Despite the importance practitioners and regulators have placed on disclosure clarity and length, there is little large-scale empirical evidence of effects of these attributes on financial statement accessibility. Most of the early work in this area investigates the readability of financial statements and footnotes in small sample sizes. Jones and Shoemaker (1994) summarize this literature, concluding that financial disclosures are difficult to read and "inaccessible" to a large proportion of unsophisticated investors.

Recent readability research focuses primarily on managerial incentives to disclose more or less readable reports under different circumstances. Li (2008) documents an association between length and readability of 10-K filings and both profitability and earnings persistence, while Nelson and Pritchard (2007) find that firms subject to greater shareholder litigation use more readable language in their disclosures and avoid boilerplate warnings. Both studies focus on the managerial discretion in reporting attributes, but neither study links the effects of reporting complexity to investor behavior.

Another line of research investigates the market reaction to report complexity. You and Zhang (2009) document that the market under-reaction to 10-K filings is stronger for firms with longer 10-K filings. Other linguistics research on financial disclosures investigates the market response to optimistic and pessimistic tone in media (Tetlock 2007; Tetlock et al. 2008) and earnings press releases (Davis et al. 2007). Li (2009) finds that MD&A tone and accruals predict future earnings and stock returns. Overall, research on length, readability, and tonality focuses on market responses, but does not address whether these reporting attributes affect the specific trade behavior of large and small investors.

A concurrent working paper by Loughran and McDonald (2010) also investigates report complexity of 10-K filings. As discussed in greater detail in Section VI, there are several differences in the research design and readability proxies between this study and Loughran and McDonald (2010). Despite these differences, both studies provide evidence that improvements in report readability lead to increased trading activity among small investors. Further, both studies provide evidence that the effects are most evident when readability is measured using proxies based on the SEC's plain English guidelines. The two studies differ in that Loughran and McDonald (2010) focus primarily on report readability, while the focus of the current study encompasses the effects of both length and readability.[4] This distinction is most apparent in the evidence provided by this study that the effects of report readability are subsumed by the effects of length when both measures are simultaneously examined. Therefore, this study suggests that the effects of length on investor trading behavior are more important than the effects of readability.

Finally, in addition to the direct contributions to the emerging literature on reporting complexity, this study also adds to several large bodies of research that (1) demonstrate the benefits of more informative disclosures (Lang and Lundholm 1996; Botosan 1997; Francis et al. 2002), (2) examine price and trading volume reactions to information releases (Beaver 1968; Morse 1981; Cready and Mynatt 1991; Asthana and Balsam 2001; Griffin 2003; Li and Ramesh 2009), and (3) document the differential trading behavior of small and large investors to various information events (Bhattacharya 2001; Shanthikumar 2004; Asthana et al. 2004; Allee et al. 2007; Bhattacharya et al. 2007; Mikhail et al. 2007). Although this literature provides a necessary background for the research conducted in this study, it does not provide any direct evidence on the effects of report complexity on different classes of investors.

Hypothesis Development

Trading Volume

Consistent with evidence that trading volume is the most visible indicator of investors' response to public disclosures (Cready and Hurtt 2002), I focus on abnormal trading activity around

[4] Loughran and McDonald (2010) do include a measure of length in their regressions. However, the authors investigate the effect of a change in readability on changes in abnormal trading and include the level (not change) in length. Thus, any deviations in length over time are not directly examined in their analysis.

the 10-K filing to assess investors' response to variations in report complexity. I hypothesize that faced with more complex filings, some investors will elect not to process the report because doing so is too costly. Consequently, these investors will not initiate trades in response to the report (Grossman and Stiglitz 1980; Bloomfield 2002). After controlling for the information content in the report, I expect that more complex filings will be associated with lower total trading volume. Formally, the first hypothesis (in alternative form) is as follows:

H1a: Total abnormal trading around a 10-K filing is lower when reports are more complex (e.g., longer/less readable).

Although more complex reports are likely to have some effect on all traders, I predict that the effects of these attributes will be most pronounced in the small investor group. This prediction is consistent with prior experimental research that suggests small (nonprofessional) investors lack investment expertise and have ill-defined valuation models (Maines and McDaniel 2000). Specifically, these non-professional investors tend to read financial statements in the order presented and are therefore more likely to be affected by more complex reports than more sophisticated investors (analysts), who use directed information search strategies to analyze financial statements (Bouwman et al. 1987; Hunton and McEwen 1997).

Although experimental evidence suggests that small investors are most likely to be affected by report attributes, other research indicates that even sophisticated investors are affected by information complexity. For instance, prior experimental research documents that the way financial statement data is presented can influence analysts' judgments (Hopkins 1996; Hirst and Hopkins 1998). Consistent with these experiments, Plumlee (2003) finds that analysts assimilate information in less complex tax changes to greater extent than they assimilate the more complex changes, while a concurrent study by Lehavy et al. (2009) documents that less readable reports are associated with less accurate analyst forecasts and greater dispersion. In sum, these studies suggest that even professional investors may not be immune to report complexity. Thus, although the effects of complex reports are likely to be most pronounced among smaller investors, there is reason to believe that larger, more sophisticated investors could also be affected. Hence, I hypothesize the following (in alternative form):

H1b: The effects of report complexity (i.e., longer/less readable) on abnormal trading are most pronounced among small investors.

Trading Consensus

In addition to trading volume, I also investigate whether more complex reports lead to dispersion in the inferences drawn by those investors who do elect to trade. Specifically, I investigate whether small (large) investors process the data in a different way from other small (large) investors when reports are more complex. This investigation contributes to a large stream of research on the causes and implications of disagreement.[5] Furthermore, this study builds on prior experimental evidence that finds that increases in disclosure lead nonprofessional investors to generate (or infer) private information, while sophisticated professional investors are unaffected by the increased disclosure (Barron et al. 2004). The authors interpret this evidence as larger investors (smaller investors) being more homogeneous (diverse) with respect to their training and

[5] Most analytical models suggest that disagreement of some form drives trading around disclosure releases (Kim and Verrecchia 1991, 1994, 1997; Kandel and Pearson 1995). Karpoff (1986) raises the possibility that this disagreement could stem from information interpreted differently by market agents. Subsequent empirical work by Barron (1995) and Bamber et al. (1997, 1999) provides evidence that the trading around earnings announcements is at least partially attributable to newfound disagreement. Recent analytical work by Bloomfield and Fischer (2009) highlights the importance of studying disagreement, since different forms of disagreement among investors can affect a firm's cost of capital.

occupational selection and therefore more (less) likely to have common interpretations of disclosures. I investigate whether these findings regarding small and large investor behavior hold in an archival market-based study.

As discussed in greater detail later, I measure small and large investors' trading consensus as the absolute value of daily *net buyer initiated* (buyer minus seller initiated) shares traded, deflated by *total shares* (buyer plus seller initiated) traded on the same day. If complexity results in a high level of disagreement within an investor group, then buyer and seller initiated trades would offset and trading consensus would approach 0. Alternatively, if investors agree about the information content of the report, then they are more likely to trade in the same direction and trading consensus would approach 1. Based on these arguments, I hypothesize that, conditional on trade, more complex reports will lead to more disagreement within an investor class. Formally, I hypothesize the following (stated in alternative form):

H2: Trading consensus within a class of investors is lower when 10-K reports are more complex (e.g., longer/less readable).

III. RESEARCH DESIGN

The research design consists of several stages. The first stage examines trading responses to complex 10-K filings using abnormal volume in aggregate as well as the specific trading behavior of small and large investors. The second stage examines the effects of length on small and large investor trading consensus. Finally, I examine whether these associations are driven by cross-sectional variation in firms' disclosure attributes and/or variations in disclosure length over time.

Total Abnormal Trading

To examine the effects of complex reports on the combined trading activity of small, medium, and large investor groups, I estimate the following regression model:

$$\begin{aligned} AVOL_{it} = {} & \alpha_0 + \alpha_1 COMPLEX_{it} + \alpha_2 AFTEAD_{it} + \alpha_3 AFTEXD_{it} + \alpha_4 ABS\_RET_{it} + \alpha_5 PVOL_{it} \\ & + \alpha_6 MV_{it} + \alpha_7 MTB_{it} + \alpha_8 EARNINGS_{it} + \alpha_9 NY\_EARNINGS_{it} + \alpha_{10} NA\_FOLL_{it} \\ & + \alpha_{11} NBSEG_{it} + \alpha_{12} NGSEG_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

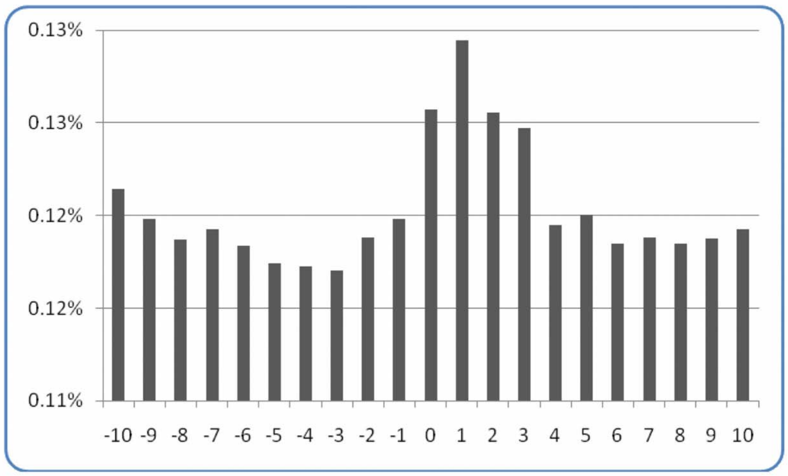
where the dependent variable, *AVOL*, is the measure of abnormal trading volume. The use of abnormal volume (versus raw volume) should mitigate the effect of both technological trading changes (e.g., increased online trading) as well as other factors, such as increases in decimalized trading during the sample period (Barber et al. 2009). Consistent with Asthana et al. (2004), I define abnormal trade, *AVOL*, as the mean daily trading volume during the event period (−1, 3) minus the mean daily trading volume during the non-filing period (−49, −5), deflated by the standard deviation of daily trading volume during the non-filing period (−49, −5).[6]

To determine whether the event windows implemented above are reasonable, I examine the average daily trade volume scaled by shares outstanding classified for each investor group (i.e., small and large traders) in the period surrounding the filing. Figure 1, Panel A provides confirming evidence that most of the small trading volume related to the 10-K filing appears to be captured in

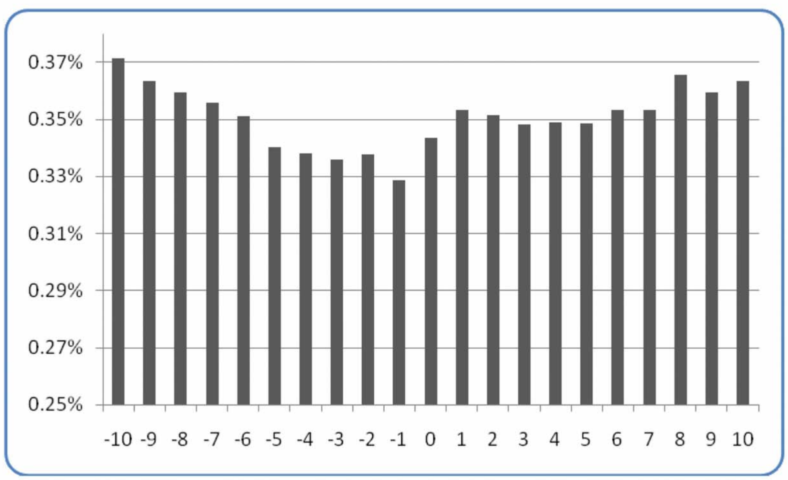
[6] In addition to abnormal volume, I also examine the effects of report complexity on abnormal number of transactions, *ANUM*. Results using the number of transactions are quantitatively similar to the volume results (untabulated). I also measure excess volume as in Barron et al. (2005), where *EXVOL* (*EXNUM*) is defined as the natural log of the cumulative trading volume (transactions) over the five-day event period (−1, 3) minus the natural log of the median volume (transactions) for contiguous five-day periods during the non-filing period (−49, −5). Results using *EXVOL* (*EXNUM*) are consistent with the *AVOL* results, where small investors are significantly affected by more complex reports and (in most cases) small investors are more affected than larger investors.

FIGURE 1
Average Daily Trading Volume around 10-K Filing Dates

Panel A: Small Investors' Daily Trading Volume



Panel B: Large Investors' Daily Trading Volume



Daily trading volume is the number of shares traded scaled by total number of shares outstanding by investor group (i.e., small or large). Panel A (B) plots the mean of small (large) trade volume.

the -1, 3 day event period. Panel B reveals that the trading behavior for large investors appears to be less concentrated around the actual filing date, which is consistent with large investors relying less on the information in the 10-K filing, potentially due to their ability to gain access to similar information prior to the release of the actual filing. Although the short event window appears to capture the trading specifically related to the 10-K filing, I provide supplementary analysis of longer windows in Section VI.

COMPLEX is the relevant measure of length or readability. Report length is measured as *WORDS* or *WORDS+TABLES*. Because of skewness in the raw number of words, I follow Li (2008) and define *WORDS* as the logarithm of the number of words in the entire document. Although this measure provides a useful metric of the amount of data in text format, it fails to incorporate data included in tables. Therefore, I also examine *WORDS+TABLES*, which is defined as the natural log of the total words plus table cells contained in the document. Since the ability to count the number of table cells requires compliance with a specific HTML standard, the measure is only available for a subset of firms after 1999. Appendix A provides details on the methods used to create these variables.

I first measure readability using the Fog Index, *READ_FOG*, which was originally developed by Gunning (1952). This measure provides a simple, well-known, and widely accepted formula for measuring readability.[7] However, the Fog Index was not developed to specifically measure the attributes of financial reporting complexity. Thus, I also use a proprietary computational software program, *StyleWriter—Plain English Editor*, to develop a unique multidimensional measure of financial readability based on the writing factors outlined by the SEC plain English guidelines, *READ_PE*.[8] As described in more detail in Appendix B, *READ_PE* is designed similar to *READ-_FOG* so that higher readability scores are interpreted as less readable reports.

In the first set of tests, I control for potential firm characteristics that may affect abnormal trading. For instance, Asthana et al. (2004) point out the importance of controlling for the effect of the timing of the 10-K filing on trading activity. To control for the effects of earnings information disclosed prior to the 10-K release, I include the variable *AFTEAD*, which is defined as the number of days after the preliminary earnings announcement date that the 10-K is filed. I expect that the longer after the earnings announcement the 10-K is filed, the lower the abnormal trading around the filing.

Prior research also shows that firms delay releasing bad news (Kross and Schroeder 1984) and, consequently, the timeliness of that release affects the market reaction (Chambers and Penman 1984). Based on these findings, I also include *AFTEXD*, which is defined as the number of days the current 10-K is filed after the date of the previous year's 10-K filing. I expect a positive association between the length of the reporting delay after the expected filing date (i.e., previous year's filing date), and abnormal trading volume.

To control for the information content of the report, I include *ABS_RET*, defined as the absolute value of the firm's abnormal (market model) return calculated over the five-day event window (-1, 3). I expect that greater information content will lead to higher abnormal trading volume (Bamber and Cheon 1995; Bamber et al. 1997). I control for uncertainty in the period prior to the 10-K filing by including *PVOL*, defined as the standard deviation of stock price in the period prior to the filing (-49, -5). Theory does not provide a clear prediction on the effects of *PVOL*. I control for firm size by including the independent variable *MV*, the logarithm of the market value

---

7 Consistent with prior literature (Li 2008; Collins-Thompson and Callan 2005; Muresan et al. 2006), I measure Fog readability as the ((*words per sentence* + *percent of complex words*) $*$ .4). Additional information on how Fog readability is calculated is provided in Appendix B.

8 I create the plain English readability measure, defined as the number of errors identified by Stylewriter that match the plain English concerns of the SEC. Specifically, I measure the number of errors defined by the program as [(Passive Verbs + Hidden Verbs + Overwriting + Legal Words & Jargon + Tautologies) $*$ 10] and scale by the approximate number of sentences in the document (number of words/average sentence length). The scalar parses out the effects of the document length, but perhaps more importantly addresses the SEC's concern about sentence length (longer sentences decrease the denominator and thus increase the readability measure).

of equity at the end of the fiscal period. The effects of *MV* on abnormal trading volume are not straightforward. Larger firms are likely to have better information environments (Atiase 1985; Bamber 1987), so firm size could be associated with lower abnormal trading around the filing. However, large firms could also attract more attention-based trading, leading to higher abnormal volume around the filing (Merton 1987). Thus, my prediction on *MV* is nondirectional. I also control for a firm's future growth opportunities on volume, *MTB*, defined as the market value to book value of equity at the close of the current fiscal year. Theory does not provide a clear prediction on *MTB*.

Li (2008) documents that firms with lower earnings tend to have longer and less readable reports. To control for the possibility that *LENGTH* is merely proxying for earnings information, I follow Li (2008) and include *EARNINGS*, which is defined as operating earnings scaled by total assets. Li (2008) also documents that firms with shorter reports tend to have higher earnings persistence. Specifically, Li finds that shorter reports are associated with a greater ability to predict subsequent earnings. In order to address the possibility that report length is simply proxying for information related to next year's earnings, I include *NY_EARNINGS* as a proxy for the expectation of future earnings.[9] Theory does not provide a clear prediction on the effects *EARNINGS* or *NY_EARNINGS* on abnormal volume.

I expect that there will be less new information in the 10-K filings for firms with greater analyst coverage. As such, I include *NA_FOLL*, which I define as the log of 1 plus the number of analysts as reported on I/B/E/S detail and excluded files. My expectation is that, all else equal, higher analyst following will be associated with lower abnormal trade volume. I attempt to control for underlying firm complexity in this analysis by including the logarithm of 1 plus the number of business segments (*NBSEG*) and geographic segments (*NGSEG*), as reported at the end of the fiscal period.[10] Theory does not provide a clear prediction on the effects *NBSEG* or *NGSEG* on abnormal volume. To minimize the effects of outliers, all variables are winsorized by year at the top and bottom 1 percent. Finally, all regressions are performed with clustered robust standard errors (Huber 1967; White 1980) to control for both within firm and within year correlation. Table 1 summarizes all variable definitions.

Small and Large Investors Abnormal Trading

In addition to examining the total trade activity of all investors, I also examine the specific trade activity of small and large investors by estimating the following equation:

$$\begin{aligned} AVOL_{it} = {} & \alpha_0 + SML * [\alpha_1 COMPLEX_{it} + \alpha_2 AFTEAD_{it} + \alpha_3 AFTEXD_{it} + \alpha_4 ABS\_RET_{it} \\ & + \alpha_5 PVOL_{it} + \alpha_6 MV_{it} + \alpha_7 MTB_{it} + \alpha_8 EARNINGS_{it} + \alpha_9 NY\_EARNINGS_{it} \\ & + \alpha_{10} NA\_FOLL_{it} + \alpha_{11} NBSEG_{it} + \alpha_{12} NGSEG_{it}] + \beta_0 + LRG * [\beta_1 COMPLEX_{it} \\ & + \beta_2 AFTEAD_{it} + \beta_3 AFTEXD_{it} + \beta_4 ABS\_RET_{it} + \beta_5 PVOL_{it} + \beta_6 MV_{it} + \beta_7 MTB_{it} \\ & + \beta_8 EARNINGS_{it} + \beta_9 NY\_EARNINGS_{it} + \beta_{10} NA\_FOLL_{it} + \beta_{11} NBSEG_{it} \\ & + \beta_{12} NGSEG_{it}] + \varepsilon_{it}. \end{aligned} \tag{2}$$

9 Perfect foreknowledge of next year's earnings is admittedly a strong assumption. However, the use of next year's earnings as a proxy for persistence (ability of report attributes to predict next year's earnings) does not appear to bias toward finding that more complex reports affect trading behavior. Further, the exclusion of this control variable does not affect the results.

10 In addition to *NBSEG* and *NGSEG*, I also add controls to all regressions for whether a firm had a merger during the year as this would also increase firm complexity. I find that the merger control does not affect the significance of the results reported in this study (untabulated).

TABLE 1
Variable Definitions

Variable	Definitions (Alphabetical Order)
ABS_RET	Market adjusted return, defined as the absolute value of the abnormal (market model) share price return over the event period (−1, 3).
AFTEAD	Number of days after the earnings announcement date, defined as the number of calendar days the 10-K is filed after the preliminary earnings announcement date.
AFTEXD	Number of days after the expected filing date, defined as the number of calendar days the 10-K is filed after the expected filing date (last year's 10-K filing date).
AVOL	Abnormal trading volume, defined as the mean daily trading volume during the event period (−1, 3) minus the mean daily trading volume during the non-filing period (−49,−5), deflated by the standard deviation of daily trading volume during the non-filing period (−49,−5).
COMPLEX	Relevant measure of reporting complexity (i.e., *WORDS*, *WORDS+TABLES*, *READ_FOG*, or *READ_PE*).
EARNINGS	Operating earnings scaled by assets, defined as Compustat items (data178/data6).
LRG	Large trades: When suffixed to a variable, implies large trades (greater than or equal to $50,000).
NA_FOLL	Number of analysts following the firm, natural logarithm of 1 plus the number of unique analysts providing a forecast from the I/B/E/S Detail and Excluded Files.
MV	Market value of equity, defined as the natural logarithm of market value of common equity at the close of the current fiscal year (data25 ∗ data199) from Compustat.
MTB	Market-to-book, defined as the market value of the firm's equity divided by its book value ((data24 ∗ data25)/data60) from Compustat.
NBSEG	Number of business segments, defined as the natural log of 1 plus the number of business segments.
NGSEG	Number of geographic segments, defined as the natural log of 1 plus the number of geographic segments.
NY_EARNINGS	Next year's operating earnings scaled by assets, defined as Compustat items (data 178/data 6).
PVOL	Price volatility, defined as the standard deviation of the firm's stock price prior to the 10-K filing (−49, −5).
READ_FOG	Fog index, calculated as [(words per sentence + percent of complex words) ∗ .40] using Perl's En Fathom module.
READ_PE	Plain English index, calculated using Stylewriter software as described in Appendix 2 as 10 ∗ ((# of errors attributable to: Passive Verbs + Hidden Verbs + Overwriting + Legal Words & Jargon + Tautologies)/(number of sentences)).
SML	Small trades: When suffixed to a variable, implies small trades (if share price is < $50, then dollar amount of trade is less than or equal to $5,000; if share price >50, but less than or equal to 100, then dollar amount of trade is less than or equal to 100 ∗ price; if share price is greater than 100, then the firm is excluded from the sample).
WORDS+TABLES	Natural logarithm of the total of number of words plus the number of table cells included in each document.

(continued on next page)

TABLE 1 (continued)

Variable	Definitions (Alphabetical Order)
TRADE_ CONS	Trade Consensus, defined as the absolute value of the daily net buys during the event period (buys minus sales), deflated by the total number of shares traded (buys plus sales) during the event period.
WORDS	Natural logarithm of the number of words included in the 10-K report.

Consistent with Bhattacharya (2001), trades are assumed to be made by small investors if the dollar amount of the trade is less than or equal to \$5,000; when the dollar amount of the trade is greater than or equal to \$50,000, the trade is assumed to be made by a large investor. Consistent with prior literature, I ignore medium-sized trades to create a "buffer-zone" between the trading activities of small and large investors.[11] Consistent with Asthana et al. (2004), I modify this formulation so that for firms with a share price greater than \$50, I define small trades as those less than or equal to 100 times the share price.[12] However, in order to keep a sufficient buffer between small and large trades, I exclude firms with a share price greater than \$100 (i.e., the maximum small trade in my sample is \$10,000).

Equation (2) represents the stacking of two regressions that allows statistical tests of differences in coefficient estimates across the small and large investor groups. *SML* (*LRG*) is an indicator variable equal to 1 when the dependent variable represents the abnormal trading behavior for small (large) investors, and 0 otherwise. Accordingly, the α (β) coefficients measure associations between small (large) investor trade behavior and the independent variables.[13] My expectation for both small and large trade groups is that the coefficients on *COMPLEX* will be negative if increases in complexity result in increased processing costs leading to lower abnormal trade. I also examine whether small investors are more likely to be affected by more complex reports. Accordingly, I provide a test of coefficients across *SML* $*$ *COMPLEX* and *LRG* $*$ *COMPLEX* and expect the effects of report complexity to be greater for small investors.

Trading Consensus

I also examine whether increases in report complexity lead investors within the same class (e.g., small investors) to draw different inferences from the same reported information. To gauge the amount of trade consensus by investor group around a 10-K filing, I first classify all buyer and seller initiated trades using the standard Lee and Ready (1991) algorithm.[14] Next, I create a

[11] Lee and Radhakrishna (2000) find that these trade size bins perform well in identifying trades initiated by individual investors and institutions. Eliminating medium-sized trades increases the power of the test, since large investors may try to break up their trades to disguise their identity (Kyle 1985; Meulbroek 1992; Barclay and Warner 1993) but for a variety of reasons are unlikely to make very small trades (Bhattacharya et al. 2007).

[12] Consistent with prior literature, I also exclude the opening trade because it is often the sum of multiple orders and including it could add noise to the measures (Lee and Ready 1991; Lee 1992; Bhattacharya et al. 2007). Further, I only include trades with a "regular sales" condition code. Bhattacharya et al. (2007, 587) point out that these "trades result from continuous two-sided auctions involving market orders, limit orders, and buys and sells against the specialists' inventories. This is not the case when the condition code indicates something other than a 'regular sale' (e.g., large block trades or stopped orders)."

[13] See Maddala (2001) for discussion of stacked regressions. Since the technique captures any (potential) correlations across the error terms, stacking allows statistical tests of coefficients across equations (i.e., small and large investor groups).

[14] This algorithm, validated by Lee and Radhakrishna (2000), classifies trades above (below) the bid/ask midpoint as buyer (seller) initiated. Trades occurring at the midpoint are classified using the tick test, which compares the trade price to

variable *TRADE_CONS*, defined as the absolute value of daily net buyer initiated shares traded (buyer minus seller initiated) deflated by total volume of shares traded (absolute value of buyer plus seller initiated) on the same day for each investor group (e.g., small).[15] I then replace the dependent variable, *AVOL*, in Equation (2) with *TRADE_CONS*.

If small or large investors process the 10-K and agree (disagree) on the information's effect on the firm's terminal value, they are likely to trade in a similar (different) direction to other investors in that same group leading to higher (lower) *TRADE_CONS*. As predicted in H2, I expect more complex reports to increase disagreement for both small and large investor groups. Hence, I predict negative coefficients on all measures of *COMPLEX*.

IV. SAMPLE AND DESCRIPTIVE DATA

Sample Collection

I gather the sample by downloading all 10-K and 10-K405 filings on EDGAR from 1994 to 2006.[16] I require a firm-year match on PERMNO (from CRSP), GVKEY (from Compustat), CIK (from EDGAR), and TAQ data for small and large volume around the 10-K filing.[17] Consistent with prior research, I eliminate observations where the ticker identifier on TAQ changed during the year, the stock price was less than one dollar, or the firm had a stock split or issued a stock dividend during the year. Using the process described in Appendix A, I also eliminate all observations with insufficient text remaining after I eliminated the header, table, and other information. In order to calculate the *AFTEXD* variable, I require the prior year filing date to be available on EDGAR, which eliminates all 1994 observations and a significant number of other observations. Finally, I eliminate observations where there is missing Compustat data (e.g., *MV*, *ASSETS*) or where analyst following is unavailable on I/B/E/S. The final sample consists of 3,809 unique firms with 12,771 firm year observations. This number reduces to 4,724 observations for *WORDS +TABLES* analysis. Table 2 provides a detailed description of the sample selection procedure.

Sample Characteristics

Table 3 provides sample characteristics. Panel A provides descriptive statistics for several variables of interest. The positive aggregate mean for *AVOL* is 0.17, and the means for small investor *AVOL* and large investor *AVOL* are 0.22 and 0.18, respectively. The positive value for small investor *AVOL* is consistent with survey evidence small traders appear to trade on the information contained in the 10-K.[18] The mean for small investor *TRADE_CONS* is 0.24, whereas the mean for large investor *TRADE_CONS* is 0.52. These averages are consistent with the general notion that small traders are more likely to have disagreement surrounding information events than

adjacent trades. Under the tick test, a trade is classified as buyer (seller) initiated when the price is higher (lower) than the price of the previous trade. In cases when the price is the same as the previous trade (a zero tick), the classification of buyer (seller) initiated trades defaults to the last trade where there was a price change.

15 The limit order trader on the other side of the buyer or seller initiated trade could be an investor from the same or a different size class. For example, the other side of a small buyer or seller initiated trade could be another small investor, the market maker, or a large or medium passive trader whose limit order is broken up into smaller lots. The important factor is not whether the limit order investor on the other side of the buyer/seller initiated transaction is a small or large trader, but rather, whether the transaction was initiated as a buy or sale by a small or large trader.

16 Li and Ramesh (2009) show that the stock market and volume reaction for quarterly and small business filings disappear after controlling for the concurrent release of earnings information. As such, I exclude small business filers and restrict my investigation to annual filings. Forms 10-K and 10-K405 are identical in substance, except that form 10-K405 indicates that an officer or director failed to file a Form 4 (or Form 3 or 5) within the required time period.

17 For comparative purposes across small and large investors, I ensure that each firm analyzed has both small and large trade activity by eliminating a trivial number of observations that have no trade for an investor type during the control and five-day window around the 10-K filing. The results are unaffected by the inclusion of these observations.

18 All *AVOL* coefficients are negative at the median, which is consistent with Asthana et al. (2004) and consistent with the earnings releases having a significant impact on pre-period volume.

TABLE 2
Sample Selection

	No. Firm-Year Observations
10-K Filings from EDGAR (1994−2006) with GVKEY and PERMO Identifiers and TAQ data	21,189
less where the TAQ ticker changed during the year	(129)
less where there was a stock split or stock dividend	(1,523)
less where the stock price was less than $1	(122)
less where the filing is missing *LENGTH* and FOG from Perl En Fathom	(4)
less where there is missing prior year filing date (*AFTEXD*)	(3,763)
less missing Compustat data (*MV*, *ASSETS*, *NBSEG*, *NGSEG*, etc.)	(1,002)
less missing I/B/E/S data to calculate analyst following	(1,875)
Observations available for primary analysis	12,771
Observations available for # of table cells in 10-K available (*WORDS+TABLES*) calculation	4,724

The ability to count the number of table cells requires firms to comply with a specific HTML standard. Hence, *WORDS+TABLES* is only available for a subset of firms after 1999.

larger more sophisticated investors. The mean *ABS_RET* is 4.8 percent, indicating an abnormal market reaction during the 10-K filing period. The mean *WORDS* is 10.39, which translates into an average of 32,533 words per 10-K, while the mean Fog Index is 19.94, which classifies the vast majority of financial statements as unreadable according to most interpretations of the index.

Panel B (C) of Table 3 provides information on report length (readability) across time. Consistent with Li (2008), there is a significant increase in *WORDS* and *WORDS+TABLES* over the sample period investigated.[19] Consistent with the increase in length, Panel C reveals that there is also a significant increase in *READ_FOG*, indicating that reports have become less readable over time. However, this pattern in readability is not evident in *READ_PE*, where there is no significant difference in readability during the sample period. In summary, there appears to be a significant increase in report length over time, but the evidence for a corresponding change in readability is only evident when the Fog measure of readability is employed.

V. REGRESSION RESULTS

Total Trading Activity

Table 4 reports the multivariate regression results for the effects of complexity on abnormal trading volume (*AVOL*). Overall, I find evidence consistent with more complex reports affecting total trading volume. Specifically, both coefficients related to longer reports as reported in columns (1) and (2) of Panel A in Table 4 are significantly negative ($p < .01$).[20] While both measure of readability are negative, only the readability measure based on plain English attributes as prescribed by the SEC is significant ($p < .01$).

Although the majority of control variables are significant in the expected direction in Table 4, Panel A, some of the controls warrant further discussion. Specifically, the significant positive

[19] In untabulated analysis, I find a high correlation between *WORDS* and *WORDS+TABLES* (85 percent Pearson and 96 percent Spearman), which suggests that the quantity of data in tables is proportional to the length of text.
[20] All p-values reported in the study are presented as two-tailed when no prediction is given and one-tailed when predicted.

TABLE 3

Sample Characteristics

Panel A: Distribution of Variables

Variables	# Obs.	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
AVOL	12771	0.173***	1.013	−0.402	−0.104#	0.403
SML**AVOL*	12771	0.222***	1.030	−0.412	−0.028###	0.573
LRG**AVOL*	12771	0.177***	1.026	−0.366	−0.121###	0.338
SML**TRADE_CONS*	12771	0.244***	0.167	0.125	0.198###	0.315
LRG**TRADE_CONS*	12771	0.521***	0.292	0.272	0.472###	0.750
WORDS	12771	10.391***	0.790	9.967	10.384###	10.845
WORDS+TABLES	4724	10.828***	0.569	10.508	10.816###	11.164
READ_FOG	12771	19.943***	1.782	18.842	19.762###	20.869
READ_PE	12771	21.157***	5.240	17.546	20.002###	23.708
AFTEAD	12771	38.431***	17.927	28.000	41.000###	51.000
AFTEXD	12771	−1.293***	10.322	−5.000	0.000###	3.000
ABS RET	12771	0.048***	0.053	0.014	0.031###	0.063
PVOL	12771	1.810***	2.137	0.675	1.203###	2.106
MV ($ billion)	12771	2.752***	7.445	0.232	0.605###	1.791
MTB	12771	1.603***	1.709	0.581	1.062###	1.938
EARNINGS	12771	0.052***	0.155	0.030	0.077###	0.125
NY_EARNINGS	12771	0.042***	0.208	0.025	0.073###	0.121
NBSEG	12771	0.693***	0.752	0.000	0.000###	1.386
NGSEG	12771	1.012***	0.631	1.099	1.099###	1.386
NA_FOLL	12771	2.065***	0.758	1.609	2.079###	2.639

(continued on next page)

Panel B: Mean and Median Length across Time

	# Obs.		*WORDS*		*WORDS+TABLES*	
Year	***WORDS***	***WORDS+TABLES***	**Mean**	**Median**	**Mean**	**Median**
1995	312	—	10.147	10.091	—	—
1996	437	—	10.136	10.088	—	—
1997	905	—	10.164	10.115	—	—
1998	1514	—	10.234	10.146	—	—
1999	1393	6	10.315	10.234	10.496	10.302
2000	1121	72	10.319	10.231	10.484	10.432
2001	1031	175	10.332	10.271	10.446	10.467
2002	1151	495	10.295	10.394	10.592	10.625
2003	1124	751	10.536	10.520	10.814	10.796
2004	1386	1098	10.601	10.531	10.878	10.825
2005	1353	1170	10.612	10.595	10.908	10.885
2006	1044	957	10.611	10.600	10.904	10.896
Change in *WORDS* 2006 less 1995			0.464[a]	0.509[b]		
Change in *WORDS+TABLES* 2006 less 2000					0.408[a]	0.594[b]

(continued on next page)

Panel C: Mean and Median Readability across Time

Year	# OBS	*READ_FOG* Mean	*READ_FOG* Median	*READ_PE* Mean	*READ_PE* Median
1995	312	19.603	19.303	21.126	20.421
1996	437	19.660	19.462	21.362	20.091
1997	905	19.681	19.517	21.388	20.501
1998	1514	19.848	19.729	21.594	20.377
1999	1393	19.759	19.560	21.329	20.158
2000	1121	19.684	19.497	21.196	19.769
2001	1031	19.561	19.351	20.757	19.274
2002	1151	19.583	19.551	20.789	19.659
2003	1124	20.149	19.918	21.241	20.125
2004	1386	20.465	20.151	21.314	20.133
2005	1353	20.380	20.311	20.905	19.912
2006	1044	20.338	20.100	20.795	19.781
Change in FOG Readability 2006 less 1995		0.735[c]	0.509[d]		
Change in Plain English Readability 2006 less 1995				−0.331	−0.640

*, **, *** (#, ##, ###) Indicate two-tailed statistical significance of whether the mean (median) coefficient estimates differ from 0 at the 10 percent, 5 percent, and 1 percent levels, respectively, based on t-tests (Wilcoxon signed rank tests).

[a,b] Represents significant differences at the 1 percent level in *LENGTH* between the corresponding years tested using t-test (Wilcoxon rank tests). Because of the minimal number of observations for *WORDS+TABLES* in 1999, the analysis of changes in *WORDS+TABLES* over time uses 2000 as the base year.

[c,d] Represents significant differences at the 1 percent level in FOG Readability between the corresponding years tested using t-test (Wilcoxon rank tests).

See Table 1 for variable definitions.

TABLE 4
The Effects of Reporting Complexity on Total Abnormal Volume

Panel A: Pooled Analysis

	Hyp. Sign	*WORDS* (1)	*WORDS+TABLES* (2)	*READ_FOG* (3)	*READ_PE* (4)
COMPLEX	−	−0.0284***	−0.0754***	−0.0008	−0.0037***
		(−2.60)	(−3.56)	(−0.15)	(−2.32)
AFTEAD	−	−0.0073***	−0.0113***	−0.0071***	−0.0072***
		(−4.37)	(−5.17)	(−4.46)	(−4.43)
AFTEXD	+	0.0022*	0.0046***	0.0022*	0.0022*
		(1.32)	(2.33)	(1.32)	(1.33)
ABS_RET	+	6.2528***	9.7724***	6.2465***	6.2494***
		(5.88)	(5.83)	(5.88)	(5.87)
PVOL	?	−0.0022	−0.0362**	−0.0020	−0.0020
		(−0.23)	(−1.88)	(−0.21)	(−0.21)
MV	+/−	0.0377***	0.0483***	0.0347***	0.0345***
		(3.88)	(2.44)	(3.71)	(3.65)
MTB	?	−0.0255***	−0.0272**	−0.0240***	−0.0249***
		(−3.58)	(−1.81)	(−3.47)	(−3.45)
EARNINGS	?	0.0445	−0.1166	0.0660	0.0625
		(0.36)	(−0.47)	(0.53)	(0.50)
NY_EARNINGS	?	0.1056	0.4194**	0.1070	0.1052
		(1.34)	(2.32)	(1.34)	(1.32)
NA_FOLL	−	−0.1027***	−0.0923***	−0.1047***	−0.1039***
		(−5.34)	(−2.79)	(−5.36)	(−5.32)
NBSEG	?	0.0119	0.0384***	0.0105	0.0104
		(0.59)	(2.51)	(0.53)	(0.53)
NGSEG	?	−0.0201	−0.0445	−0.0194	−0.0200
		(−1.04)	(−1.34)	(−0.99)	(−1.04)
R^2		12.20%	18.47%	12.16%	12.20%

(continued on next page)

Panel B: Within-Year Analysis

	Hyp. Sign	*WORDS* (1)	*WORDS+TABLES* (2)	*READ_FOG* (3)	*READ_PE* (4)
COMPLEX	−	−0.0302***	−0.0878***	−0.0023	−0.0035***
		(−2.33)	(−2.94)	(−0.46)	(−2.22)
CONTROLS		Yes	Yes	Yes	Yes
R^2		12.71%	18.88%	12.66%	12.64%

Panel C: Within-Firm Analysis

	Hyp. Sign	*WORDS* (1)	*WORDS+TABLES* (2)	*READ_FOG* (3)	*READ_PE* (4)
COMPLEX	−	−0.0203**	−0.0679**	0.0007	−0.0027*
		(−1.75)	(−2.24)	(0.10)	(−1.49)
CONTROLS		Yes	Yes	Yes	Yes
R^2		11.06%	16.69%	11.04%	11.05%

*, **, *** Indicate two-tailed statistical significance of coefficient estimates at the 10 percent, 5 percent, and 1 percent levels, respectively, when no prediction is given and one-tailed significance when predicted.

This table reports the regression results for total (i.e., small, medium, and large investors combined) abnormal trading volume (*AVOL*).

Panel A reports results from estimating Equation (1). Panel B reports results from estimating Equation (1) after adding in year fixed effects. Panel C reports results from estimating Equation (1) after adding in firm fixed effects.

Columns 1, 2, 3, 4 report results when *COMPLEX* is measured as *WORDS*, *WORDS+TABLES*, *READ_FOG*, *READ_PE*, respectively. There is one observation per firm year for a total of 12,771 for all regressions except in column 2 where there are 4,724 observations when *WORDS+TABLES* is the variable of interest. All regressions include a constant term. Regressions are performed with clustered robust standard errors (Rogers 1993) to control for within-firm and -year correlation, except when a specific fixed effect is already included in the model.

coefficient on *MV* suggests that firm size is likely to be correlated with more familiarity and, thus, greater abnormal trading surrounding the filing. The coefficient on *MTB* is significantly negative in all regressions, suggesting that 10-K filings may contain less relative information to traders investing in growth firms. The remaining control variables appear to be significant in the predicted direction or do not exhibit enough of a consistent pattern to warrant discussion.

The analysis in Table 4, Panel A documents an association between report complexity and abnormal trading volume. However, it is unclear whether this association is driven by cross-sectional variation in firms' disclosure attributes and/or variations in disclosure complexity over time. Figure 2 reveals that longer and less readable reports tend to be concentrated in industries that are generally more complex (e.g., utilities or financial institutions). To address whether cross-sectional differences in length and readability lead to abnormal timing while holding time constant, I add year fixed effects to regression 1. The results in Table 4, Panel B are consistent with those in Panel A, where *LENGTH*, *WORDS+TABLES*, and *READ_PE* are all significantly negative ($p < .01$). It appears that the association between report complexity and abnormal trading is attributable to cross-sectional differences in firms' reporting after controlling for time.

Based on the previous analysis, it appears that firms with more complex reports are associated with less trading volume. However, the question of whether the significant increase in report length during the sample period affects investor trading behavior remains. In order to examine whether variations in reporting complexity over time impact trading volume after holding cross sectional differences in disclosure constant, I add firm fixed effects to regression Equation (1).[21] This analysis enables me to investigate whether the variations of a particular firm's report length over time lead to variations in trading volume and transactions for that particular firm's investors. Table 4, Panel C provides the results from the within-firm analysis, where the coefficients on *WORDS*, *WORDS+TABLES*, and *READ_PE* are once again significantly negative (although slightly weaker than in other panels).

Overall, the results in Table 4 provide evidence consistent with a decrease in total trading activity when reports are more complex.[22] Within-year and within-firm analyses suggest that the association between more complex reports and lower abnormal trading is driven by both cross sectional differences in firm reporting complexity as well as variation in disclosure complexity over time. From an economic perspective, after controlling for firm fixed effects, I find that a 55-page increase in a firms 10-K filing (roughly equivalent to increase in report length from 1995 to 2006) results in a 10.1 percent reduction in total abnormal volume around the filing.[23]

Small and Large Investor Trading Activity

Table 5 reports the multivariate regression results for the effects of report complexity on small and large investors' abnormal trading volume. The evidence is consistent with the results from Table 4 being driven by small investor trade. Columns (1) and (2) of Panel A show that the effects

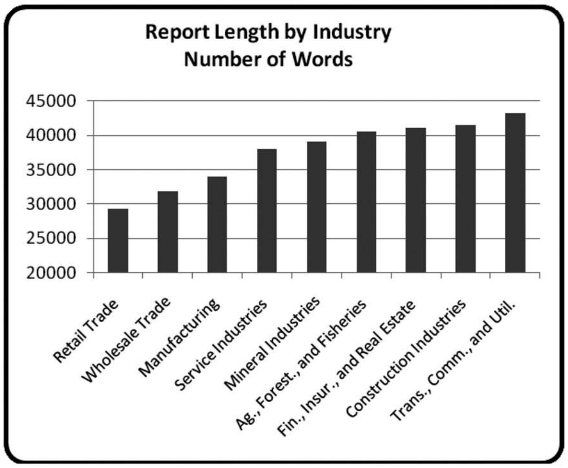
[21] In my primary analyses, I examine firm and year fixed effects separately, as including both effects simultaneously would likely eliminate any meaningful variation in the complexity measures. Specifically, including both effects would provide a test of the effects of report complexity on trading activity relative to the average complexity of the same firm and relative to the average of other firms in the same year. Consistent with controlling away firms' increases in complexity measures over time, the results after including both fixed effects in the same model are greatly diminished. While the effects of longer reports on total and small investor abnormal volume remaining significant at conventional levels, all the analyses involving readability and trading consensus are insignificant.

[22] In untabulated results, I examine the effects of complexity on the short-term abnormal market reaction and find significant evidence that longer reports (and to a lesser extent less readable reports) have more muted market reactions. This is consistent with Bloomfield's (2002) and You and Zhang's (2009) long-window return evidence that information that is hard to extract from financial statements will not be reflected immediately in stock prices.

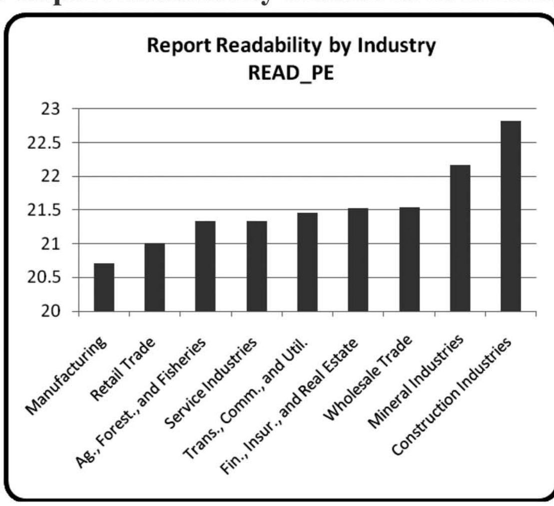
[23] The number of words increased from a median of approximately 24,000 words in 1995 to a median of approximately 39,000 words in 2006. The page estimate provided assumes 270 words per page, which is the approximate number of words contained on a standard 8-1/2 by 11 page that is double-spaced with 12-point font.

FIGURE 2
Report Length by Industry Classification

Panel A: Report Length Measured as Number of Words



Panel B: Report Readability Measured as READ_PE (Plain English)



This figure provides a summary of average report length by the major SIC code groups as identified by the U.S. Census Bureau (http://www.census.gov/epcd/naics/nsic2ndx.htm). Panel A (B) plots the average report length using number of words (plain English readability).

of longer reports are significant for small investors, wherein both the coefficients on *SML* $*$ *WORDS* and *SML* $*$ *WORDS+TABLES* are significant ($p < .01$). There is marginally significant evidence that large investors are affected by longer reports, reported in column (2) ($p = .09$).

TABLE 5

The Effects of Reporting Complexity on Small and Large Investor Abnormal Volume

Panel A: Pooled Analysis

		WORDS		***WORDS+TABLES***		***READ_FOG***		***READ_PE***	
	Hyp. Sign	***SMALL***	***LARGE***	***SMALL***	***LARGE***	***SMALL***	***LARGE***	***SMALL***	***LARGE***
		(1)		**(2)**		**(3)**		**(4)**	
COMPLEX	−	−0.0492***	0.0114	−0.0939***	−0.0333*	−0.0133***	0.0153	−0.0092***	0.0026
		(−4.00)	(1.17)	(−3.79)	(−1.37)	(−2.72)	(3.18)	(−4.07)	(1.29)
AFTEAD	−	−0.0062***	−0.0057***	−0.0099***	−0.0086***	−0.0061***	−0.0055***	−0.0067***	−0.0051***
		(−3.39)	(−5.63)	(−3.53)	(−7.16)	(−3.39)	(−5.46)	(−3.89)	(−4.85)
AFTEXD	+	0.0023***	0.0013	0.0026***	0.0033*	0.0023***	0.0012	0.0026***	0.0010
		(2.46)	(0.78)	(2.04)	(1.35)	(2.53)	(0.73)	(3.02)	(0.61)
ABS_RET	+	7.1042***	4.3407***	8.9660***	6.9747***	7.0712***	4.3668***	6.8853***	4.5562***
		(7.46)	(5.65)	(6.62)	(6.16)	(7.51)	(5.70)	(7.43)	(5.70)
PVOL	?	0.0062	−0.0041	−0.0042	−0.0389**	0.0063	−0.0038	0.0076	−0.0051
		(1.21)	(−0.44)	(−0.24)	(−2.39)	(1.24)	(−0.42)	(1.47)	(−0.54)
MV	+/−	0.0776***	−0.0054	0.0849***	−0.0002	0.0718***	−0.0038	0.0507***	0.0173
		(5.06)	(−0.63)	(3.36)	(−0.01)	(4.86)	(−0.41)	(3.36)	(1.52)
MTB	?	−0.0179***	−0.0160***	−0.0364***	−0.0168*	−0.0156**	−0.0162***	−0.0182**	−0.0153**
		(−2.68)	(−2.51)	(−4.08)	(−1.68)	(−2.31)	(−2.58)	(−2.51)	(−2.43)
EARNINGS	?	0.3071***	−0.0763	0.0142	0.0113	0.3383***	−0.0769	0.3516***	−0.0986
		(3.84)	(−0.76)	(0.11)	(0.06)	(4.53)	(−0.76)	(4.61)	(−0.97)
NY_EARNINGS	?	−0.1346**	0.1826***	0.1858	0.2497*	−0.1333**	0.1837***	−0.1230**	0.1694***
		(−2.33)	(4.60)	(1.61)	(1.91)	(−2.22)	(4.57)	(−2.03)	(4.27)
NA_FOLL	−	−0.0813***	−0.0885***	−0.0614	−0.0827***	−0.0836***	−0.0891***	−0.0752***	−0.0959***
		(−2.72)	(−5.12)	(−1.10)	(−2.71)	(−2.77)	(−5.09)	(−2.49)	(−5.40)
NBSEG	?	0.0175	0.0195	0.0387***	0.0437*	0.0146	0.0205	0.0161	0.0187
		(0.76)	(1.14)	(2.85)	(1.83)	(0.64)	(1.21)	(0.72)	(1.11)
NGSEG	?	−0.0208	−0.0078	−0.0231	−0.0335	−0.0219	−0.0054	−0.0287	0.0000
		(−0.88)	(−0.51)	(−1.09)	(−1.15)	(−0.92)	(−0.34)	(−1.16)	(0.00)
R^2			10.36%		13.84%		10.33%		10.16%
Test of ($SML * COMPLEX - LRG * COMPLEX$) < 0			−0.061###		−0.061###		−0.029###		−0.012###

(continued on next page)

Panel B: Within-Year Analysis

	Hyp. Sign	*WORDS* *SMALL* (1)	*WORDS* *LARGE* (1)	*TABLES + WORDS* *SMALL* (2)	*TABLES + WORDS* *LARGE* (2)	*READ_FOG* *SMALL* (3)	*READ_FOG* *LARGE* (3)	*READ_PE* *SMALL* (4)	*READ_PE* *LARGE* (4)
COMPLEX	−	−0.0443***	0.0054	−0.0648***	−0.0657**	−0.0093**	0.0120	−0.0085***	0.0027
		(−4.43)	(0.56)	(−2.49)	(−2.66)	(−2.26)	(2.91)	(−5.69)	(1.87)
CONTROLS			Yes		Yes		Yes		Yes
R^2			11.01%		14.34%		10.97%		10.71%
Test of (*SML* ∗ *COMPLEX* − *LRG* ∗ *COMPLEX*) < 0			−0.050###		0.001		−0.021###		−0.011###

Panel C: Within-Firm Analysis

	Hyp. Sign	*WORDS* *SMALL* (1)	*WORDS* *LARGE* (1)	*WORDS+TABLES* *SMALL* (2)	*WORDS+TABLES* *LARGE* (2)	*READ_FOG* *SMALL* (3)	*READ_FOG* *LARGE* (3)	*READ_PE* *SMALL* (4)	*READ_PE* *LARGE* (4)
COMPLEX	−	−0.0269**	0.0029	−0.1018***	−0.0501*	0.0002	0.0044	−0.0026*	−0.0023
		(−2.06)	(0.29)	(−3.01)	(−1.49)	(0.02)	(0.77)	(−1.62)	(−1.23)
CONTROLS			Yes		Yes		Yes		Yes
R^2			9.41%		12.58%		9.40%		9.10%
Test of (*SML* ∗ *COMPLEX*−*LRG* ∗ *COMPLEX*) < 0			−0.030##		−0.052		−0.004		0.000

*, **, *** Indicate two-tailed statistical significance of coefficient estimates at the 10 percent, 5 percent, and 1 percent levels, respectively, when no prediction is given and one-tailed significance when predicted.

#, ##, ### Indicate one-tailed statistical significance of differences between small and large investor coefficients for *COMPLEX* using F-statistics.

This table reports the regression results for small and large investor abnormal trading volume (*AVOL*).

Panel A reports results from estimating Equation (2). Panel B reports results from estimating Equation (2) after adding in year fixed effects. Panel C reports results from estimating Equation (2) after adding in firm fixed effects..

Columns 1, 2, 3, 4 report results when *COMPLEX* is measured as *WORDS*, *WORDS+TABLES*, *READ_FOG*, *READ_PE*, respectively. All regressions include a constant term. The reported regressions are stacked regressions of small and large investor groups, where there are two observations (i.e., small and large) for each firm year. Hence, there are a total of 25,542 for each regression, except in column 2 where there are 9,448 observations when *WORDS+TABLES* is the variable of interest. To minimize the effects of outliers, all variables are winsorized at the top and bottom 1 percent by year. Regressions are performed with clustered robust standard errors (Rogers 1993) to control for within-firm and -year correlation, except when a specific fixed effect is already included in the model.

Further, small investors are more affected by longer reports than large investors as the differences in coefficients in columns (1) and (2) on *SML* ∗ *COMPLEX* and *LRG* ∗ *COMPLEX* are both significant ($p < .01$).

I find that the effects of less readable reports also appear to be driven by small investors. Specifically, columns (3) and (4) of Table 5, Panel A show the effects of less readable reports for small investors, where both the coefficients on *SML* ∗ *READ_FOG* and *SML* ∗ *READ_PE* are both significant ($p < .01$). There is no evidence of less readable reports reducing the trading behavior of large investors. Further, small investors are more affected by less readable reports than large investors; the differences in coefficients in columns (3) and (4) on *SML* ∗ *COMPLEX* and *LRG* ∗ *COMPLEX* are both significant ($p < .01$).

As with Table 4, most of the control variables in Table 5 are significant in the expected direction. However, some of the specific coefficients on small and large investors warrant additional discussion. Specifically, coefficients on *MV* are significantly positive only for small investors, which is consistent with small investors trading more around 10-K filings that are larger potentially because these firms are more familiar. The coefficients on *MTB* are significantly negative for both small and large investors, suggesting that the 10-K filing for growth firms contains less pertinent information for both sets of investors. The coefficients on *EARNINGS* are positive for small trade activity in three of the four regressions, which indicates that small investors trade more when earnings are higher. Furthermore, the coefficients on *NY_EARNINGS* are significantly negative (positive) for small (large) investors in most regressions. These differences suggest that small (large) investors' trade less (more) when the filings contain information related to positive future earnings, which could be interpreted as more sophisticated investors taking more of a long-term perspective.

Another interesting insight provided in Table 5 are the coefficients on *LRG* ∗ *COMPLEX* when *READ_FOG* and *READ_PE* are investigated. The positive association between the readability measures and increased abnormal trading is inconsistent with the prediction and appears to be consistent with large investors being attracted to more complex reports. This attraction could be due to large investors trading more either because they have a processing advantage over other investors, or because certain firms cater to institutional investors by making their reports more technical.

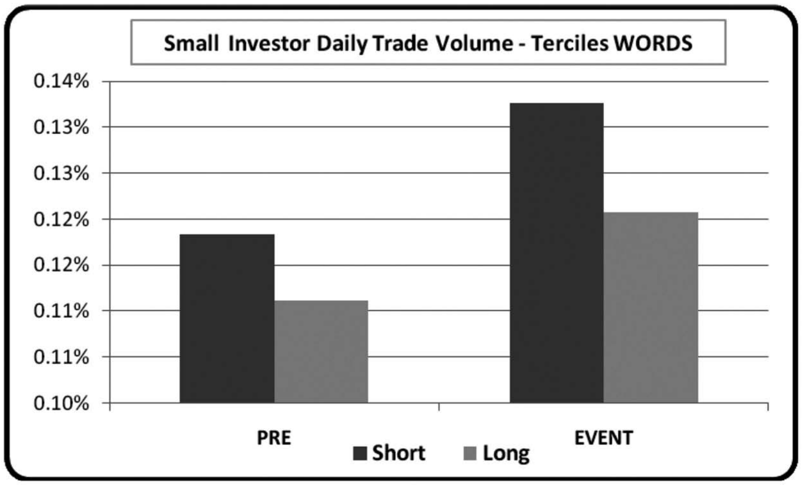
To address whether this association is consistent with investors' overall trading strategies, I investigate whether large (small) investors are associated with firms that have more (less) complex filings. I first create a measure of trading volume consistent with You and Zhang (2009) by scaling the average daily trading volume during the pre- and event periods by the total shares outstanding. I then compare the trading volume by event period across terciles of report length and readability.[24] The results are graphed in Figure 3(a) and 3(b), where Panel A (C) reveals that small investors trade more in both the pre- and event periods when reports are shorter (more readable). In untabulated results, small investor trading volume in the tercile of short reports in Panel A is significantly higher than the trading volume for the tercile of long reports (i.e., *WORDS*) during both the pre- and event periods ($p = .06$ and $p = .02$, respectively). Small investor trading volume is also higher for more readable reports in Panel C, but the differences are insignificant.

In contrast to small investor trading being associated with shorter reports, Panels B and D of Figure 3(b) show that large trade volume is actually greater for firms with longer and less readable reports. Specifically, in Panel B the large investor trade is significantly greater for long reports relative to shorter reports in both the pre- and event periods ($p < .01$; untabulated). Similar

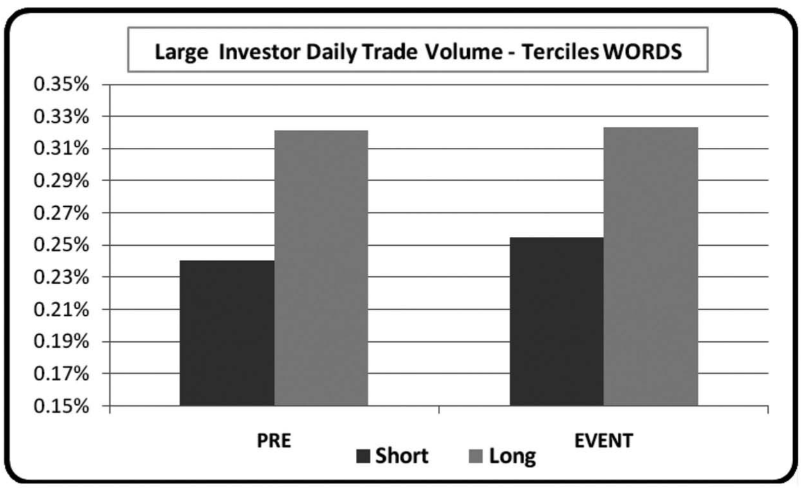
[24] Terciling by year enables me to compare firms within a given year, while parsing out the effects of decimalized trading in the latter periods. I use terciles, based on evidence provided by Lys and Sabino (1992).

FIGURE 3a
Trading by Tercile of Report Complexity

Panel A: Small Investors' Daily Trading Volume by Tercile of *WORDS*



Panel B: Large Investors' Daily Trading Volume by Tercile of *WORDS*



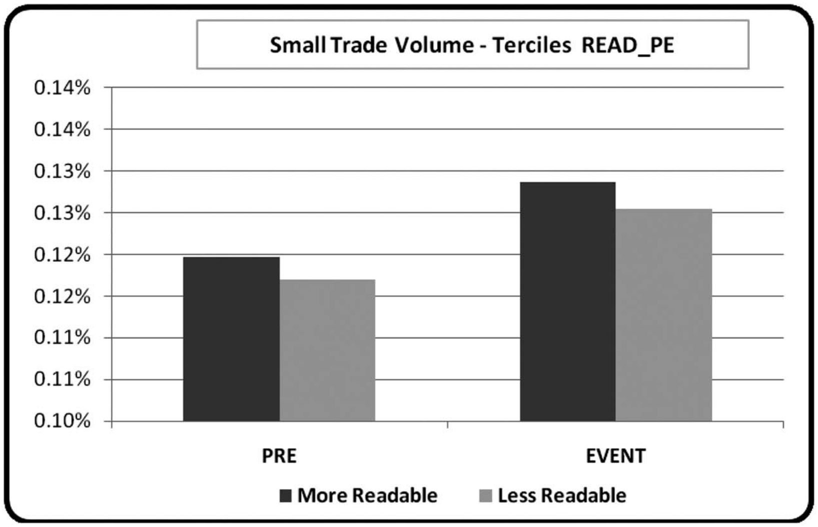
Daily trading volume is the number of shares traded scaled by total number of shares outstanding by investor group (i.e., small or large). Panel A (B) plots the mean of small (large) trade volume based on *WORDS*.

evidence exists in Panel D, wherein large investors trade significantly more during both the pre- and event periods when reports are less readable ($p < .01$ and $p = .03$, respectively).[25] Overall,

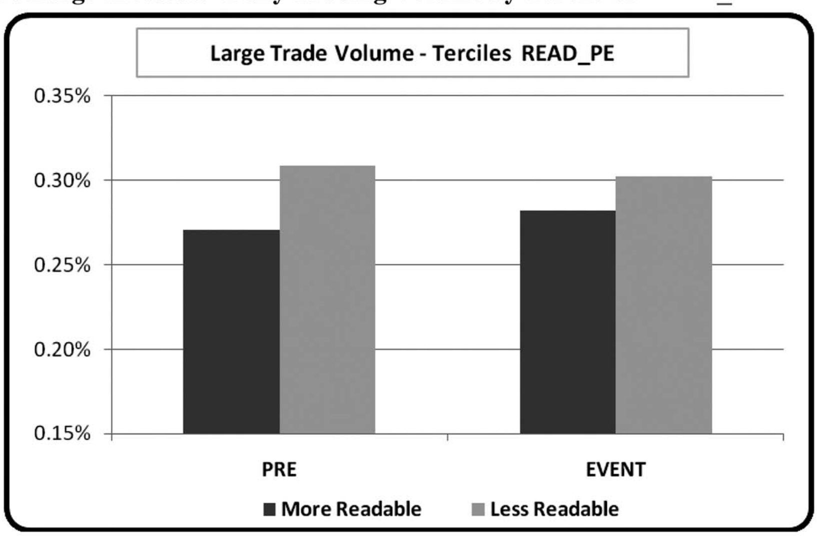
[25] Results using the alternative measures of *WORDS+TABLES* are similar, but more significant for all the relationships

FIGURE 3b
Trading by Tercile of Report Complexity

Panel C: Small Investors' Daily Trading volume by Tercile of *READ_PE*



Panel D: Large Investors' Daily Trading Volume by Tercile of *READ_PE*



Panel C (D) plots the mean of small (large) trade volume based on *READ_PE*. Terciles are created by the appropriate report complexity variable (i.e., *WORDS* or *READ_PE*) within each year to control for the increased proportion of small trade to total trade volume during the latter part of the sample. The middle tercile is eliminated to limit the comparison to more extreme groups.

examined in Figure 2. Similarly, the results for *READ_FOG* are also more significant for large investors, but are insignificant in the predicted direction for small investors.

the evidence in Figure 3(a) and Figure 3(b)and supports the notion that small (large) investors are associated with short (long) reports in both the pre- and event period.[26]

I further examine whether cross-sectional differences in reporting complexity (while holding time constant) affects small and large investor trading behavior in Panel B of Table 5. Consistent with Panel A, the coefficients on *SML* ∗ *COMPLEX* columns (1) through (4) are negative and significant. I also find that the coefficients on *LRG* ∗ *COMPLEX* are negative and significant when the length is measured as the total of both textual and tabulated content in column (2). This finding is consistent with more sophisticated investors being affected by more complex reports issued by certain firms. I continue to find evidence that more complex reports are more likely to lead to lower abnormal trade for small investors relative to large investors, except when examining the effects of *WORDS+TABLES*. However, this lack of difference between large and small investors in column (2) appears more related to large investors being affected by the complexity as measured by the text and tabulated information than by a lack of impact on small investors. Overall, the evidence from Table 5, Panel B is consistent with small investors trading less in the short-window around firms with 10-K filings when firms' reports are more complex.

I also investigate whether small investors are affected by deviations in reporting complexity over time (holding the firm constant) in Table 5, Panel C. Overall, the results are consistent with the earlier panels, although the significance levels of the complexity measures are diminished in all the regressions and the specific effects on *READ_FOG* (*READ_PE*) are insignificant (weakly significant). The weaker findings on *READ_PE* are most likely due to limited variation in the measure over time (see Table 3, Panel C). In summation, the evidence from Panel C supports the notion that increases in report complexity over time have a significant impact on small investors.

Overall, the results in Table 4 and Table 5 provide evidence consistent with a decrease in total trading activity when reports are more complex. This evidence appears due primarily to small investor trading behavior, although there is some evidence that length also has an effect on large investors. Further within-year and within-firm analyses suggest that the association between complex reports and lower abnormal trading appears to be driven by both underlying firm reporting complexity as well as variation in disclosure complexity over time.

Trading Consensus

The negative association between report complexity and small investor trade volume in the previous section is consistent with more complex reports increasing processing costs. I next investigate whether small (large) investors process data in a different way from other small (large) investors when reports are more complex by replacing the dependent variable in Equation (2) with *TRADE_CONS*. Table 6, Panel A provides regression results for small and large investors' consensus trade behavior. Overall, the results are consistent with more complex reports leading to more disagreement among small investors who elect to trade. For example, the coefficients on *SML* ∗ *COMPLEX* in columns (1), (2), (3), and (4) are all negative and significant (all $p < .01$). The coefficients on *LRG* ∗ *COMPLEX* are unexpectedly positive, which is consistent with large investors processing complex disclosures in a similar manner to other large investors when reports are more complex. Finally, I find support in all four columns that more complex reports result in

[26] Although it is possible that report length is a criterion investors use to base their decisions on which firms to follow, investors are more likely to start following a firm based on attributes such as familiarity (Merton 1987).

TABLE 6

The Effects of Reporting Complexity on Small and Large Investor Trade Consensus

Panel A: Pooled Analysis

		WORDS		*WORDS+TABLES*		*READ_FOG*		*READ_PE*	
	Hyp. Sign	*SMALL*	*LARGE*	*SMALL*	*LARGE*	*SMALL*	*LARGE*	*SMALL*	*LARGE*
		(1)		**(2)**		**(3)**		**(4)**	
COMPLEX	−	−0.0489***	0.0245	−0.0627***	0.0352	−0.0201***	0.0144	−0.0076***	0.0060
		(−4.33)	(2.50)	(−3.97)	(2.27)	(−5.00)	(3.52)	(−4.04)	(3.27)
AFTEAD	−	0.0008***	0.0001***	0.0001***	0.0001***	0.0008***	0.0001***	0.0002***	0.0007***
		(2.15)	(0.45)	(0.56)	(0.89)	(1.97)	(0.96)	(0.38)	(2.67)
AFTEXD	+	0.0004***	0.0004	0.0002***	0.0009*	0.0005***	0.0004	0.0008***	0.0000
		(0.68)	(1.96)	(1.11)	(4.32)	(0.78)	(1.66)	(1.00)	(0.12)
ABS_RET	+	−0.3333***	−0.4934***	−0.1485***	−0.5127***	−0.3761***	−0.4583***	−0.6080***	−0.2227***
		(−3.64)	(−7.28)	(−3.75)	(−4.65)	(−4.26)	(−7.12)	(−4.97)	(−2.58)
PVOL	?	0.0119***	−0.0124***	0.0040**	−0.0263***	0.0119***	−0.0123***	0.0135***	−0.0138***
		(4.23)	(−4.79)	(2.28)	(−17.04)	(4.04)	(−4.85)	(5.24)	(−4.47)
MV	+/−	−0.0489***	−0.0992***	−0.0173***	−0.1069***	−0.0547***	−0.0955***	−0.0812***	−0.0696***
		(−9.35)	(−25.73)	(−3.46)	(−24.87)	(−11.73)	(−23.39)	(−10.10)	(−8.43)
MTB	?	−0.0137***	−0.0083***	−0.0130***	0.0028	−0.0116***	−0.0093***	−0.0138***	−0.0073*
		(−5.94)	(−2.30)	(−8.20)	(0.97)	(−5.85)	(−2.57)	(−4.75)	(−1.70)
EARNINGS	?	0.0586***	0.0569	0.0031	0.1013*	0.0859***	0.0450*	0.1088***	0.0239
		(1.86)	(2.25)	(0.12)	(1.95)	(2.89)	(1.94)	(3.39)	(0.94)
NY_EARNINGS	?	0.0132***	−0.0536***	0.0027	−0.1121*	0.0136***	−0.0538***	0.0292***	−0.0692***
		(0.70)	(−3.15)	(0.25)	(−3.24)	(0.69)	(−3.05)	(1.28)	(−3.69)
NA_FOLL	−	−0.0251***	−0.0679***	−0.0234***	−0.0576***	−0.0267***	−0.0677***	−0.0173***	−0.0770***
		(−4.13)	(−11.72)	(−6.41)	(−11.56)	(−4.44)	(−11.70)	(−2.33)	(−11.23)
NBSEG	?	−0.0078	0.0116***	0.0060***	0.0113***	−0.0109*	0.0132***	−0.0087	0.0112***
		(−1.23)	(3.67)	(3.09)	(3.15)	(−1.68)	(4.17)	(−1.43)	(3.29)
NGSEG	?	0.0022	−0.0102**	−0.0085*	−0.0071	−0.0001	−0.0080*	−0.0074	−0.0001
		(0.32)	(−2.22)	(−4.60)	(−1.40)	(−0.02)	(−1.76)	(−1.26)	(−0.02)

(continued on next page)

Panel A: Pooled Analysis

	Hyp. Sign	*WORDS*		*WORDS+TABLES*		*READ_FOG*		*READ_PE*	
		SMALL	***LARGE***	***SMALL***	***LARGE***	***SMALL***	***LARGE***	***SMALL***	***LARGE***
		(1)		**(2)**		**(3)**		**(4)**	
R^2			55.99%		67.29%		55.50%		51.33%
Test of (*SML* ∗ *COMPLEX* − *LRG* ∗ *COMPLEX*) < 0			−0.073###		−0.098###		−0.034###		−0.014###

Panel B: Within-Year Analysis

	Hyp. Sign	*WORDS*		*WORDS+TABLES*		*READ_FOG*		*READ_PE*	
		SMALL	***LARGE***	***SMALL***	***LARGE***	***SMALL***	***LARGE***	***SMALL***	***LARGE***
		(1)		**(2)**		**(3)**		**(4)**	
COMPLEX	−	−0.0335***	0.0187	−0.0203***	−0.0001**	−0.0127***	0.0103	−0.0071***	0.0049
		(−16.96)	(8.79)	(−5.18)	(−0.02)	(−17.16)	(11.09)	(−24.68)	(13.39)
CONTROLS			Yes		Yes		Yes		Yes
R^2			59.12%		68.52%		58.90%		55.94%
Test of (*SML* ∗ *COMPLEX*−*LRG* ∗ *COMPLEX*) < 0			−0.052###		−0.020###		−0.023###		−0.012###

(continued on next page)

Panel C: Within-Firm Analysis

	Hyp. Sign	*WORDS*		*WORDS+TABLES*		*READ_FOG*		*READ_PE*	
		SMALL	*LARGE*	*SMALL*	*LARGE*	*SMALL*	*LARGE*	*SMALL*	*LARGE*
		(1)		(2)		(3)		(4)	
COMPLEX	−	−0.0085**	−0.0002	−0.0127***	0.0036	−0.0027**	0.0000	−0.0001	−0.0006*
		(−1.62)	(−0.08)	(−3.22)	(0.64)	(−1.95)	(0.01)	(−0.21)	(−1.41)
CONTROLS			Yes		Yes		Yes		Yes
R^2			16.46%		11.78%		16.44%		16.41%
Test of (*SML* ∗ *COMPLEX*−*LRG* ∗ *COMPLEX*) < 0			−0.008#		−0.016##		−0.003#		0.001

*, **, *** Indicate two-tailed statistical significance of coefficient estimates at the 10 percent, 5 percent, and 1 percent levels, respectively, when no prediction is given and one-tailed significance when predicted.

#, ##, ### Indicate one-tailed statistical significance of differences between small and large investor coefficients for *COMPLEX* using F-statistics.

This table reports the regression results for small and large investor abnormal trading volume (*TRADE_CONS*).

Panel A reports results from estimating Equation (2) after replacing the dependent variable with *TRADE_CONS*. Panel B reports results from estimating Equation (2) after replacing the dependent variable with *TRADE_CONS* and adding year fixed effects. Panel C reports results from estimating Equation (2) after replacing the dependent variable with *TRADE_CONS* and adding firm fixed effects.

Columns 1, 2, 3, 4 report results when *COMPLEX* is measured as *WORDS*, *WORDS+TABLES*, *READ_FOG*, *READ_PE*, respectively. The reported regressions are stacked regressions of small and large investor groups, where there are two observations (i.e., small and large) for each firm year. Hence, there are a total of 25,542 for each regression, except in column 2 where there are 9,448 observations when *WORDS+TABLES* is the variable of interest. All regressions include a constant term. Regressions are performed with clustered robust standard errors (Rogers 1993) to control for within-firm and -year correlation, except when a specific fixed effect is already included in the model.

greater disagreement among small investors thanamong large investors.[27]

As with abnormal trading volume regressions, the majority of control variables are significant in the expected direction in Table 6, but some of these coefficients also warrant further discussion. Specifically, *PVOL* is significant in different directions for small and large investors, implying that the 10-K resolves prior disagreement for small filers but leads to lower consensus for large investors. However, this interpretation should be taken with caution, as large investors could merely be unraveling their positions based on their different priors about the 10-K filing. The coefficients on both *MV* and *MTB* are significantly negative in all but one of the regressions, suggesting that there is more disagreement among investors of large and growth firms. Finally, the positive coefficients on *EARNINGS* can be interpreted as greater consensus when the underlying profitability is positive, whereas the negative coefficients on *LRG* $*$ *NY_EARNINGS* suggests disagreement among large investors regarding the forward-looking information in the filing.

Consistent with the analysis on trading activity, Table 6 also reports the regression equations including both within-year and within-firm analyses. The coefficients on *SML* $*$ *COMPLEX* are significantly negative in all four of the reported regressions in Panel B. Furthermore, the evidence in all four regressions suggests that small traders are more likely to disagree than their larger, more sophisticated counterparts. Table 6, Panel C provides similar evidence of an association between report complexity and lower consensus trade for small investors. However, the evidence is weaker in all such regressions, and the evidence for *READ_PE*, which has little variation over time, is insignificant. Overall, the evidence in this section reveals that more complex reports appear to be associated with a small but statistically significant decrease in consensus among small investors. For perspective, a 55-page increase results in a decrease in small investor consensus from a median value of 19.9 percent down to 19.5 percent.

In sum, the findings related to consensus are consistent with experimental evidence in Barron et al. (2004), where increases in disclosure lead nonprofessional investors to generate (or infer) private information. However, as opposed to Barron et al.'s (2004) finding that sophisticated professional investors are unaffected by the increased disclosure, there is some evidence that large investors are actually more likely to have increased consensus when more data is provided and the writing is more technical (less readable).

VI. ADDITIONAL ANALYSES

Combined Reporting Attributes

In addition to separately examining the effects of length and readability, I also re-run all analyses including both measures of complexity in the same model. When both length and readability are included in the regressions, the effects of longer reports are similar to those reported in Table 4, Table 5, and Table 6, albeit slightly weaker in a few regressions.[28] However, the effects of readability are insignificant in the predicted direction in all but one regression. This evidence is

[27] Small and large investors are likely to have different levels of prior information. Although these potential differences in private information between large and small investor groups do not affect the within-group comparison, they do make it difficult to interpret the implications of the differential consensus between small and large investors on the abnormal trading results. Specifically, if large investors have more private information, they may be more likely to process information in a similar manner because they have more precise priors leading to greater consensus. As such, it is difficult to determine whether large investors' lower trading reaction to the filings (compared to small investors) is due to common processing or superior processing capabilities.

[28] The coefficients and significance levels on measures of length coefficients are not significantly affected by the inclusion of the readability metrics. Specifically, when the readability measures are included, all the coefficients on *WORDS* and *WORDS+TABLES* in the pooled regressions are significant at the 1 percent level (one-tailed), except when *READ_PE* is examined in the total abnormal volume regressions where the coefficients are significant at the 5 percent and 10 percent levels, respectively. The coefficients on measures of length are quantitatively similar for the within-firm and within-year as well.

consistent with both measures of reporting complexity serving as substitutes, with the effects of longer reports appearing to dominate the readability of the reports when both measures of complexity are analyzed simultaneously.

This analysis is useful in highlighting the differences between this study and a concurrent study by Loughran and McDonald (2010), who also investigate the reporting attributes of the 10-K filings during a similar time frame. While their study focuses primarily on the readability (not length) of financial statements, the two studies overlap in the investigation of small investor trade surrounding the filing. Both studies document that after implementing more sophisticated measures of readability (plain English), improvements in readability lead to increased small investor trading activity. The studies differ in the strength of that relation after simultaneously investigating alternative measures of length.

The discrepancy between the two studies could stem from several differences in composition. For instance, the studies differ in sample size, size cut-offs for small investors, inclusion of certain control variables, trading windows, and the measurement of plain English readability. Perhaps most importantly, differences could stem from research design choices. Specifically, Loughran and McDonald (2010) investigate a change in abnormal trading but include level-control variables. Hence, any deviations in firm characteristics (e.g., size, complexity) or report characteristics (e.g., length) over time are uncontrolled in their analysis. Additionally, as opposed to the abnormal volume measure used in this study, they use a dependent variable that is not de-trended to account for the increase in decimalized trading during the latter part of the sample they investigate. In sum, the evidence across both studies is consistent with small investors being affected by less readable reports, but differences in proprietary measures of plain English readability and research design choices make it difficult to directly compare differences in significance of that association when accounting for report length.

Short-Term versus Long-Term Trading Effects

As previously discussed, the evidence in Figure 1 suggests that the majority of trading occurs in the five-day window surrounding the filing. As such, this study's primary focus is on the effects report complexity on investor trading activity in the short window around the filing. The underlying assumption is that, as processing costs increase, small investors would continue to follow certain stocks but would elect to delay their trades either to give them time to process the reports or to time their trades to coincide with easier to access information events.

To determine whether the trading effects documented above are short-term or long-term in nature, I re-run the analyses in Table 4, Table 5, and Table 6 after increasing the trading window to 10- and 20-day periods. When the event window is lengthened to 10 days, the coefficients on small investors remain negative in the abnormal volume regressions. However, the coefficients and significance is diminished on most tests and become insignificant at conventional levels in about half the regressions. When the windows are expanded to 20 days, the significance on the all the coefficients is further diminished. In contrast to the abnormal volume regressions, the results on *TRADE_CONS* are relatively unaffected by lengthening the windows, as all the coefficients remain negative and significant at the 1 percent level for both the 10- and 20-day windows for all measures of report complexity. Overall, the evidence suggests that while the effects of report complexity are observable in longer windows, they are most pronounced in the short window around the filing.

Other Information Releases

Concurrent Information Releases

As with any event study, it is possible that other information released during the event window could affect the results. To provide additional assurance that the earnings announcements released in the short window surrounding the 10-K filing are not affecting the results, I eliminate all observations where *AFTEAD* is less than or equal to five days and find that the results are unaffected by removing these observations (untabulated). It is possible that other concurrent information releases may also affect trading behavior. However, in this setting, concurrent information releases would likely act as a filtering mechanism that would bias against finding an effect on information processing.

Prior Information Releases

During the latter part of the sample period investors likely have greater access to alternative sources of information (e.g., financial blogs) that may pre-empt the information in the 10-K filing. These alternative sources of information released prior to the filing could lead to increased trade during the control window and decreased trade during the event window. Due to the trend in report length, this possibility could provide a potential alternative explanation for the findings in this study. To rule out this alternative, I examine variations in the ratio of daily average trading volume during the pre-period divided by the event period by year during the sample period. I find that the ratio of pre-period/event period trading behavior significantly decreases for small investors from the beginning to the end of the sample period ($p < .01$; untabulated), while there is no significant change in the proportion of large investor pre-volume to event period trade. In summary, there is no evidence that increased access to information by either small or large investors during the latter part of the sample period affects trading behavior in a manner that would bias toward the findings.

MD&A Reporting Complexity

In my primary analyses, I examine the length of the entire 10-K document including MD&A, footnotes, contracts, and other exhibits. However, it is possible that the effects are driven by certain parts of the document, such as the MD&A section. To address this issue, I obtain MD&A measures from Li (2009) and examine the MD&A section separately. I find only weak evidence of an effect of MD&A-specific reporting complexity on investor trading, which suggests that the complexity of the MD&A section is not driving the results.

VII. CONCLUSION

The evidence in this study is consistent with more complex filings being too costly for some investors to process. Specifically, I find evidence that more complex filings are associated with reduced trading activity and lower consensus for small investors, but have only a limited impact on large investors. I perform additional within-firm and within-year analyses and find similar results, which suggest that the association between more complex reports and lower abnormal trading appears driven by both relative firm reporting complexity as well as deviations in reporting complexity over time. Additional analysis reveals that the effects of readability and length appear to act as substitutes, with longer reports appearing to dominate the readability of the reports when analyzing both measures of complexity simultaneously.

The evidence provided in this study should prove useful to regulators. For instance, the results highlight the importance of considering processing costs in future disclosure regulation and, therefore, challenge the assumption that more disclosure helps level the playing field between small and large investors. Further, although the SEC has made progress in assisting small investors in gaining electronic access to financial information (Asthana et al. 2004), simply making more data publicly available may not necessarily aid small investors, as the increased cost of processing the additional data makes the 10-K filings too costly for many small investors to process. Finally, initiatives to reduce the processing costs of financial filings may serve as an important factor in ensuring information is impounded quickly into market prices.

APPENDIX A
10-K FILING EDIT PROCEDURES

This appendix provides details of the methods used to download and edit the 10-K filings. I first download all 10-K reports from EDGAR and then edit the filings before calculating the readability scores. I follow the process documented in Li (2008), with some slight modifications.

I delete the heading information that is contained between ⟨SEC-HEADER⟩ and ⟨/SEC-HEADER⟩ and all text that begins with ⟨TABLE⟩ and ends with ⟨/TABLE⟩.[29] I also eliminate all lines that contain ⟨S⟩ or ⟨C⟩ or special characters ⟨…⟩ and ⟨&..⟩, along with all lines that contain strings such as ⟨TEXT⟩, ⟨DOCUMENT⟩, ⟨PAGE⟩, ⟨TYPE⟩, or /PRIVACY-ENHANCED/. Li (2008) eliminates all paragraphs containing these tags. However, these strings often fail to contain end tags making it difficult to delete specific sections. To address this issue, I eliminate only the lines containing this coding.

Further, I convert embedded HTML code to proper ASCII characters and run a Perl package to strip all remaining HTML tags (for further information see http:/www.ascii.cl/htmlcodes.htm). All ".jpg," ".pdf," and ".gif" files are eliminated. Finally, I delete all paragraphs (defined as two lines containing text with a blank line before and after) with more than 50 percent non-alphabetic characters to ensure that all tables, tabulated texts, and financial statements are eliminated. Although this approach is not perfect in eliminating all numeric or HTML code, my review of a large number of these filings indicates that the code does a reasonable job at editing the text. Further, the En Fathom module with Perl attempts to distinguish words from acronyms and other characters, which should minimize any noise attributable to remaining HTML code. There is no reason to believe that any remaining HTML code biases the findings in this study.

Word and Table Counts

I run the En Fathom module in Perl to identify the number of words in the document. To count the number of cells included in the document, I locate all of the HTML tags that correspond to the syntax ⟨TABLE or ⟨table (prior to their deletion as documented above). The number of cells within a table is then computed by counting the number of ⟨TD or ⟨td tags found within a table. Finally, I sum the number of cells across all tables and add that count to the number of words in the document to create the *WORDS+TABLES* variable.

Financial Statements Included by Reference

Finally, to ensure that the results in this study are not affected by firms that include their financial statement by reference, I use a PERL script to identify these firms and find that the results are unaffected by eliminating these observations (untabulated).

APPENDIX B
CALCULATION OF FOG AND PLAIN ENGLISH READABILITY MEASURES

This appendix explains the details of measuring length and creating readability indices after the text has been edited (as described in Appendix A).

[29] I follow Li (2008) and delete tables "that begin with ⟨TABLE⟩ and end with ⟨/TABLE⟩." However, I find that certain reports contain significant amounts of text between table tags. For example, in Lowe's Companies 1994 10-K (http://www.sec.gov/Archives/edgar/data/60667/0000060667-94-000015.txt), large portions of text, including the entire MD&A section, are eliminated under this approach. Hence, I repeat the entire analysis without deleting the information between the table tags (but keeping the requirement to delete all paragraphs with more than 50 percent non-alphabetic characters). The results are quantitatively similar using both approaches.

Fog Readability

After the file has gone through the edit process described in Appendix A, the text is then analyzed using the En Fathom package in Perl. This package calculates a variety of textual statistics, including number of characters, number of words, percent of complex words, number of sentences, number of text lines, number of paragraphs, syllables per word, and words per sentence. Based on these statistics, the package produces the Fog readability index.

Plain English Readability

I compute the plain English readability score used in this study by identifying the specific plain English problems highlighted by the SEC and matching them to the specific variables identified by a proprietary text-editing program called StyleWriter (http://www.stylewriter-usa.com).

Plain English Writing Factors

SEC Plain English Problems	StyleWriter Plain English Measure
Passive voice	Passive verbs
Weak/Hidden verbs	Hidden verbs
Superfluous words	Overwriting (overuse of qualifying words)
Legal and financial jargon	Legal words and Jargon/Abstract words
Numerous defined terms	NA
Abstract words	Jargon/Abstract words
Unnecessary details	Tautologies/Overwriting
Long sentences	Number of words/Avg. sentence length
Unreadable design and layout	NA

This software is designed as an add-in editing program to be used in text processing software and, thus, requires the document to be opened in a "word processor" before the document can be analyzed. This limitation results in several additional processing requirements.

First, each document must be opened in text-processing software and then individually analyzed by StyleWriter. I automate this process using a keyboard/mouse click macro to open and score each document, but the need to open and analyze each document individually severely limits the number of documents that can be efficiently processed. Second, the Perl output in .txt format has a "¶" symbol (i.e., carriage return) at the end of each line. This means StyleWriter sees each line as a paragraph, which invalidates several of the plain English results. Hence, prior to processing the documents, I use a Perl script to replace all ¶ with a space and keep all instances where there were two consecutive ¶ symbols (i.e., actual paragraph break). Finally, the program is designed to write out limited summary statistics to allow writers to improve their writing style. However, as originally designed, the program does not output the frequency of all plain English violations. Therefore, I worked with StyleWriter programmers to modify the program to enable me to export the relevant plain English violations for each document.

REFERENCES

Allee, K., N. Bhattacharya, E. Black, and T. Christensen. 2007. Pro forma disclosure and investor sophistication: External validation of experimental evidence using archival data. *Accounting, Organizations and Society* 32 (April): 201–222.

Asthana, S., and S. Balsam. 2001. The effect of EDGAR on the market reaction to 10-K Filings. *Journal of Accounting and Public Policy* 20 (December): 349–372.

———, ———, and S. Sankaraguruswamy. 2004. Differential response of small versus large investors to 10-K filings on EDGAR. *The Accounting Review* 79 (3): 571–589.

Atiase, R. K. 1985. Predisclosure information, firm capitalization and security price behavior around earnings announcements. *Journal of Accounting Research* 23 (Spring): 21–36.

Bamber, L. S. 1987. Unexpected earnings, firm size, and trading volume around quarterly earnings announcements. *The Accounting Review* 62 (July): 510–532.

———, and Y. Cheon. 1995. Differential price and volume reactions to accounting earnings announcements. *The Accounting Review* 70 (July): 417–441.

———, O. Barron, and T. Stober. 1997. Trading volume and different aspects of disagreement coincident with earnings announcements. *The Accounting Review* 72 (October): 575–597.

———, ———, and ———. 1999. Differential interpretations and trading volume. *Journal of Financial and Quantitative Analysis* 34 (September): 369–386.

Barber, B., T. Odean, and N. Zhu. 2009. Do retail traders move markets? *Review of Financial Studies* (January): 151–186.

Barclay, M., and J. Warner. 1993. Stealth trading and volatility: Which trades move prices? *Journal of Financial Economics* (December): 281–305.

Barron, O. 1995. Trading volume and belief revisions that differ among individual analysts. *The Accounting Review* 70 (October): 581–597.

———, D. Byard, and C. Enis. 2004. Leveling the information playing field. *Review of Accounting and Finance* 3 (4): 21–46.

———, D. Harris, and M. Stanford. 2005. Evidence that investors trade on private event period information around earnings announcements. *The Accounting Review* 80 (2): 403–421.

Beaver, W. H. 1968. The information content of annual earnings announcements. *Journal of Accounting Research* 6 (Supplement): 67–92.

Bhattacharya, N. 2001. Investors' trade size and trading responses around earnings announcements: An empirical investigation. *The Accounting Review* 76 (2): 221–244.

———, E. Black, T. Christensen, and R. Mergenthaler. 2007. Who trades on pro forma earnings information? *The Accounting Review* 82 (3): 581–619.

Bloomfield, R. 2002. The "Incomplete Revelation Hypothesis" and financial reporting. *Accounting Horizons* 16 (September): 233–243.

———. 2008. Discussion of: Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics* (August): 248–252.

———, and P. Fischer. 2009. Disagreement and the cost of capital. Working paper, Cornell University and The Pennsylvania State University.

Botosan, C. 1997. Disclosure level and the cost of equity capital. *The Accounting Review* 72 (July): 323–349.

Bouwman, M., P. Frishkoff, and P. Frishkoff. 1987. How do financial analysts make decisions? A process model of the investment screening decisions. *Accounting, Organizations and Society* 12 (1): 1–30.

Chambers, A., and S. Penman. 1984. Timeliness of reporting and the stock price reaction to earnings announcements. *Journal of Accounting Research* 22 (Spring): 21–47.

Collins-Thompson, K., and J. Callan. 2005. Predicting reading difficulty with statistical language models. *Journal of the American Society for Information Science and Technology* 56 (November): 1448–1462.

Cready, W., and P. Mynatt. 1991. The information content of annual reports: A price and trading response analysis. *The Accounting Review* 66 (April): 291–312.

———, and D. Hurtt. 2002. Assessing investor response to information events using return and volume metrics. *The Accounting Review* 77 (4): 891–909.

Davis, A., J. Piger, and L. Sedor. 2007. Beyond the numbers: An analysis of optimistic and pessimistic language in earnings press releases. Working paper, University of Oregon.

Firtel, K. 1999. Plain English: A reappraisal of the intended audience of disclosure under the Securities Act of 1933. *Southern California Law Review* 72 (March): 851–897.

Francis, J., K. Schipper, and L. Vincent. 2002. Expanded disclosures and the increased usefulness of earnings announcements. *The Accounting Review* 77 (3): 515–546.

Griffin, P. A. 2003. Got information? Investor response to form 10-K and form 10-Q EDGAR filings. *Review of Accounting Studies* 8 (December): 433–460.

Grossman, S., and J. Stiglitz. 1980. On the impossibility of informationally efficient markets. *The American*

Economic Review 70 (June): 393–407.

Gunning, R. 1952. *The Technique of Clear Writing*. New York, NY: McGraw-Hill International Book Co.

Hirst, D. E., and P. E. Hopkins. 1998. Comprehensive income reporting and analysts' valuation judgments. *Journal of Accounting Research* 36 (Supplement): 47–75.

Hopkins, P. 1996. The effect of financial statement classification of hybrid financial instruments on financial analysts' stock price judgments. *Journal of Accounting Research* (Supplement): 33–50.

Huber, P. J. 1967. The behavior of maximum likelihood estimates under nonstandard conditions. *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability*. University of California Press, Berkeley, CA.

Hunton, J., and R. McEwen. 1997. An assessment of the relation between analysts' earnings forecast accuracy, motivational incentives, and cognitive information search strategy. *The Accounting Review* 72 (October): 497–516.

Jones, M., and P. Shoemaker. 1994. Accounting narratives: A review of empirical studies of content and readability. *Journal of Accounting Literature* 13: 142–185.

Kandel, E., and N. Pearson. 1995. Differential interpretation of public signals and trade in speculative markets. *The Journal of Political Economy* 103 (August): 831–872.

Karpoff, M. 1986. A theory of trading volume. *The Journal of Finance* 41 (December): 1069–1087.

Kim, O., and R. Verrecchia. 1991. Trading volume and price reactions to public announcements. *Journal of Accounting Research* 29 (Autumn): 302–321.

———, and ———. 1994. Market liquidity and volume around earnings announcements. *Journal of Accounting and Economics* 17 (January): 41–67.

———, and ———. 1997. Pre-announcement and event period private information. *Journal of Accounting and Economics* 24 (December): 395–419.

Kross, W., and D. Schroeder. 1984. An empirical investigation of the effect of quarterly earnings announcement timing on stock returns. *Journal of Accounting Research* 22 (Spring): 153–176.

Kyle, A. 1985. Continuous auction and insider trading. *Econometrica* (November): 1315–1335.

Lang, M., and R. Lundholm. 1996. Corporate disclosure policy and analyst behavior. *The Accounting Review* 71 (4): 467–492.

Lee, C., and M. J. Ready. 1991. Inferring trade direction from intraday data. *The Journal of Finance* 46 (June): 733–746.

———. 1992. Earnings news and small traders: An intra-day analysis. *Journal of Accounting and Economics* 15 (June/September): 265–302.

———, and B. Radhakrishna. 2000. Inferring investor behavior: Evidence from TORQ data. *Journal of Financial Markets* 3 (2): 83–111.

Lehavy, R., F. Li, and K. Merkley. 2009. The effect of annual report readability on analyst following and the properties of their earnings forecasts. Working paper, University of Michigan.

Levitt, A. 1997. Corporate finance in the information age. Remarks delivered to the Securities Regulation Institute, San Diego, California, January 23. Available at: http://www.sec.gov/news/speech/speecharchive/1997/spch135.txt.

Li, E., and K. Ramesh. 2009. Market reaction surrounding the filing of periodic SEC reports. *The Accounting Review* 84 (4): 1171–1208.

Li, F. 2008. Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics* (August): 221–247.

———. 2009. The information content of the forward-looking statements in corporate filing—A naive Bayesian machine learning approach. Working paper, University of Michigan.

Loughran, T., and B. McDonald. 2010. Measuring readability in financial text. Working paper, University of Notre Dame.

Lys, T., and J. Sabino. 1992. Research design issues in grouping-based tests. *Journal of Financial Economics* 32 (December): 355–387.

Maddala, G. 2001. *Introduction to Econometrics*. 3rd edition. New York, NY: John Wiley & Sons.

Maines, L., and L. McDaniel. 2000. Effects of comprehensive-income characteristics on nonprofessional investors' judgments: The role of financial-statement presentation format. *The Accounting Review* 75 (2): 179–207.

Mikhail, M., B. Walther, and R. Willis. 2007. When security analysts talk, who listens? *The Accounting Review* 82: 1227–1253.

Merton, R. 1987. A simple model of capital market equilibrium with incomplete information. *The Journal of Finance* 42: 483–510.

Meulbroek, L. 1992. An empirical analysis of illegal insider trading. *The Journal of Finance* (December): 1661–1699.

Morse, D. 1981. Price and trading volume reaction surrounding earnings announcements: A closer examination. *Journal of Accounting Research* (Autumn): 374–383.

Muresan, G., M. Cole, C. Smith, L. Liu, and N. Belkin. 2006. Does familiarity breed content? Taking account of familiarity with a topic in personalizing information retrieval. *Proceedings of the Hawaii International Conference on System Sciences* (HICSS-39).

Nelson, K., and A. Pritchard. 2007. Litigation risk and voluntary disclosure: The use of meaningful cautionary language. Working paper, Rice University.

Paredes, T. 2003. Blinded by the light: Information overload and its consequences for securities regulation. *Washington University Law Quarterly* 81 (Summer): 417–485.

Plumlee, M. 2003. The effect of information complexity on analysts' use of that information. *The Accounting Review* 78 (1): 275–296.

Radin, A. 2007. Have we created financial statement disclosure overload? Available at: http://www.nysscpa.org/cpajournal/2007/1107/perspectives/p6.htm.

Rogers, W. 1993. *Regression Standard Errors in Clustered Samples*. Stata Technical Bulletin 13. College Station, TX: Stata Press.

Securities and Exchange Commission. 1998. A plain English handbook: How to create clear SEC disclosure. SEC Office of Investor Education and Assistance. Available at: http://www.sec.gov/pdf/handbook.pdf.

———. 2000a. Fair Disclosure Regulation FD. Available at: http://www.sec.gov/rules/final/33-7881.htm.

———. 2000b. Final rule: Disclosure of order execution and routing practices. Available at: http://www.sec.gov/rules/final/34-43590.htm.

———. 2010. The investor's advocate: How the SEC protects investors, maintains market integrity, and facilitates capital formation. Available at: http://www.sec.gov/about/whatwedo.shtml.

Shanthikumar, D. 2004. Small trade reactions to consecutive earnings surprises. Dissertation, Stanford University.

Tetlock, P. 2007. Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance* 62 (3): 1139–1168.

———, M. Saar-Tsechansky, and S. Macskassy. 2008. More than words: Quantifying language to measure firms' fundamentals. *The Journal of Finance* 63 (3): 1437–1467.

You, H., and X. Zhang. 2009. Financial reporting complexity and investor under-reaction to 10-K information. *Review of Accounting Studies* 14 (4): 559–586.

White, H. 1980. A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity. *Econometrica* 48: 817–883.