Do enhanced derivative disclosures work? An informational perspective

Guanming He
Durham University Business School, Durham University
Durham, United Kingdom
Email: guanming.he@durham.ac.uk
ORCID: 0000-0002-4879-6795

Helen Mengbing Ren*
University of Liverpool Management School, the University of Liverpool
Liverpool, United Kingdom
Email: Helen.Ren@liverpool.ac.uk
ORCID: 0000-0001-6721-6269

Richard Taffler
Warwick Business School, the University of Warwick
Coventry, United Kingdom
Email: Richard.taffler@wbs.ac.uk
ORCID: 0000-0003-1621-8533

* Correspondence: Helen Mengbing Ren, Accounting and Finance Group, University of Liverpool Management School, University of Liverpool, Chatham Street, Liverpool, L69 7ZH, United Kingdom. Telephone: +44 (0) 1517940165; Email: Helen.Ren@liverpool.ac.uk.

ACKNOLEDGEMENTS
The authors are grateful for helpful comments from Bob Webb (the editor) and an anonymous reviewer. We thank Constantinos Antoniou, Jimmy Downes (discussant), Edward Lee, Christian Leuz, Philippe Mueller, Eduardo Schiehll (discussant), Gunther Wuyts (discussant), Konstantinos Stathopoulos (discussant), Chendi Zhang, and other seminar participants at the Canadian Academic Accounting Association (CAAA) 2021 Annual Conference, 2020 International Conference on Derivatives and Capital Markets, 4th SAFE Market Microstructure conference, 2019 Financial Management Association (FMA) Annual Meeting, 5th Annual International Corporate Governance Society Conference, 28th Eurasia Business and Economics Society Conference, 2020 International Conference on Derivatives and Capital Markets, 11th International Conference of Japanese Accounting Review, 2021 Hawaii Accounting Research Conference, 28th Annual Conference on Pacific Basin Finance, Economics, Accounting and Management, University of Warwick, University of Liverpool, and University of Essex for their helpful comments and suggestions. We also thank Stephen Brown for sharing the probability of informed trading data and Brian Bushee for sharing the institutional investor classification data. All errors remain our own.

Do enhanced derivative disclosures work? An informational perspective

Abstract

Firms use derivatives both for hedging and non-hedging purposes. The Statement of Financial Accounting Standards No. 161 (SFAS 161) requires firms to disclose the purposes of their derivatives usage, thereby helping investors to evaluate the effects of derivatives usage on firm performance. Using a hand-collected sample of U.S. listed firms and a difference-in-differences research design, we find that, compared with non-derivative-users, derivative-users compliant with SFAS 161 experience a significantly greater reduction in stock illiquidity and the probability of informed trading in the post-SFAS 161 period, and such impact is evident only for firms with a high degree of investor attention.

KEYWORDS

derivative disclosures, SFAS 161, information asymmetry, stock liquidity, PIN, investor attention

JEL CLASSIFICATION

G32, G38, M48

1 | INTRODUCTION

Financial statement users have expressed a concern that the derivative disclosures regulated by the Statement of Financial Accounting Standards No. 133 (hereafters, SAFS 133) did not provide adequate information about a firm's derivatives usage and hedging activities (Kawaller, 2004). In response to this concern, the Financial Accounting Standards Board (FASB) issued the Statement No. 161, *Disclosures about Derivative Instruments and Hedging Activities* (henceforth, SFAS 161), in the year 2008 to "*better convey the purpose of derivative use in terms of the risks that the entity is intending to manage*" (FASB, 2008).[1] Given that investors tend to assign higher values to firms, which use derivatives to reduce risks, than those using derivatives for speculation and other purposes (Koonce et al., 2008), information about the objectives of firms' derivative use can aid in investors' trading decisions. It is expected that SFAS 161 renders a firm's derivative disclosures more transparent to investors. Nonetheless, SFAS 161 may either increase or decrease information asymmetry among different investors, depending on their differential abilities to process the derivative information disclosed under SFAS 161. Tension exists to imply that SFAS 161 plausibly increases the information asymmetry, as the enhanced derivative disclosures may not be comprehensible to relatively uninformed investors due to the complex nature of derivatives. The objective of our study is to examine how the enhanced derivative disclosures, as mandated by SFAS 161, affect the information asymmetry between informed and uninformed investors.

Before SFAS 161 was issued in the year 2008, SFAS 133 was deemed the first step toward fair value accounting in that the standard started to recognize derivative instruments that affect the earnings in firms' financial statements. Nonetheless, lack of guidance and requirements of disclosures to distinguish between derivative instruments used for hedging purposes and those

[1]The SAFS 133, *Accounting for Derivative Instruments and Hedging Activities*, was issued by the FASB in the year 1998. SFAS 133 and SFAS 161 were codified under the Accounting Standards Codification (ASC) Topic 815, *Derivatives and Hedging*, in the year 2014.

used for non-hedging purposes under SFAS 133 led to inconsistent and inadequate derivative disclosures by firms (Kawaller, 2004). Therefore, SFAS 161 aims to improve disclosures about (i) how and why a firm uses derivative instruments; (ii) how derivative instruments are accounted for; and (iii) how derivative instruments affect a firm's financial position, financial performance, and cash flow (FASB, 2008). To improve the disclosures of how and why firms use derivative instruments, SFAS 161 imposes the requirement on firms to distinguish between derivatives designated as hedging instruments and those not designated as hedging instruments, and display this information further by the types of hedges in a tabular format. Accordingly, our study focuses on looking at this fundamental regulatory change regarding the additional tabular disclosures, which are mandated by the standard to categorize the intended purposes of derivative use by firms.[2]

If firms comply with the requirements of SFAS 161, their information transparency is expected to increase after the adoption of the standard. Improved transparency of firms' disclosures indicates a reduction in information asymmetry between managers and outsiders, but not necessarily an improved understanding of such information by all investors. The complexity and expanded use of derivatives by firms pose significant challenges to both the reporting entities and the users of financial statements. Not only derivatives per se but also associated measurements and reporting are complex (Peterson, 2012; Chang et al., 2016), which make it difficult for investors to infer the value implications of derivative disclosures (Kawaller, 2004). Chang et al. (2016) argue that even financial experts, such as analysts, routinely misjudge the earnings implications of firms' derivative activities.

For the users of financial statements, complexity refers to "*the difficulty that a user may have in understanding the mapping of economic transactions and reporting standards into*

[2]SFAS 161 might bring about a change in the amount of other information provided in the firms' derivative disclosures, but such a change is not the focus of our study.

financial statements (Chang et al., 2016, p.585)." Investors have differential abilities to understand complex information. Previous research argues that transient or short-term institutional investors are relatively better informed than other institutional investors (e.g., Chakravarty, 2001; Ke and Ramalingegowda, 2005; Sias et al., 2006); and that, compared with retail investors, institutional investors can better comprehend the information disclosed by firms (Kumar, 2009).[3] If SFAS 161 facilitates previously uninformed investors to understand corporate derivatives usage better, compared to previously informed investors, then the information gap between informed and uninformed investors would be reduced. Nonetheless, the opposing possibility exists. The required tabular disclosures distinguishing the purposes of derivatives usage, and enhanced quantitative disclosures about fair value and derivative gains and losses, after the passage of SFAS 161 may not be comprehensible to unsophisticated investors. If SFAS 161 improves informed investors' understanding of corporate derivatives usage more, relative to uninformed investors, then the information gap between informed and uninformed investors would be enlarged. Therefore, whether the enhanced derivative disclosures reduce or increase information asymmetry among varied investors remains an open empirical question to explore.

Our empirical analysis is based on a hand-collected sample of derivative disclosures by the non-financial and non-utility U.S. listed firms for the period 2006-2011 that surrounds the implementation of SFAS 161. We employ two proxies for information asymmetry between informed and uninformed investors: stock liquidity and the probability of informed trading. First, we measure stock (il)liquidity as the natural logarithm of relative effective spreads. Second, we apply Brown and Hillegeist's (2007) measure of the probability of informed trading (hereafters, PIN) that is extended from Easley et al. (1997) model. In our initial stock liquidity

[3] The amount of value-relevant information held by different investors varies. Sophisticated investors normally acquire and hold more value-relevant information for their trading decisions than unsophisticated investors. Therefore, sophisticated (unsophisticated) investors and informed (uninformed) investors can be used interchangeably in describing information asymmetry between investors.

sample (PIN sample), there are 1,180 (1,175) unique firms. 394 (404) of them are identified as compliers that provide tabular disclosures of the purposes of their derivative use pursuant to SFAS 161, and 456 (455) firms are non-users that do not use derivatives in any year over our sample period. The remaining 330 (316) firms are recognized as non-compliers which do not follow the new standard to distinguish between derivatives designated as hedges and those that are not.

We utilize a difference-in-differences (DID) research design to perform our empirical tests. To provide a cleaner test of the treatment effect of SFAS 161, we assign derivative-using firms, which comply with SFAS 161, to our treatment group, and classify non-derivatives-users, which are not affected by the standard, as our control group. We apply a propensity-score-matching approach to mitigate any potential endogeneity issue and to purge the potential effect of derivative usage on information asymmetry. Based on the propensity-score-matched sample, we find that compliers experience a greater reduction in information asymmetry between informed and uninformed investors following the implementation of SFAS 161, compared with a matched control sample of non-users. The finding is both statistically and economically significant. On the other hand, there is no evidence to suggest that, post SFAS 161, non-compliers exhibit any greater reduction in information asymmetry than non-derivative-users. This underlines the importance of compliance in achieving the regulatory outcome of reduced information asymmetry.

We further examine whether the impact of SFAS 161 on information asymmetry is moderated by firm visibility and investor attention. Larger, more visible firms tend to have a larger investor base, which implies a higher extent of investor attention to the firms' derivative disclosures regulated by SFAS 161. Using firm size and an abnormal search volume variable, which is constructed based on the Google Trends' Search Volume Index (SVI) data, as proxies for firm visibility, we find evidence that the effect of SFAS 161 in reducing information asymmetry between informed and uninformed investors is significant only for large, visible firms that attract a high degree of investor attention.

Our study contributes to the literature in a number of ways. First, disclosures reduce information asymmetry between informed and uninformed investors conditional on the disclosed information being comprehensible to uninformed investors. This condition is not satisfied for disclosures of complex business transactions or events that are difficult for an uninformed investor to comprehend in terms of their implications for firm value. Little research attention has been paid to the impact of complex information disclosures on information asymmetry among investors. We fill this gap in the literature by showing that enhanced disclosures of derivatives, which are complex by nature, reduce information asymmetry.

Second, we extend the mandatory disclosure literature by showing that the enhanced derivative disclosures mandated by SFAS 161 help uninformed investors understand corporate derivatives usage better than do informed investors, thereby increasing stock liquidity and reducing the probability of informed trading. Compared to the related literature, we perform cleaner and more powerful tests of the treatment effect of the regulation by drawing comparisons both between compliers and non-users, and between non-compliers and non-users. Our results suggest that SFAS 161 is effective in reducing stock illiquidity and the probability of informed trading only for derivative-using firms that are compliant with the standard. Our study provides insights into compliance with accounting standards issued by the FASB, and contributes to the sparse literature on the economic consequences of a disclosure regulation (and SFAS 161 in particular) to its compliers *vis-à-vis* non-compliers.

Third, we contribute to the limited research on capital market effects of disclosures in the notes to firms' financial statements (e.g., Franco et al., 2011; Inger et al., 2018; Campbell et al., 2021). Our study suggests that information about a highly complex area — the use of derivative instruments, if disclosed in a proper manner in the notes, will help to enhance investor understanding of firms and to level the playing field for varied investors.

Lastly, this study adds to extant research on investor attention (Da et al., 2011; Drake et al., 2012) by examining how it affects the economic consequences of a disclosure regulation. In particular, we show that the impact of SFAS 161 on information asymmetry varies by investor attention. To the extent that the implementation of SFAS 161 has brought investors' attention to corporate derivative disclosures made in the notes to firms' financial statements, high firm visibility with a high level of investor attention amplifies the regulatory effect on stock liquidity and the probability of informed trading. Our findings thereby highlight the importance of firm visibility and investor attention in promoting the capital market effects of a disclosure regulation.

The paper is organized as follows. Sections 2 reviews the related literature and develops our main hypothesis. Section 3 describes data, variable measurements, and sample selection procedure. Research design is provided in Section 4. Section 5 discusses our empirical results, followed by further analyses in Section 6. Section 7 concludes.

2 | LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 | The complexity of derivative disclosures to investors

Information of derivatives is complex to investors not only because derivative contracts are complex by nature but also because the accounting and disclosures for derivatives are complex too. Derivatives are one of the most complex types of financial contracts (Battiston et al., 2013). Over the past two decades, there have been continuing concerns among regulators, investors, and academics regarding the complexity of financial derivatives. The value of a derivative contract is based on the prices of its underlying variables over time, and the fluctuation of the variables' prices leaves investors a difficult task of interpreting the effects of derivatives on firm value. Some empirical studies (e.g., Jarrow, 2011) find that the complexity of credit derivatives lead to mis-valuation of derivatives and ultimately the 2007-2010 global financial crisis. Recent experimental evidence by Durney et al. (2021) shows that investors regard derivatives-using firms as risky and refrain from trading on their stocks.

In addition, prior research (e.g., Kawaller, 2004; Chang et al., 2016) suggests that the reporting for derivatives is highly complex. Firms need to satisfy onerous, indeterminate conditions to be able to apply hedge accounting for derivative contracts.[4] This often leads to inconsistency in the reporting of derivatives, which complicates the assessment of firm risks by financial analysts (Kawaller, 2004). In line with this argument, Chang et al. (2016) find that analyst earnings forecasts are less accurate and more dispersed after firms initiate derivatives. The complexity in accounting and disclosures for derivatives would increase the likelihood of corporate misreporting of derivatives and obstruct investor understanding of derivatives usage. In view of this concern, FASB issued the *Accounting Standards Update No. 2017-12* to simplify hedge accounting and to "*decrease the complexity of understanding hedge results for investors*" (FASB, 2017). This standard update was effective from 15 December 2019 and reflects the SEC's and FASB's concern over the complex derivative disclosures prior to the effective date.

In a nutshell, the complexity in both derivatives and the reporting for them makes it difficult for investors to comprehend the disclosed derivative information, leaving it an open question of whether enhanced derivative disclosures would decrease or increase information asymmetry. Accordingly, we develop competing hypotheses in the following sub-section to reflect this tension.

---

[4]One condition to satisfy for applying hedge accounting was to demonstrate that the intended hedges of derivative-using firms would be "highly effective"; "*at the inception of the hedge, the firm must provide formal documentation of the hedging relationship and the entity's risk management objective and strategy for undertaking the hedge, including identification of the hedging instrument, the hedged item, the nature of the risk being hedged, and how the hedging instrument's effectiveness in offsetting the exposure to changes in the hedged item's fair value will be assessed* (FASB, 1998)."

2.2 | Hypothesis development

Companies use derivatives for various purposes. Many firms use derivative instruments to reduce risk, as derivatives used for hedging lower cash flow volatility (Froot et al., 1993), alleviate financial distress (Smith and Stulz, 1985), and smooth earnings (DeMarzo and Duffie, 1995). Other evidence (e.g., Brown, 2001; Faulkender, 2005; Géczy et al., 2007; Chernenko and Faulkender, 2011; Manchiraju et al., 2018) shows that derivatives are also used for non-hedging purposes such as speculation and earnings management. The impact of corporate derivatives usage on firm valuation and risk assessments remains ambiguous, which is largely due to firms' insufficient disclosures about the purposes of their derivative use that can be hard to disentangle by outsiders.

Disclosures by a firm essentially turn private information into public information. The previous chairman of the Securities and Exchange Commission (SEC), Arthur Levitt, pointed out how "*high quality accounting standards result in greater investor confidence, which improves liquidity, reduces capital costs, and makes market prices possible*" (Levitt, 1998, p.81). Enhanced public disclosures reduce information asymmetry by providing investors with better knowledge about firms (Healy and Palepu 2001; Eleswarapu et al., 2004; Fu et al., 2012). The FASB issued the Statement of Financial Accounting Standards (SFAS) No. 161 in the year 2008, requiring firms to disclose the fair values of derivatives and their gains and losses in a tabular format. In so doing, firms should provide a more complete portrait of their derivative use during the reporting period (FASB, 2008). By showing that the mispricing of derivatives-using firms no longer persists after the implementation of SFAS 161, Campbell et al. (2021) argue that the mandatory derivative disclosures set forth in SFAS 161 enhance investor understanding of the economic effects of firms' derivative use.

The primary requirement of SFAS 161 is that the "*objectives for using derivative instruments be disclosed in terms of underlying risk and accounting designation*" (FASB, 2008). To this end, firms need to put greater effort into distinguishing between "derivatives designated as hedging instruments" and "derivatives not designated as hedging instruments" in a tabular disclosure. This disclosure further provides the fair value of derivative assets and liabilities in the balance sheet and derivative-related gains and losses in the income statement, and also classifies derivatives into risk exposure categories such as interest rate, commodity, and foreign currency. Under such a disclosure, derivatives used for non-hedging purposes such as speculation are much less likely to be designated as hedging instruments.

The derivatives, if used for hedging (non-hedging) purposes, would generally reduce (increase) firm risk and increase (decrease) firm value (Allayannis and Weston, 2001; Bartram et al., 2011; Gilje and Taillard, 2017). Manchiraju et al. (2018) find that firms' use of derivatives that are (are not) designated as hedging instruments is associated with lower (higher) firm risk. Their results suggest that derivatives designated (not designated) as hedges are likely to relate to hedging (non-hedging) activities, and hence the accounting designation of derivatives provided under SFAS 161 is informative as to the manner and purposes of firms' derivatives usage. To the extent that the designation of derivatives captures the economic substance of these derivatives, uninformed investors might benefit more, than do informed investors, from making use of the derivative disclosures to trade on the stocks of derivatives-using firms after the implementation of SFAS 161. As such, it would lower information asymmetry among investors.

However, when more information is available following SFAS 161, it is also possible that sophisticated investors use their professional knowledge and other information advantage to process the additional derivative disclosures better, while relatively uninformed investors who are not able to digest such information will protect themselves by trading less. Furthermore, the complexity of derivative information, as discussed in Section 2.1, may complicate the overall information environment of a firm. Since investors use derivative information in conjunction with other information in financial statements to assess the risk profile and future prospects of a firm, the complex nature of derivatives may require extra effort and expertise from investors to make such evaluations. If SFAS 161 improves the derivative disclosures to the extent such that they are more comprehensible by informed investors than by uninformed investors, then information asymmetry between informed and uninformed investors will be magnified as a result of SFAS 161.

The third possible outcome from the enhanced derivative disclosures is that the information gap between informed and uninformed investors remains unchanged after the passage of SFAS 161. This might be because SFAS 161 has either the same or no impact on these two types of investors. First, it is possible that the firms' enhanced derivative disclosures, as prescribed by SFAS 161, are digested by informed and uninformed investors to the same extent. In other words, there is no difference in investors' abilities to decipher the implications of derivative disclosures for firm value. Second, it is possible that even informed investors such as institutional investors or other investors who take financial analysts' advice cannot digest the improved derivative information, leading to no impact of the disclosures in improving either informed or uninformed investors' understanding. For example, Chang et al. (2016) find that even sell-side analysts, despite their financial expertise, routinely misjudge the earnings implications of firms' derivative activities. Campbell et al. (2015) argue that sophisticated investors cannot fully incorporate the information, which is related to a firm's cash flow hedges (one type of derivatives designated as hedges under SFAS 161), into their earnings forecasts. Besides, since derivative disclosures are provided in the footnotes to financial statements, investors may not pay sufficient attention to the improved information after SFAS 161, leading to minimal impact of the regulation.

The second argument, however, is unlikely to hold according to recent studies. Campbell et al. (2021) find that the mispricing of firms that use derivatives disappears after the implementation of SFAS 161, suggesting that investor understanding of firms' hedging activities improves. Therefore, if no change in the information gap between informed and uninformed investors is observed after the passage of SFAS 161, this is probably due to the same impact, rather than no impact, on these two types of investors. Based on the above discussion, we establish our hypothesis in a null form as follows:

H1: *The enhanced derivative disclosures, as mandated by SFAS 161, lead to no change in information asymmetry between informed and uninformed investors for firms that provide tabular disclosures of the purposes of derivative use.*

If the SEC's aim of leveling the playing field, and the FASB's purpose of enhancing disclosures on derivatives usage, are fulfilled such that its value implication can be better understood, then previously uninformed investors who are not able to possess such information are likely to benefit more. In such a case, information asymmetry between informed and uninformed investors is expected to be reduced after SFAS 161.

3 | DATA AND SAMPLE

3.1 | Data and sample selection

Following prior research on derivatives (e.g., Guay, 1999; Zhang, 2009; Bartram et al., 2011; Chang et al., 2016), we conduct our empirical analysis based on a hand-collected sample of non-financial and non-utility U.S. listed firms. Companies from the financial sectors (with the first two-digit Standard Industrial Classification (SIC) coded 60-69) and utility industries (with the first two-digit SIC coded 49) are excluded from our sample, because they "*use derivatives primarily for trading purposes or act as a derivatives dealer*", and are subject to substantively different financial reporting requirements (Chang et al., 2016, p.588). Since SFAS 161 was issued in the year 2008 and is effective for annual reporting periods commencing after 15 November 2008, companies generally started applying this standard from the beginning of the fiscal year 2009. To investigate the impact of SFAS 161, our sample period spans the years 2006-2011, including the three-year pre-SFAS 161 period (i.e., 2006-2008) and the three-year post-SFAS 161 period (i.e., 2009-2011).

We obtain data primarily from four public sources including the Center for Research in Security Prices (CRSP), New York Stock Exchange's Trade and Quote (TAQ), Compustat, and Institutional Brokers Estimate System (I/B/E/S) databases.[5] The information asymmetry measures used in this study are stock liquidity and the probability of informed trading. They are constructed using bid and ask prices data from the CRSP database, and intraday trades and quotes data from the TAQ database.[6] Financial analyst data are taken from the I/B/E/S database. Data on stock and financial information are collected from the CRSP and Compustat databases. Before hand-collecting the data on derivative disclosures, we first screen out the listed firms that do not have necessary data required for constructing the variables used in the multivariate tests. We also remove firm-year observations with negative values of total assets. As with Donohoe (2015) and Chang et al. (2016), we further require that firms must have at least three years of consecutive data surrounding SFAS 161, including the years 2008 and 2009, for our regression analysis. Appendix B reports our sample selection procedure.

Disclosures on firms' derivatives usage and hedging activities are provided in the notes to financial statements. We extract firms' 10-K reports manually from the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system (see derivative disclosures in the Dynegy Inc.'s 2007 and 2010 annual reports in Appendix C, for example). Among the derivative users in our stock liquidity sample (PIN sample), we find that approximately 46% (44%) did not

[5]We thank Brian Bushee for sharing the institutional investor classification data which we use to construct the variable for dedicated institutional stock ownership.
[6]We use the daily CRSP data (intraday TAQ data) to calculate the bid-ask spreads (PIN) to avoid potential measurement errors arising from using the same database. Chung and Zhang (2014) find that the CRSP-based spreads are highly correlated with the TAQ-based spreads, and argue that the simple CRSP-based spreads can be used as a good approximation of information asymmetry in research that focuses on cross-sectional analysis.

make a real change in response to the disclosure requirements of SFAS 161, consistent with Drakopoulou (2014) which finds that most of the Dow 30 (Dow Jones Industrial Average) companies fail to disclose information required by SFAS 161.

In order to pursue a rigorous test on the impact of SFAS 161, we identify three types of firms in our sample: (i) compliers – derivative users that follow SFAS 161 to provide tabular disclosures distinguishing between derivatives *designated* and *not designated* as hedging instruments; (ii) non-compliers – derivative users that make no real change per the disclosure requirements of SFAS 161 within our sample period; and (iii) non-users – firms that do not use derivatives in any year over our sample period. By definition, the non-compliers in our sample are derivative-using firms whose derivative disclosures after the passage of SFAS 161 are qualitatively the same as before, and hence the regulatory treatment effect on these firms are expected to be minimal.

Both compliers and noncompliers are firms that use derivatives in at least one year in both the pre-SFAS 161 period (i.e., 2006-2008) and the post-SFAS 161 period (i.e., 2009-2011). Any firm that stopped or started using derivatives as a result of SFAS 161 implemented in 2008 is excluded from our sample. After the data screening, we have got 4,842 (4,021) firm-year observations for 1,180 (1,175) unique firms in our stock liquidity (the probability of informed trading) sample, of which 394 (404) are compliers, 330 (316) are non-compliers, and 456 (455) are non-users. In our main regression, we classify compliers into the treatment group and non-users into the control group to test the effects of SFAS 161. We classify non-compliers (compliers) and non-users (non-compliers) into alternative treatment and control groups, respectively, in additional analyses.

3.2 | Measures of information asymmetry

One common measure of information asymmetry used in previous studies (e.g., Eleswarapu et al., 2004; Mohd, 2005; Silber, 2005; Fu et al., 2012; Chen et al., 2021) is bid-ask spread. The spread reflects the adverse selection problem that arises when informed investors generate informational advantage and exploit it to gain at the expense of uninformed investors (Glosten and Milgrom, 1985; Easley and O'Hara, 1987). The higher the information asymmetry between informed and uninformed investors, the larger the bid-ask spread required by market-makers to cover their expected greater losses from trading with informed investors (Easley and O'Hara, 1987). Welker (1995), Healy et al. (1999), and Heflin et al. (2005) document a negative relationship between disclosure quality and spread-based measures of information asymmetry. Following Fang et al. (2009), we measure stock liquidity as the annual relative effective spread. For each stock, the annual relative effective spread is calculated as the arithmetic mean of daily relative effective spreads over a fiscal year. The relative effective spread is the distance between the closing transaction price and midpoint of prevailing bid-ask quote divided by the midpoint of the prevailing bid-ask quote. We employ the natural logarithm of annual relative effective spread (*LOG_SPREAD*) to deal with the non-normality of effective spreads and use *LOG_SPREAD* for our regression analyses. By construction, *LOG_SPREAD* is negatively related to stock market liquidity.

Second, we use the probability of informed trading (PIN) as another proxy for information asymmetry between informed and uninformed investors. Brown and Hillegeist (2007) argue that spread-based measures of the information asymmetry have some problems. For example, market makers might protect themselves from the information asymmetry by manipulating the quoted bid and ask prices. Furthermore, part of the bid-ask spread may also be attributed to information asymmetry between corporate insiders and outside investors.[7] Therefore, sole

[7]To further mitigate the concern, we control for the variables for information asymmetry between insiders and investors in all our regressions.

reliance on the spread-based measure is inadequate. Following Brown and Hillegeist (2007), we use the extended measure of PIN based on Easley et al.'s (1997) model.[8] This measure is calculated in the following way:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} = \frac{\alpha\nu\varepsilon}{\alpha\nu\varepsilon + 2\varepsilon} = \frac{\alpha\nu}{\alpha\nu + 2} \quad (1)$$

where $\mu = \nu\varepsilon$, meaning that informed buy or sell orders arrive at a rate (ν) proportional to the arrival rates of uninformed orders (ε). When an information event occurs with the probability α, PIN increases with the absolute and relative trading intensity of informed investors (μ and ν) and decreases with trading intensity of uninformed investors (ε). Equation (1), which is based on Venter and De Jongh's (2006) extension from the Easley et al.'s (1997) model, assumes that the arrival rates of uninformed buy and sell orders are positively correlated on a particular day with events such as earnings announcements. In the context of derivative disclosures being made to the public, this measure is more appropriate for our study. By construction, the probability of informed trading increases with information asymmetry between informed and uninformed investors.

Panels A and B of Table 1 report the descriptive statistics for *LOG_SPREAD* and *PIN*, as well as other variables we use for our difference-in-differences regressions. *LOG_SPREAD* has a mean of -6.18 and standard deviation of 1.15, consistent with, and similar to, the statistics in Fang et al. (2009) that uses the TAQ data. The average probability of informed trading (*PIN*) for our sample is about 14.17%, which is somewhat lower than the 19% of the Brown and Hillegeist's (2007) sample covering the years 1986-1996. This suggests that the overall information environment has improved in our sample period relative to the sample period of Brown and Hillegeist (2007).

[8]We thank Stephen Brown for sharing the data on the probability of informed trading, which cover the years 1993-2010, and the SAS programming codes, which estimate the PIN from the raw buy and sell data.

4 | RESEARCH DESIGN

4.1 | Matching of observations between treatment and control groups

In order to study the impact of SFAS 161, we define treatment firms as those that are affected by SFAS 161 and make changes to their derivative disclosures in response to the requirements of the new standard. We also require that these firms use derivatives in the years both before and after the implementation of SFAS 161. To avoid the potential confounding effects of other concurrent events, we require that the control group consists of firms that are unaffected by the regulation – those that do not use derivatives in any year over our sample period. Although a firm's decision to use derivatives and comply with SFAS 161 is unlikely to be driven by the outcome variable (i.e., stock liquidity or the probability of informed trading), the information asymmetry between the treatment and control firms can be influenced by derivatives usage. To address this concern and mitigate associated selection bias in our analysis, we employ a propensity-score-matching approach. Specifically, we match each treatment firm (i.e., a complier) with a control firm (i.e., a non-derivative-user), with replacement, by using the closest propensity score within a caliper of 1%, in the pre-SFAS 161 sample period. We have limited observations in the treatment group (1,663 and 1,518 firm-years) relative to the control group (1,825 and 1,545 firm-years) in our samples (the stock liquidity sample and PIN sample) before the matching. Thus, allowing an untreated control firm to be used more than once in our matching procedure guarantees the power of our tests. Furthermore, matching with replacement for a small sample improves the quality of matching and reduces bias (Caliendo and Kopeinig, 2008; Shipman et al., 2017).

Following previous literature (Zhang, 2009; Donohoe, 2015; Chang et al., 2016), we use seven covariates as determinants of derivatives usage: market value of equity (*SIZE*), book-to-market ratio (*BTM*), financial constraints (*SA*), financial leverage (*LEV*), dedicated institutional stock ownership (*DEDI*), earnings volatility (*STDEARN*), and idiosyncratic stock return volatility (*IDIOSYN*). We estimate propensity scores from a logistic regression of derivatives usage on these covariates, which are measured in the pre-SFAS 161 period (i.e., 2006-2008) to avoid the matching being affected by the event. We expect that larger and more profitable firms are more likely to employ derivatives (Donohoe, 2015; Chang et al., 2016). High-growth firms, featured by low book-to-market ratio, tend to have high growth risk and should thus be more inclined to hedge with derivatives. We use financial constraints and financial leverage to capture financial risk, which prior research (Froot et al., 1993; Acharya et al., 2007) has found to be positively correlated with the likelihood of a firm using derivatives for hedging. Dedicated institutional investors might pressure managers into using derivatives to actively manage downside risk of their firm, and thus dedicated institutional stock ownership is expected to be positively correlated with derivatives usage. We also control for earnings volatility and firm-specific idiosyncratic risk, which are associated with firms' incentives to engage in risk management. The higher the earnings volatility or the idiosyncratic risk, the greater incentives for firms to hedge (DeMarzo and Duffie, 1995; Bartram et al., 2011). We include industry dummies and year dummies as well in the regression, since derivatives usage is likely to vary systematically across industries and years. The logistic regression results are reported in Panel A of Table 2.

After the matching, we end up with 3,326 (3,034) firm-year observations in our stock liquidity sample (PIN sample) made up of 1,663 (1,517) observations from compliers and 1,663 (1,517) observations from non-users. We then conduct covariate balance check for our post-matched sample. To this end, we calculate standard t-statistics for the mean differences in all the matching covariates between the compliers and non-users. We report the results in Panel B of Table 2. The differences in the matching covariates for the pre-matched sample are statistically and economically significant, implying that derivatives usage is materially beneficial to derivative users relative to non-users. On the other hand, for the post-matched sample, the majority of the covariates for compliers do not statistically differ from those of non-users.

An alternative way to check the covariate balance is to examine the standardized bias (SB) for each covariate, which is defined by Rosenbaum and Rubin (1985) as:

$$SB = \frac{B}{\sqrt{\frac{V_1(X_k)+V_0(X_k)}{2}}} \times 100\% \tag{2}$$

where $V_1(X_k)$ ($V_0(X_k)$) is the variance of a covariate for the observations in the treatment (control) group, which comprises compliers (non-users), and B is the mean difference in a covariate between the treatment and control groups. The last columns in Panel B of Table 2 show that the standardized bias is below 10% for all covariates, suggesting that our matching procedure has sufficiently reduced the covariate imbalance between the treatment and control firms in our stock liquidity sample and PIN sample, respectively. As such, we achieve the end of purging the effect of derivatives usage via the matching, and leaving the treatment effect of derivative disclosures, for our difference-in-differences regression analysis.

4.2 | Regression specification

To examine the impact of SFAS 161 on information asymmetry, we use the following difference-in-differences regression models:

$$\begin{aligned} LOG\_SPREAD_{i,t} &= \alpha_0 + \alpha_1 TREAT_i + \alpha_2 POST_t + \alpha_3 TREAT_i \times POST_t \\ &+ \sum_k \alpha_k CONTROLS^k_{i,t} + \sum_z \alpha_z IND^z_i + \sum_t \alpha_t YR^t_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

$$\begin{aligned} PIN_{i,t} &= \beta_0 + \beta_1 TREAT_i + \beta_2 POST_t + \beta_3 TREAT_i \times POST_t \\ &+ \sum_k \beta_k CONTROLS^k_{i,t} + \sum_z \beta_z IND^z_i + \sum_t \beta_t YR^t_{i,t} + u_{i,t} \end{aligned} \tag{4}$$

The dependent variables *LOG_SPREAD* and *PIN* in Models (3) and (4) are the proxies for information asymmetry between informed and uninformed investors, as described in Section 3. *TREAT* is the group indicator variable that equals 1 (0) for compliers (non-users) in the treatment (control) group. The coefficient on *TREAT* measures *LOG_SPREAD* or *PIN* of treatment firms in the pre-SFAS 161 period relative to *LOG_SPREAD* or *PIN* of control firms in the pre-SFAS 161 period. *POST* is the time indicator variable that equals 1 (0) if the firm is in the post-(pre-) SFAS 161 period of 2009-2011 (2006-2008). The coefficient on *POST* measures *LOG_SPREAD* or *PIN* of control firms in the post-SFAS 161 period relative to that in the pre-SFAS 161 period. Our variable of interest capturing the treatment effect of SFAS 161 on information asymmetry is the interaction term *TREAT*×*POST*; its coefficient (α_3 or β_3) estimates the changes in *LOG_SPREAD* or *PIN* of treatment firms, relative to that of control firms, from the pre-SFAS 161 period to the post-SFAS 161 period. The difference-in-differences estimator (α_3 or β_3) avoids any omitted permanent differences between the treatment and control groups, as well as any common time-series trend affecting both groups. If SFAS 161 reduces (increases) information asymmetry between informed and uninformed investors, the coefficients on the interaction terms, α_3 and β_3, will be negative (positive) and statistically significant at conventional levels, rejecting the null hypothesis H1, and indicating that SFAS 161 has a negative (positive) impact on information asymmetry in terms of decreasing stock illiquidity and the probability of informed trading. If the coefficients α_3 and β_3 are statistically insignificant, the hypothesis H1 will not be rejected, suggesting no change in information asymmetry between informed and uninformed investors post SFAS 161.

Prior literature (e.g., Mohd, 2005; Fu et al., 2012; Dhaliwal et al., 2016; He et al., 2019) finds that information asymmetry is associated with firm size (*SIZE*), book-to-market ratio (*BTM*), financial leverage (*LEV*), analyst coverage (*LANACOV*), analyst forecast dispersion (*DISPERSION*), trading volume (*TRADEVOL*), abnormal stock returns (*QTRRET*), financial constraints (*SA*), dedicated institutional stock ownership (*DEDI*), and idiosyncratic risk (*IDIOSYN*). We include these determinants of information asymmetry as control variables in Models (3) and (4).

We measure firm size (*SIZE*) as the natural logarithm of market value of equity. Larger firms tend to have higher information transparency to outsiders (Bushman et al., 2004). As information intermediaries, sell-side analysts help disseminate information in the capital market and reduce information asymmetry (Givoly and Lakonishok, 1979; Francis and Soffer, 1997).[9] Hence, we expect that firm size and analyst coverage are negatively associated with information asymmetry. In a similar vein, we expect analyst forecast dispersion (*DISPERSION*), measured as the natural logarithm of the standard deviation of analyst earnings forecasts, to be positively related to information asymmetry. According to previous literature (e.g., Easley et al., 1996), the probability of informed trading is lower for stocks with high trading volume, since higher order arrival rates from informed traders are more than offset by higher order arrival rates from uninformed traders. Trades on less active stocks are more likely based on private information and made by informed traders, and hence we expect that trading volume (*TRADEVOL*) is negatively associated with stock illiquidity and PIN. Since market makers require higher spreads to make up for uncertainty in stock returns, we expect idiosyncratic risk (*IDIOSYN*) to be positively related to the spreads (Stoll, 1978; Mohd, 2005). Higher firm risk implies a higher probability that insiders can gain from private information, and hence we predict that idiosyncratic risk (*IDIOSYN*) is also positively associated with PIN.

In addition, stocks with higher abnormal stock returns (*QTRRET*) are expected to have greater information asymmetry (Huddart and Ke, 2007), and thus we include *QTRRET* in the regression. Firm characteristics including book-to-market ratio (*BTM*), financial leverage (*LEV*), financial constraints (*SA*), and dedicated institutional stock ownership (*DEDI*) are also included because they have impacts on the firm's information environment. Specifically, value firms with lower financial leverage and lower financial constraints tend to be more transparent

[9] As a robustness check, we exclude the control variable of analyst coverage (*LANACOV*) from our regression estimation, and obtain qualitatively identical results.

(e.g., Agrawal et al., 2004; He et al., 2021). Therefore, we expect *BTM* (*LEV* and *SA*) to be negatively (positively) correlated with information asymmetry. If dedicated institutional investors can fulfil their fiduciary responsibilities and serve a monitoring role, they can prompt firms to disclose more information to investors (Bushee, 1998; Mitra and Cready 2005; Chen et al., 2007). Thus, we expect *DEDI* to be negatively associated with information asymmetry. Both Models (3) and (4) include interacted industry (*IND*) and year (*YR*) fixed effects to control for variation in derivatives disclosures over years and across industries.[10] All the variables are defined in detail in Appendix A.

5 | EMPIRICAL TESTS

5.1 | Tests of parallel trends assumption

The parallel trends assumption behind the difference-in-differences regression estimation requires that, absent the treatment event, the difference in outcome variable between treatment and control groups is constant over time. To test this assumption, we first calculate the annual growth rates in stock illiquidity (the probability of informed trading) as the change in *LOG_SPREAD* (*PIN*) from the previous year to the current year, divided by the value of *LOG_SPREAD* (*PIN*) in the previous year, for the pre-SFAS 161 sample period. In Panel A of Table 3, the t-test results show that the annual growth rates of *LOG_SPREAD* and *PIN* are statistically indifferent between the treatment and control groups for the years 2006, 2007, and 2008, respectively. In addition, we re-define our pre- and post-event periods as 2005 and 2006 (as well as 2006 and 2007, or 2007 and 2008), respectively, and estimate the treatment effect by our difference-in-differences regression models (3) and (4). We find no evidence of a

[10]To mitigate the impact of managerial opportunism on the information asymmetry between informed and uninformed investors, we add insider trades (*INSITRADE*) as a control variable in Models (3) and (4), and re-test the treatment effects. The un-tabulated results show that the coefficients on the interaction term, *TREAT*×*POST*, remain negative and statistically significant at the 5% level for both the stock liquidity sample and the PIN sample.

significant change in either *LOG_SPREAD* or *PIN* prior to SFAS 161. These results suggest that the parallel trends assumption is not violated for our DID regression analysis.

5.2 | Baseline difference-in-differences regression results

Table 4 reports the baseline regression results from testing the hypothesis H1. Column (1) shows that the coefficient on *TREAT×POST* is statistically significant and negative at the 1% level (p=0.003) for the stock liquidity sample. This indicates that firms using derivatives and complying with SFAS 161 experience a greater increase in stock liquidity following the implementation of SFAS 161 relative to firms with no derivatives. The point estimate on the DID estimator is -0.0926, suggesting that the enhanced derivative disclosures by treatment firms leads to a greater reduction in *LOG_SPREAD* that is about 8% of one standard deviation of *LOG_SPREAD*. Similarly, Column (2) reports the results from using *PIN* as the dependent variable. The coefficient on *TREAT×POST* is also significantly negative at the 1% level (p=0.002). The point estimate is -0.0131, indicating that the enhanced derivative disclosures by treatment firms leads to a greater decrease in *PIN* that is about 15% of one standard deviation of *PIN*. Thus, the DID estimators are both statistically and economically meaningful. Together, these results imply that the derivative disclosures required by SFAS 161 effectively improve uninformed investors' understanding of the objectives as well as value impacts of firms' derivative use, thereby reducing information asymmetry between informed and uninformed investors, as manifested in higher stock liquidity and a lower probability of informed trading. Results also show that the majority of the control variables are significantly associated with relative effective spreads and PIN with expected signs, consistent with the related literature mentioned in Section 4.2.

An alternative explanation for our main results is that plausibly high information asymmetry between informed and uninformed investors induces the production and passage of

SFAS 161 which in turn reduces the information asymmetry. This concern is mitigated because, as indicated by our results for the tests of parallel trends assumption in the previous section, there is no substantial increase in information asymmetry between informed and uninformed investors before the implementation of SFAS 161.

5.3 | Robustness checks of the baseline regression results

In this section, we conduct several tests to check the robustness of our baseline regression results.

5.3.1 | Anticipation effect

It is plausible that the market had anticipated the adoption of SFAS 161 before it was promulgated. Thus, when collecting data, we ensure that all the firms included in our samples start applying SFAS 161 from the fiscal year 2009 to eliminate any such potential anticipation effect on our results. Our foregoing tests of the parallel trends assumption also allay the concern of the anticipation effect. To further address the concern, we re-run the difference-in-differences regression models (3) and (4) by excluding 2008, the year before the adoption of SFAS 161, and re-defining our pre- and post-event periods as 2005-2007 and 2009-2011, respectively. In our results not tabulated for brevity, the difference-in-differences estimators remain negative and statistically significant at the 10% (1%) level for the stock liquidity sample (PIN sample), suggesting that the anticipation effect is unlikely to drive our baseline regression results.

5.3.2 | Financial crisis

Another concern with our study is the potential countervailing effect of the 2007-2010 financial crisis on information asymmetry between informed and uninformed investors. As the impact of the financial crisis lasts from 2007 to 2010 (e.g., Chang, 2011; Boyallian and Ruiz-Verdú, 2018), and the adoption of SFAS 161 stands at the midpoint of this crisis period (i.e., the end of 2008), our results from the difference-in-differences specifications should not be confounded by the crisis. To further allay this concern, we conduct three different robustness tests. First, we use a post-SFAS 161 sample, which covers the years 2009-2012, to conduct a placebo test. Specifically, we define the crisis period as 2009-2010 and the post-crisis period as 2011-2012, and use DID regressions to test the treatment effect of the financial crisis. We run the same DID regression models (3) and (4), where *TREAT* is equal to 1 (0) for a complier (non-user), and *POST* is replaced by *POSTCRISIS* that equals 0 (1) if the firm is in the crisis (post-crisis) period (i.e., 2009-2010 (2011-2012)). If the reduction in information asymmetry, as documented in our baseline regression analysis, is attributable to the relief of the financial crisis, we should observe significantly lower stock illiquidity and PIN in 2011-2012 compared with 2009-2010. Our results in Columns (1) and (2) in Panel A of Table 5 show that the coefficients on both DID estimators are not statistically significant, thereby confuting the possibility that the crisis alternatively explains our baseline results.

Second, we use the pre-SFAS 161 sample, which spans the years 2005-2008, to conduct another placebo test. In particular, we define the pre-crisis period as 2005-2006 and the crisis period as 2007-2008 to re-test the treatment effect of the financial crisis. To this end, we define the time indicator variable, *CRISIS*, as equal to 0 (1) for firms that are in the pre-crisis (crisis) period (i.e., 2005-2006 (2007-2008)). If the financial crisis explains the greater information asymmetry prior to the implementation of SFAS 161, we should find positive and statistically significant results on the DID estimators. However, results in Columns (3) and (4) in Panel A of Table 5 show that the coefficients on the interaction term, $TREAT \times CRISIS$, are not statistically significant for the stock liquidity sample and the PIN sample.

Third, we exclude the years 2008 and 2009 from our sample period and re-estimate our baseline models (3) and (4), where the time indicator variable, *POST'*, is re-defined as equal to 0 (1) if the firm is in the years 2006-2007 (2010-2011). In Panel B of Table 5, we find that the coefficients for *TREAT*×*POST'* remain negative and statistically significant at the 5% level for the stock liquidity sample and the PIN sample in Columns (1) and (2), respectively. Taken together, our results in Table 5 suggest that the reduced information asymmetry post SFAS 161 is not driven by the financial crisis.

5.3.3 | Firm-fixed effects

In our baseline regression models (3) and (4), we include industry-year interacted fixed effects to control for any time-invariant unobserved factors at both the industry and year levels. To further control for any time-invariant differences between treatment and control firms, we include firm-fixed effects in our models and re-estimate the treatment effects. Results for this analysis are reported in Table 6. The coefficients for the interaction term, *TREAT*×*POST*, in Columns (1) and (2) are both negative and statistically significant at the 1% level, suggesting that our main results reported in Table 4 are not driven by unobserved heterogeneity between treatment and control groups. Also, we conduct additional tests by including only *TREAT*, *POST*, *TREAT*×*POST*, and industry-year interacted dummies in the firm-fixed effects models to address potential concern of overcontrolling variables. Results in Columns (3) and (4) of Table 6 are consistent with those in Columns (1) and (2), drawing the same inferences.

5.4 | Comparison between non-compliers and non-users

In our stock liquidity sample (PIN sample), 330 (316) firms out of 724 (720) derivative users are identified as non-compliers whose derivative disclosures after the passage of SFAS 161 are qualitatively the same as those before the implementation of the standard. Manual inspection of the disclosures made by non-compliers shows that these firms did not make a distinction between the purposes of their derivative use, and did not provide tabular disclosures classifying fair values of derivatives and derivative gains and losses by the underlying risk exposure and accounting designation, as required by SFAS 161. Therefore, we expect no treatment effect for non-compliers. To test this expectation, we classify non-compliers into our treatment group (*NONCOMPLIER*=1), and non-users, as the benchmark firms, into our control group (*NONCOMPLIER*=0), and replace *TREAT* with *NONCOMPLIER* to run Models (3) and (4).

Each treatment firm is matched with a control firm using the same matching procedure as introduced in Section 4.1. The same set of covariates is used as with our matching of compliers with non-users. Before using Models (3) and (4) to estimate the treatment effects in this case, we check the covariate balance, in the same way as we do in Section 4.1, to assure the quality of our matching. Panels A and B of Table 7 show that the covariate differences are statistically insignificant between non-compliers and non-users in the post-matched sample. Also, the standardized biases for all the covariates are reduced to less than 10% after the matching in both the stock liquidity sample and PIN sample, respectively. Hence, our matching can be considered effective in balancing the distributions of the covariates (Pan and Bai, 2015) and thereby isolating the effect of derivatives usage on information asymmetry.

Table 8 reports the results from testing the impact of SFAS 161 on information asymmetry, comparing non-compliers and non-users. Results from Columns (1) and (2) of Table 8 show that the coefficients on the interaction term, $NONCOMPLIER \times POST$, are not statistically significant in both samples. These are robust to the foregoing tests covered in Section 5.2, and suggest that SFAS 161 does not reduce information asymmetry between informed and uninformed investors when firms do not comply with the standard.

6 | FURTHER ANALYSIS

6.1 | The moderating effect of firm visibility

The implementation of SFAS 161 attracts greater attention from the public to firms' derivative disclosures, yet the scope of derivatives usage and investors' attention vary from firm to firm. For less visible firms, retail investors might pay little, or even no, attention to their derivative disclosures. In this case, information asymmetry might not be reduced after SFAS 161. By contrast, investors may be more attentive to a firm that has good public visibility, in which case information asymmetry would be reduced substantially. Previous research suggests that corporate voluntary disclosures increase both analyst following and investor following (e.g., Botosan, 1997), but this effect generally happens on large, highly visible firms. By contrast, smaller and less-visible firms may not be able to attract investor attention even if they do provide enhanced disclosures (Bushee and Miller, 2012). Therefore, we expect that the impact of SFAS 161 on information asymmetry would be more pronounced for more visible firms.

To test the moderating effect of firm visibility, we first use firm size (*SIZE*) as a simple proxy. Larger firms are more visible and hence attract more investors. We estimate the treatment effect using Models (3) and (4) in two subsamples constructed based on the sample median of *SIZE*. Since the propensity-score matching is conducted separately for each subsample, the number of observations differs in the two subsamples. Corresponding to our settings in the main regression analysis, we use compliers as treatment firms and non-users as control firms. Results for this test are reported in Table 9. As expected, the coefficient on the interaction term, *TREAT×POST,* is only statistically significant and negative in the large-firm subsample.

Following Da et al. (2011) and Drake et al. (2012), we employ another measure, based on the Search Volume Index (SVI) for stock ticker symbols provided by Google Trends, to capture investor attention and visibility of firms. Prior evidence shows that greater investors' attention, which can be captured by greater advertising expenditures (Grullon et al., 2004), greater media coverage (Fang and Peress, 2009), or higher search frequencies of stock tickers in Google (Ding and Hou, 2015), improves stock liquidity. Thus, we predict that the impact of SFAS 161 on information asymmetry between informed and uninformed investors is more pronounced for firms with greater investors' attention.

The Search Volume Index (SVI) data have been available from Google Trends (http://www.google.com/trends) since January 2004. We measure investor attention for a stock based on its daily SVI data. Specifically, the variable of abnormal search volume around the earnings announcement (*ASVI*) is calculated as follows:

$$ASVI_t = \ln\left[1+\left(\mathrm{Mean}(SVI_{t-1}, SVI_{t-2}) - \mathrm{Mean}(SVI_{t-3}, \ldots, SVI_{t-10})\right)\right] \tag{5}$$

where $[\mathrm{Mean}(SVI_{t-1}, SVI_{t-2})]$ is the average of the daily SVI over the two weeks prior to the earnings announcement, and $[\mathrm{Mean}(SVI_{t-3}, \ldots, SVI_{t-10})]$ is the average of the daily SVI over the prior eight weeks ending at the beginning of the prior two weeks. Following previous studies (e.g., Da et al., 2011; Drake et al., 2012; Ding and Hou, 2015), we exclude SVIs with values of zero, and use the natural logarithm to normalize the variable distribution. By construction, a high value of *ASVI* indicates a surge in investor attention prior to the earnings announcement. To the extent that investors may start to pay attention to a stock by searching in Google when close to the earnings announcement date, we measure the abnormal search volume (*ASVI*) as in Equation (5) to proxy for investor attention.

We conduct similar subsample tests to examine the moderating effect of investor attention. Table 10 reports our results. Column (1) (Column (2)) shows that, for the stock liquidity regression (PIN regression), the coefficient on the interaction term is not statistically significant in the low-*ASVI* subsample whereas the coefficient for $TREAT \times POST$ is statistically significant with the negative sign in the high-*ASVI* subsample, thus consistent with our prediction. Compared to firm size, Google search volume is a more direct measure of investor attention (Da et al., 2011). However, our results should be interpreted with caution because the sample size is substantially reduced after merging the SVI data.

6.2 | Comparison of the effect of SFAS 161 between compliers and non-compliers

We also examine whether the effect of SFAS 161 on information asymmetry differs between compliers and non-compliers. To this end, we classify compliers (*COMPLIER*=1) and non-compliers (*COMPLIER*=0) into our treatment and control groups and replace *TREAT* with *COMPLIER* to run Models (3) and (4) again. Whereas firm managers decide whether to comply or not comply with SFAS 161, our outcome variable, stock liquidity or PIN, is determined by outside investors. Hence, any potential endogeneity associated with a firm's decision to comply with the standard is of less concern in our DID analysis. That said, as non-compliers (compliers) might deem the extra derivative disclosures to be immaterial (material), we employ a similar propensity-score-matching procedure as we do in Section 4.1 to match compliers with non-compliers. The covariates used for matching are potentially related to the determinants of firms' compliance decisions. These determinants include firm size (*SIZE*), book-to-market ratio (*BTM*), financial leverage (*LEV*), analyst coverage (*LANACOV*), dedicated institutional stock ownership (*DEDI*), earnings volatility (*STDEARN*), idiosyncratic stock return volatility (*IDIOSYN*), and indicator for a big-4 auditor (*BIG4*). Analyst coverage (*LANACOV*) and dedicated institutional ownership (*DEDI*) capture the degree of monitoring on financial reporting processes and hence plausibly affect a firm's tendency to comply or not comply with SFAS 161. Potential compliance costs to a firm include documentation costs and auditing costs, which are determined by firm size (*SIZE*), book-to-market ratio (*BTM*), Big-4 audits (*BIG4*), and financial conditions such as financial leverage (*LEV*) (e.g., Ge and McVay, 2005; Krishnan et al., 2008). On the other hand, firm size (*SIZE*), book-to-market ratio (*BTM*), earnings volatility (*STDEARN*), and idiosyncratic return volatility (*IDIOSYN*) capture the risk profile of derivative users, which is plausibly associated with a firm's low propensity to comply with the standard.

We first check the covariate balance. Table 11 shows that the mean differences in the covariates between compliers and non-compliers generally become insignificant after the matching, and that the standardized biases for all the covariates are reduced to less than 10%, thus assuring the quality of our matching. Un-tabulated results from univariate tests comparing the annual growth rates in *LOG_SPREAD* and *PIN*, and from multivariate tests estimating the treatment effect in each year prior to SFAS 161, validate the parallel trends assumption for the DID regression analysis.

Table 12 reports the results from testing the impact of SFAS 161 on information asymmetry, comparing between compliers and non-compliers in our stock liquidity sample (PIN sample) in Column (1) ((2)). We can see significantly negative coefficients on the interaction terms, *COMPLIER×POST*. The point estimate on the DID estimator is -0.0603 (-0.0117), which accounts for about 6% (15%) of one standard deviation of *LOG_SPREAD* (*PIN*) and is economically significant. Collectively, these results support the proposition that corporate compliance with SFAS 161 reduces information asymmetry among investors, and reconcile with our baseline regression results.

7 | CONCLUSION

The purpose of this study is to examine whether SFAS 161 reduces information asymmetry between informed and uninformed investors. Implementation of SFAS 161 could lead to (i) reduction in informed trading by sophisticated investors, and improvement in stock market liquidity, (ii) no change in information asymmetry between informed and uninformed investors, or (iii) a widening information gap due to the complex nature of derivative disclosures whose value implications are less comprehensible to uninformed investors. The impact of SFAS 161 depends crucially on the differential abilities of investors to incorporate the enhanced derivative disclosures into their assessments of firm value. We find evidence that derivative users, which comply directly with SFAS 161 by distinguishing the purposes of their derivative use in the required tabular form, experience an increase in stock liquidity, and a reduction in the probability of informed trading, following SFAS 161. This implies that SFAS 161 is effective in reducing the information asymmetry for compliers, and helping less informed investors to make better use of derivative disclosures in their trading decisions. We also find that such effect is evident only for large, highly visible firms that attract high investors' attention. We find no evidence that SFAS 161 has the same impact on non-compliant derivative users. This underscores the importance of enforcing reporting by derivative users in accordance with SFAS 161 to further promote the SEC's aim of leveling the playing field among investors.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system of the U.S. Securities and Exchange Commission (SEC), Brian Bushee's website (https://accounting-faculty.wharton.upenn.edu/bushee), Google Trends, the Center for Research in Security Prices (CRSP), Compustat, New York Stock Exchange's Trade and Quote (TAQ), and Institutional Brokers' Estimate System (I/B/E/S). Third party restrictions apply to the data from CRSP, Compustat, TAQ, and I/B/E/S, which were used under license for this study and hence are not available to share.

REFERENCES

Acharya, V. V., Almeida, H., & Campello, M. (2007). Is cash negative debt? A hedging perspective on corporate financial policies. *Journal of Financial Intermediation* 16 (4), 515-554.

Agrawal, V., Kothare, M., Rao, R. K. S., & Wadhwa. P. (2004). Bid-ask spreads, informed investors, and the firm's financial condition. *Quarterly Review of Economics and Finance*, 44(1), 58-76.

Allayannis, G., & Weston, J. P. (2001). The use of foreign currency derivatives and firm market value. *Review of Financial Studies*, 14(1), 243-276.

Bartram, S. B., Brown, G. W., & Conrad, J. (2011). The effects of derivatives on firm risk and value. *Journal of Financial and Quantitative Analysis*, 46(4), 967-999.

Battiston, S., Caldarelli, G., Georg, C-P., May, R., & Stiglitz, J. (2013). Complex derivatives. *Nature Physics*, 9, 123-125.

Botosan, C. (1997). Disclosure level and the cost of equity capital. *Accounting Review*, 72(3), 323-350.

Boyallian, P., & Ruiz-Verdú, P. (2018). Leverage, CEO risk-taking incentives, and bank failure during the 2007-10 financial crisis. *Review of Finance*, 22(5), 1763-1805.

Brown, G. W. (2001). Managing foreign exchange risk with derivatives. *Journal of Financial Economics*, 60(2-3), 401-448.

Brown, S., & Hillegeist, S. A. (2007). How disclosure quality affects the level of information asymmetry. *Review of Accounting Studies*, 12(2-3), 443-477.

Bushee, B. J. (1998). The influence of institutional investors on myopic R&D investment behavior. *Accounting Review*, 73(3), 305-333.

Bushee, B. J., & Miller, G. S. (2012). Investor relations, firm visibility, and investor following. *Accounting Review*, 87(3), 867-897.

Bushman, R. M., Piotroski, J. D., & Smith, A. J. (2004). What determines corporate transparency? *Journal of Accounting Research*, 42(2), 207-252.

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, 22(1), 31-72.

Campbell, J. L., Downes, J. F., & Schwartz Jr., W. C. (2015). Do sophisticated investors use the information provided by the fair value of cash flow hedges? *Review of Accounting Studies*, 20(2), 934-975.

Campbell, J. L., Khan, U., & Pierce, S. (2021). The effect of mandatory disclosure on market inefficiencies: Evidence from FASB Statement No. 161. *The Accounting Review*, 96(2), 153-176.

Chakravarty, S. (2001). Stealth-trading: Which traders' trades move stock prices? *Journal of Financial* Economics, 61(2),289-307.

Chang, H. R., Donohoe, M., & Sougiannis, T. (2016). Do analysts understand the economic and reporting complexities of derivatives? *Journal of Accounting and Economics*, 61(2-3), 584-604.

Chang, W. W. (2011). Financial Crisis of 2007-2010. *Keio Economic Studies*, 47(2011), 25-56.

Chen, J., Dou, Y., & Zou, Y. (2021). Information externalities of SFAS 161: Evidence from supply chains. *The Accounting Review*, 96(4), 179-202.

Chen, X., Harford, J., & Li, K. (2007). Monitoring: Which institutions matter? *Journal of Financial* Economics, 86(2), 279-305.

Chernenko, S., & Faulkender, M. (2011). The two sides of derivatives usage: Hedging and speculating with interest rate swaps. *Journal of Financial and Quantitative Analysis* 46 (6), 1727-1754.

Chung, K. H., & Zhang, H. (2014). A simple approximation of intraday spreads using daily data. *Journal of Financial Markets* 17 (January), 94-120.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *Journal of Finance*, 66(5), 1461-1499.

DeMarzo, P. M., & Duffie, D. (1995). Corporate incentives for hedging and hedge accounting. *Review of Financial* Studies, 8(3), 743-771.

Dhaliwal, D., Judd, J. S., Serfling, M., & Shaikh, S. (2016). Customer concentration risk and the cost of equity capital. *Journal of Accounting and* Economics, 61(1), 23-48.

Ding, R., & Hou, W. (2015). Retail investor attention and stock liquidity. *Journal of International Financial Markets, Institutional and Money*, 37:12-26.

Donohoe, M. (2015). The economic effects of financial derivatives on corporate tax avoidance. *Journal of Accounting and Economics*, 59(1), 1-24.

Drake, M. S., Roulstone, D. T., & Thornock, J. R. (2012). Investor information demand: Evidence from Google searches around earnings announcements. *Journal of Accounting Research*, 50(4), 1001-1040.

Drakopoulou, V. (2014). Accounting for derivative instruments and hedging activities. *Journal of Financial Risk Management*, 3(4), 151-165.

Durney, M. T., Libby, R., & Silva, F. B. G. (2021). *Complexity as a proxy for risk when evaluating derivative securities* (Working paper).

Dynegy Inc. and Dynegy Holdings Inc. (2008). *2007 10-K form*. pp. 84-86. Available at: https://www.sec.gov/Archives/edgar/data/1105055/000119312508041975/d10k.htm

Dynegy Inc. and Dynegy Holdings Inc. (2011). *2010 10-K form*. pp. F35-F42. Available at: https://www.sec.gov/Archives/edgar/data/1105055/000114036111015138/form_10-k.htm

Easley, D., Kiefer, N. M., O'Hara, M., & Paperman, J. B. (1996). Liquidity, information, and infrequently traded stocks. *Journal of Finance* 51(4), 1405-1436.

Easley, D., Kiefer, N. M., & O'Hara, M. (1997). One day in the life of a very common stock. *Review of Financial Studies*, 10(3), 805-835.

Easley, D., & O'Hara, M. (1987). Price, trade size and information in securities markets. *Journal of Financial Economics*, 19(1), 69-90.

Eleswarapu, V. R., Thompson, R., & Venkataraman, K. (2004). The impact of Regulation Fair Disclosure: Trading costs and information asymmetry. *Journal of Financial and Quantitative Analysis*, 39(2), 209-225.

Fang, V. W., Noe, T. H., & Tice, S. (2009). Stock market liquidity and firm value. *Journal of Financial Economics*, 94(1), 150-169.

Fang, L. H., & Peress, J. (2009). Media coverage and the cross-section of stock returns. *Journal of Financial*, 64(5), 2023-2052.

Faulkender, M. (2005). Hedging or market timing? Selecting the interest rate exposure of corporate debt. *Journal of Finance*, 60(2), 931-962.

Financial Accounting Standards Board (FASB). (1998). *Statement of Financial Accounting Standards No.133: Accounting for derivative instruments and hedging activities*. Norwalk, CT: FASB.

Financial Accounting Standards Board (FASB). (2008). *Statement of Financial Accounting Standards No.161: Disclosures about derivative instruments and hedging activities*. Norwalk, CT: FASB.

Financial Accounting Standards Board (FASB). (2017). *Accounting Standards Update No. 2017-12, Derivatives and hedging (Topic 815): Targeted improvements to accounting for hedging activities*. Norwalk, CT: FASB.

Francis, J., & Soffer, L. (1997). The relative informativeness of analysts' stock recommendations and earnings forecast revision. *Journal of Accounting Research*, 35(2), 193-211.

Franco, G. D., Wong, M. H. F., & Zhou, Y. (2011). Accounting adjustments and the valuation of financial statement note information in 10-K filings. *The Accounting Review*, 86(5), 1577-1604.

Froot, K., Scharfstein, D., & Stein, J. (1993). Risk management: Coordinating corporate investment and financing policies. *Journal of Finance*, 48(5), 1629-1648.

Fu, R., Kraft, A., & Zhang, H. (2012). Financial reporting frequency, information asymmetry, and the cost of equity. *Journal of Accounting and Economics*, 54(2-3), 132-149.

Ge, W., & McVay, S. (2005). The disclosure of material weakness in internal control after the Sarbanes-Oxley Act. *Accounting Horizons*, 19(3), 137-158.

Géczy, C. C., Minton, B. A., & Schrand, C. M. (2007). Taking a view: Corporate speculation, governance, and compensation. *Journal of Finance*, 62(5), 2405-2443.

Gilje, E. P., & Taillard, J. P. (2017). Does hedging affect firm value? Evidence from a natural experiment. *Review of Financial Studies*, 30(12), 4083-4132.

Givoly, D., & Lakonishok, J. (1979). The information content of financial analysts' forecasts of earnings. *Journal of Accounting and Economics*, 1(3), 165-185.

Glosten, L., & Milgrom, P. (1985). Bid, ask and transaction pries in a specialist market with heterogeneously informed traders. *Journal of Financial Economics*, 14(1), 71-100.

Grullon, G., Kanatas, G., & Weston, J. P. (2004). Advertising, breadth of ownership, and liquidity. *Review of Financial Studies*, 17(2), 439-461.

Guay, W. R. (1999). The impact of derivatives on firm risk: An empirical examination of new derivative users. *Journal of Accounting and Economics*, 26(1-3), 319-351.

Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *Review of Financial Studies*, 23(5), 1909-1940.

He, G., Bai, L. & Ren, H. M. (2019). Analyst coverage and future stock price crash risk. *Journal of Applied Accounting Research*, 20(1), 63-77.

He, G., Ren, H. M. & Gao, H.G (2021). *Are financially constrained firms susceptible to a stock price crash?* (Working paper).

Healy, P. M., Hutton, A. P., & Palepu, K. G. (1999). Stock performance and intermediation changes surrounding sustained increases in disclosures. *Contemporary Accounting Research*, 16(3), 485-520.

Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosures, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, 31(1-2), 405-440.

Heflin, F. L., Shaw, K. W., & Wild, J. J. (2005). Disclosure policy and market liquidity: Impact of depth quotes and order sizes. *Contemporary Accounting Research*, 22(4), 829-865.

Huddart, S. J., & Ke, B. (2007). Information asymmetry and cross-sectional variation in insider trading. *Contemporary Accounting Research*, 24(1), 195-232.

Inger, K. K., Meckfessel, M. D., Zhou, M. J., & Fan, W. P. (2018). An examination of the impact of tax avoidance on the readability of tax footnotes. *The Journal of the American Taxation Association*, 40(1), 1-29.

Jarrow, R. A. (2011). *The role of ABS, CDS, and CDOs in the credit crisis and the economy* (Working paper).

Kawaller, I. G. (2004). What analysts need to know about accounting for derivatives. *Financial Analysts Journal*, 60(2), 24-30.

Ke, B., & Ramalingegowda, S. (2005). Do institutional investors exploit the post-earnings announcement drift? *Journal of Accounting and Economics*, 39(1), 25-53.

Kim, J-B., Li, Y., & Zhang, L. (2011). Corporate tax avoidance and stock price crash risk: Firm-level analysis. *Journal of Financial Economics*, 100(3), 639-662.

Koonce, L., Lipe, M. G., & McAnally, M. L. (2008). Investor reactions to derivative use and outcomes. *Review of Accounting Studies*, 13(4), 571-597.

Krishnan, J., Rama, D., & Zhang, Y. (2008). Costs to comply with SOX Section 404. *AUDITING: A Journal of Practice & Theory*, 27(1), 169-186.

Kumar, A. (2009). Who gambles in the stock market? *Journal of Finance*, 64(4), 1889-1933.

Levitt, A. (1998). The importance of high quality accounting standards. *Accounting Horizon*, 12(1), 79-82.

Manchiraju, H., Pierce, S., & Sridharan, S. S. (2018). *Is hedge accounting designation informative about how firms use derivatives?* (Working paper).

Mitra, S., & Cready, W. M. (2005). Institutional stock ownership, accrual management, and information environment. *Journal of Accounting, Auditing & Finance*, 20(3), 257-286.

Mohd, E. (2005). Accounting for software development costs and information asymmetry. *Accounting Review*, 80(4), 1211-1231.

Pan, W., & Bai, H. (2015). Chapter 1 – Propensity score analysis: Concepts and issues. In *Propensity score analysis: Fundamentals and developments*, edited by Pan, W., and Bai, H. New York: The Guilford Press.

Peterson, K. (2012). Accounting complexity, misreporting, & the consequences of misreporting. *Review of Accounting Studies*, 17(1), 72-95.

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *American Statistician*, 39(1), 33-38.

Shipman, J. E., Swanquist, Q. T., & Whited, R. L. (2017). Propensity score matching in accounting research. *Accounting Review*, 92(1), 213-244.

Sias, R. W., Starks, L. T., & Titman, S. (2006). Changes in institutional ownership and stock returns: Assessment and methodology. *Journal of Business*, 79(6), 2869-2910.

Silber, W. L. (2005). What happened to liquidity when World War I shut the NYSE? *Journal of Financial Economics*, 78(3), 685-701.

Smith, C. W., & Stulz, R. M. (1985). The determinants of firms' hedging policies. *Journal of Financial and Quantitative Analysis*, 20(4), 391-405.

Stoll, H. R. (1978). The pricing of security dealer services: An empirical study of NASDAQ stocks. *Journal of Finance*, 33(4), 1153-1172.

Venter, J. H., & De Jongh, D. C. J. (2006). Extending the EKOP model to estimate the probability of informed trading. *Studies in Economics and Econometrics*, 30(2), 25-39.

Welker, M. (1995). Disclosure policy, information asymmetry, and liquidity in equity markets. *Contemporary Accounting Research*, 11(2), 801-827.

Zhang, H. (2009). Effect of derivative accounting rules on corporate risk-management behavior. *Journal of Accounting and Economics*, 47(3), 244-264.

[dataset] Bushee, B. J.; 1981-2018; Institutional Investor Classification. Available from: https://accounting-faculty.wharton.upenn.edu/bushee.

[dataset] Center for Research in Security Prices (CRSP); 2005-2012; Stocks; Retrieved from Wharton Research Data Service.

[dataset] Compustat; 2005-2012; Fundamentals Annual; Retrieved from Wharton Research Data Service.

[dataset] Institutional Brokers' Estimate System (I/B/E/S); 2005-2012; Detail history; Retrieved from Wharton Research Data Service.

[dataset] New York Stock Exchange's Trade and Quote (TAQ); 2005-2012; Trades and quotes; Retrieved from Wharton Research Data Service.

APPENDIX A: SUMMARY OF VARIABLE DEFINITIONS

Variables	Definitions
LOG_SPREAD	The natural logarithm of annual relative effective spread, which is the arithmetic mean of daily relative effective spreads for a stock. The daily relative effective spread is calculated as the absolute value of the difference between the closing transaction price and the midpoint of the prevailing bid-ask quote, divided by the midpoint of the prevailing bid-ask quote, at a trading date.
PIN	The probability of informed trading (see Brown and Hillegeist (2007) for the measure); it is computed based on Venter and De Jongh's (2006) extension of Easley et al.'s (1997) model.
POST	1 if a firm is in the three-year period (i.e., 2009-2011) after the passage of SFAS 161, and 0 if a firm is in the three-year pre-SFAS 161 period (i.e., 2006-2008).
POST'	1 if a firm is in the two-year post-SFAS 161 sample period (i.e., 2010-2011), and 0 if a firm is in the two-year pre-SFAS 161 sample period (i.e., 2006-2007).
TREAT	1 for a treatment firm that provides tabular disclosures of derivatives designated or not designated as hedging instruments in the 10-K report in any year after the implementation of SFAS 161, and 0 for a control firm that reports no derivative in any year over the sample period 2006-2011.
COMPLIER	1 for a treatment firm that provides tabular disclosures of derivatives designated or not designated as hedging instruments in the 10-K report in any year after the implementation of SFAS 161, and 0 for a control firm that does not comply with, and makes no real change per the disclosure requirements of, SFAS 161 within our sample period 2006-2011.
NONCOMPLIER	1 for a treatment firm that does not comply with, and makes no real change per the disclosure requirements of SFAS 161, and 0 for a control firm that reports no derivative in any year over the sample period 2006-2011.
POSTCRISIS	1 if a firm is in the post-crisis period of 2011-2012, and 0 if a firm is in the crisis period of 2009-2010.
CRISIS	1 if a firm is in the crisis period of 2007-2008, and 0 if a firm is in the pre-crisis period of 2005-2006.
SIZE	The natural logarithm of the market value of a firm's equity at the end of a fiscal year. *SIZE* is winsorized at the 1% and 99% levels, respectively.
BTM	The book value of firm equity, divided by the market value of firm equity, at the end of a fiscal year. *BTM* is winsorized at the 1% and 99% levels, respectively.
DEDI	Dedicated institutional investors' stock ownership as a percentage of a firm's total outstanding shares at the end of a fiscal year.
LANACOV	The natural logarithm of 1 plus the number of analysts that make at least one annual EPS forecast for a firm over a fiscal year.
DISPERSION	Dispersion in analyst forecasts, which is measured as the standard deviation of analysts' annual EPS forecasts made during four months prior to the end of a fiscal year, divided by stock price at the beginning of the fiscal year. *DISPERSION* is winsorized at the 1% and 99% levels, respectively.
QTRRET	Buy-and-hold abnormal stock returns of a firm for a fiscal year.
LEV	The sum of short-term and long-term debt, divided by total assets, over a fiscal year. We set missing values of short-term debt to be zero and drop the observations for which the value of long-term debt is missing.
SA	A financial constraint index (*SA*) developed by Hadlock and Pierce (2010). $SA=-0.737\times size+0.043\times size^2-0.040\times age$, where *size* is the natural logarithm

	of total assets capped at \$4.5 billion, and *age* is the number of years for which a firm has been listed. *SA* index is re-scaled by 1,000.
TRADEVOL	The natural logarithm of the average of monthly trading volume for a firm over a fiscal year, scaled by total shares outstanding at the end of the year.
IDIOSYN	Idiosyncratic stock return volatility, calculated as the standard deviation of the residuals from the following market model over the 52-week window before the end of a fiscal year: $r_{i,t} = \alpha_i + \beta_{1i} r_{m,t-1} + \beta_{2i} r_{m,t-2} + \beta_{3i} r_{m,t} + \beta_{4i} r_{m,t+1} + \beta_{5i} r_{m,t+2} + \varepsilon_{i,t}$, where $r_{i,t}$ is the weekly return on firm i, and $r_{m,t}$ is the value-weighted CRSP index return (see Kim et al., 2011).
ASVI	$ASVI_t = \ln\left[1 + \left(\text{Mean}(SVI_{t-1}, SVI_{t-2}) - \text{Mean}(SVI_{t-3}, \dots, SVI_{t-10})\right)\right]$, where $[\text{Mean}(SVI_{t-1}, SVI_{t-2})]$ is the average of the SVI during the two weeks prior to the earnings announcement, and $[\text{Mean}(SVI_{t-3}, \dots, SVI_{t-10})]$ is the average of the SVI during the prior eight weeks ending at the beginning of the prior two weeks. As with Drake et al. (2012), SVI data is constructed on the daily basis.
STDEARN	The standard deviation of income before extraordinary items in the current and previous four fiscal years.
BIG4	1 for a firm that is audited by a big-4 auditor for a fiscal year and 0 otherwise.

APPENDIX B: SAMPLE SELECTION

Sample selection procedure	No. of Observations
Listed firms that issued annual reports from 2006 to 2011	**34,856**
Less:	
Observations in financial (SIC coded 6000-6999) and utility (SIC coded 4900-4999) industries	(11,779)
Observations with negative or missing total assets	(11)
Observations for firms that do not have at least three years (including the years 2008 and 2009) of consecutive data surrounding SFAS 161	(5,751)
Observations for firms that stopped or started using derivatives from 2009	(4,382)
	12,933
Less:	
Observations with missing data necessary for constructing control variables	(8,091)
Final stock-liquidity sample	**4,842**
Less:	
Observations with missing data necessary for constructing control variables	(8,912)
Final PIN sample	**4,021**

APPENDIX C: EXAMPLES OF DERIVATIVE DISCLOSURES BEFORE AND AFTER SFAS 161

C.1 | An excerpt from the notes to Consolidated Financial Statements of Dynegy Inc. for the fiscal year ended on December 31, 2007

"The absolute notional contract amounts associated with our commodity risk-management and interest rate contracts are discussed in Item 7A. Quantitative and Qualitative Disclosures About Market Risk below.

Item 7A. Quantitative and Qualitative Disclosures About Market Risk

We are exposed to commodity price variability related to our power generation business and legacy trading portfolio. In addition, fuel requirements at our power generation facilities represent additional commodity price risks to us. In order to manage these commodity price risks, we routinely utilize various fixed-price forward purchase and sales contracts, futures and option contracts traded on the New York Mercantile Exchange and swaps and options traded in the over-the-counter financial markets to:

- *manage and hedge our fixed-price purchase and sales commitments;*
- *reduce our exposure to the volatility of cash market prices; and*
- *hedge our fuel requirements for our generating facilities.*

The potential for changes in the market value of our commodity, interest rate and currency portfolios is referred to as "market risk". A description of each market risk category is set forth below:

- *commodity price risks result from exposures to changes in spot prices, forward prices and volatilities in commodities, such as electricity, natural gas, coal, fuel oil, emissions and other similar products; and*
- *interest rate risks primarily result from exposures to changes in the level, slope and curvature of the yield curve and the volatility of interest rates.*

In the past, we have attempted to manage these market risks through diversification, controlling position sizes and executing hedging strategies. The ability to manage an exposure may, however, be limited by adverse changes in market liquidity, our credit capacity or other factors.

Credit Risk. *Credit risk represents the loss that we would incur if a counterparty fails to perform pursuant to the terms of its contractual obligations. To reduce our credit exposure, we execute agreements that permit us to offset receivables, payables and mark-to-market exposure. We attempt to further reduce credit risk with certain counterparties by obtaining third party guarantees or collateral as well as the right of termination in the event of default.*

Our Credit Department, based on guidelines approved by the Board of Directors, establishes our counterparty credit limits. Our industry typically operates under negotiated credit lines for physical delivery and financial contracts. Our credit risk system provides current credit exposure to counterparties on a daily basis.

The following table represents our credit exposure at December 31, 2007 associated with the mark-to-market portion of our risk-management portfolio, on a net basis.

Credit Exposure Summary

		Investment Grade Quality
		(in millions)
Type of Business:		
Financial institutions	$	263
Utility and power generators		35
Total	$	298

Interest Rate Risk. *Interest rate risk primarily results from variable rate debt obligations. Although changing interest rates impact the discounted value of future cash flows, and therefore the value of our risk management portfolios, the relative near-term nature and size of our risk management portfolios minimizes the impact. Management continues to monitor our exposure to fluctuations in interest rates and may execute swaps or other financial instruments to change our risk profile for this exposure.*

We are exposed to fluctuating interest rates related to variable rate financial obligations. As of December 31, 2007, our fixed rate debt instruments as a percentage of total debt instruments was 78 percent. Adjusted for interest rate swaps, net notional fixed rate debt as a percentage of total debt was approximately 82 percent. Based on sensitivity analysis of the variable rate financial obligations in our debt portfolio as of December 31, 2007, it is estimated that a one percentage point interest rate movement in the average market interest rates (either higher or lower) over the twelve months ended December 31, 2008 would either decrease or increase interest expense by approximately $11 million. However, interest rate risk associated with our $850 million variable rate term letter of credit facility is mitigated by restricted cash backing this facility. Variable rate interest income earned on the investment of the restricted cash effectively offsets the risk associated with the variable rate interest expense. Over time, we may seek to adjust the variable rate exposure in our debt portfolio through the use of swaps or other financial instruments.

Derivative Contracts. *The absolute notional financial contract amounts associated with our interest rate contracts were as follows at December 31, 2007 and 2006, respectively:"*

Absolute Notional Contract Amounts

		December 31, 2007		December 31, 2006
Cash flow hedge interest rate swaps (in millions of U.S. dollars)	$	310	$	—
Fixed interest rate paid on swaps (percent)		5.32		—
Fair value hedge interest rate swaps (in millions of U.S. dollars)	$	25	$	525
Fixed interest rate received on swaps (percent)		5.70		4.33
Interest rate risk-management contracts (in millions of U.S. dollars)	$	231	$	306
Fixed interest rate paid (percent)		5.35		5.29
Interest rate risk-management contracts (in millions of U.S. dollars)	$	206	$	281
Fixed interest rate received (percent)		5.28		5.23

C.2 | An excerpt from the notes to Consolidated Financial Statements of Dynegy Inc. for the fiscal year ended on December 31, 2010

"On January 1, 2009, we adopted authoritative guidance which requires disclosure of the fair values of derivative instruments and their gains and losses in a tabular format. It also provides more information about an entity's liquidity by requiring disclosure of derivative features that are credit risk-related and it requires cross-referencing within footnotes to enable financial statement users to locate important information about derivative instruments.

The following disclosures and tables present information concerning the impact of derivative instruments on our consolidated balance sheets and statements of operations. In the table below, commodity contracts primarily consist of derivative contracts related to our power generation business that we have not designated as accounting hedges, that are entered into for purposes of economically hedging future fuel requirements and sales commitments and securing commodity prices. Interest rate contracts primarily consist of derivative contracts related to managing our interest rate risk. As of December 31, 2010, our commodity derivatives were comprised of both long and short positions; a long position is a contract to purchase a commodity, while a short position is a contract to sell a commodity. As of December 31, 2010, we had net long/(short) commodity derivative contracts outstanding and notional interest rate swaps outstanding in the following quantities:

Contract Type	Hedge Designation	Quantity (in millions)	Unit of Measure	Net Fair Value (in millions)
Commodity derivative contracts:				
Electric energy (1)	Not designated	(63)	MW	$ 264
Natural gas (1)	Not designated	134	MMBtu	$ (207)
Electricity/natural gas spread options	Not designated	(7)/60	MW/MMBtu	$ (31)
Other (2)	Not designated	—	Misc.	$ 8
Interest rate contracts:				
Interest rate swaps	Fair value hedge	(25)	Dollars	$ 1
Interest rate swaps	Not designated	206	Dollars	$ (5)
Interest rate swaps	Not designated	25	Dollars	$ (1)
Interest rate swaps	Not designated	(206)	Dollars	$ 5

(1) Mainly comprised of swaps, options and physical forwards.

(2) Comprised of coal, crude oil, fuel oil options, swaps and physical forwards.

***Derivatives on the Balance Sheet.** The following table presents the fair value and balance sheet classification of derivatives in the consolidated balance sheet as of December 31, 2010 and 2009, segregated between designated, qualifying hedging instruments and those that are not, and by type of contract segregated by assets and liabilities. We do not offset fair value amounts recognized for derivative instruments executed with the same counterparty under a master netting agreement and we did not elect to adopt the netting provisions that allow an entity to offset the fair value amounts recognized for the Daily Cash Settlements paid or received against the fair value amounts recognized for derivative instruments executed with the same counterparty under a master* *netting agreement. As a result, our consolidated balance sheets present derivative assets and liabilities, as well as related Daily Cash Settlements, on a gross basis.*

Contract Type	**Balance Sheet Location**	**December 31, 2010**	**December 31, 2009**
		(in millions)	
Derivatives designated as hedging instruments:			
Derivative Assets:			
Interest rate contracts	Assets from risk management activities	$ 1	$ 2
Derivative Liabilities:			
Interest rate contracts	Liabilities from risk management activities	—	—
Total derivatives designated as hedging instruments, net		1	2
Derivatives not designated as hedging instruments:			
Derivative Assets:			
Commodity contracts	Assets from risk management activities	1,265	861
Interest rate contracts	Assets from risk management activities	5	13
Derivative Liabilities:			
Commodity contracts	Liabilities from risk management activities	(1,231)	(844)
Interest rate contracts	Liabilities from risk management activities	(6)	(65)
Total derivatives not designated as hedging instruments, net		33	(35)
Total derivatives, net		$ 34	$ (33)

Impact of Derivatives on the Consolidated Statements of Operations

The following discussion and tables present the disclosure of the location and amount of gains and losses on derivative instruments in our consolidated statements of operations for the twelve months ended December 31, 2010, 2009 and 2008 segregated between designated, qualifying hedging instruments and those that are not, by type of contract.

Cash Flow Hedges. *We may enter into financial derivative instruments that qualify, and that we may elect to designate, as cash flow hedges. Interest rate swaps have been used to convert floating interest rate obligations to fixed interest rate obligations.*

Our former investee, PPEA, which we consolidated through December 31, 2009, had certain interest rate swap agreements which were designated as cash flow hedges. Therefore, the effective portion of the changes in value prior to July 28, 2009 was reflected in other comprehensive income (loss). On July 28, 2009, we determined the interest rate swap agreements no longer qualified for cash flow hedge accounting because the hedged *forecasted transaction (that is, the future interest payments arising from the PPEA Credit Agreement Facility) was no longer probable of occurring. We performed a final effectiveness test as of July 28, 2009 and no ineffectiveness was recorded. The associated risk management liability was classified as current at December 31, 2009, as the interest rate swap agreements could have been terminated at the discretion of a third-party guarantor of PPEA's obligations under the agreements. Effective January 1, 2010, we deconsolidated our investment in PPEA Holding, and we sold our interest in this entity in the fourth quarter of 2010. Please read Note 15—Variable Interest Entities—PPEA Holding Company LLC for further discussion of our association with PPEA. The amounts previously deferred in Accumulated other comprehensive income (loss) were recognized in earnings upon our sale of our investment in PPEA Holding in the fourth quarter of 2010, resulting in a loss of $28 million, included in Losses from unconsolidated investments on our consolidated statement of operations.*

During the twelve-month periods ended December 31, 2010, 2009 and 2008, we recorded zero, zero and $2 million, respectively, related to ineffectiveness from changes in fair value of derivative positions and no amounts were excluded from the assessment of hedge effectiveness related to the hedge of future cash flows in any of the periods. During the twelve-month periods ended December 31, 2010, 2009 and 2008, no amounts were reclassified to earnings in connection with forecasted transactions that were considered probable of not occurring.

The amount of gain (loss) recognized in Other comprehensive loss on the effective portion of interest rate swap contracts designated as cash flow hedges was a gain of $166 million and a loss of $142 million for the years ended December 31 2009 and 2008, respectively. As of July 28, 2009, these derivatives no longer qualified for cash flow hedge accounting, and therefore, no additional gains or losses have been recognized in Other comprehensive income since that date.

Fair Value Hedges. *We also enter into derivative instruments that qualify, and that we may elect to designate, as fair value hedges. We use interest rate swaps to convert a portion of our non-prepayable fixed-rate debt into floating-rate debt. The maximum length of time for which we have hedged our exposure for fair value hedges is through 2011. During the twelve-month periods ended December 31, 2010, 2009 and 2008, there was no ineffectiveness from changes in the fair value of hedge positions and no amounts were excluded from the assessment of hedge effectiveness. During the twelve-month periods ended December 31, 2010, 2009 and 2008, there were no gains or losses related to the recognition of firm commitments that no longer qualified as fair value hedges.*

The impact of interest rate swap contracts designated as fair value hedges and the related hedged item on our consolidated statements of operations for the twelve months ended December 31, 2010, 2009 and 2008 was immaterial.

Financial Instruments Not Designated as Hedges. *We elect not to designate derivatives related to our power generation business and certain interest rate instruments as cash flow or fair value hedges. Thus, we account for changes in the fair value of these derivatives within the consolidated statements of operations (herein referred to as "mark-to-market accounting treatment"). As a result, these mark-to-market gains and losses are not reflected in the consolidated statements of operations in the same period as the underlying activity for which the derivative instruments serve as economic hedges.*

For the twelve months ended December 31, 2010, our revenues included approximately $21 million of mark-to-market gains related to this activity compared to $180 million of mark-to-market losses and $252 million of mark-to-market gains in the periods ended December 31, 2009 and 2008, respectively.

The impact of derivative financial instruments that have not been designated as hedges on our consolidated statements of operations for the twelve-month periods ended December 31, 2010 and 2009 is presented below. Note that this presentation does not reflect the expected gains or losses arising from the underlying physical transactions associated with these financial instruments. Therefore, this presentation is not indicative of the economic gross profit we expect to realize when the underlying physical transactions settle.

Derivatives Not Designated as Hedging Instruments	**Location of Gain (Loss) Recognized in Income on Derivatives**	**Amount of All Gain (Loss) Recognized in Income on Derivatives for the Twelve Months Ended December 31,**		
		2010	**2009**	**2008**
		(in millions)		
Commodity contracts	Revenues	$ 185	$ 337	$ 264
Interest rate contracts	Interest expense	—	(12)	(2)

Fair Value of Financial Instruments. *On June 30, 2009, we adopted authoritative guidance which requires the disclosure of the estimated fair value of financial instruments. We have determined the estimated fair-value amounts using available market information and selected valuation methodologies. Considerable judgment is required in interpreting market data to develop the estimates of fair value. The use of different market assumptions or valuation methodologies could have a material effect on the estimated fair value amounts.*

The carrying values of financial assets and liabilities (cash, accounts receivable, short-term investments and accounts payable), not presented in the table below, approximate fair values due to the short-term maturities of these instruments. The carrying amounts and fair values of debt are reflected in Note 18—Debt.

	December 31, 2010		**December 31, 2009**	
	Carrying Amount	**Fair Value**	**Carrying Amount**	**Fair Value**
	(in millions)			
Interest rate derivatives designated as fair value accounting hedges (1)	$ 1	$ 1	$ 2	$ 2
Interest rate derivatives not designated as accounting hedges (1)	(1)	(1)	(52)	(52)
Commodity-based derivative contracts not designated as accounting hedges (1)	34	34	17	17
Other—DHI (2)	175	175	8	8
Other—Dynegy (3)	16	16	1	1

(1) Included in both current and non-current assets and liabilities on the consolidated balance sheets.

(2) Other represents short-term investments, including $85 million of short-term investments included in the Broker

(3) Other represents short-term investments at December 31, 2010."

TABLE 1 Descriptive statistics

Panel A: Stock liquidity (*LOG_SPREAD*) sample

Variables	No. of obs.	No. of firms	Mean	Std. dev.	25th	Median	75th
LOG_SPREAD	4,842	1,180	-6.1794	1.1528	-6.9352	-6.4017	-5.6046
SIZE	4,842	1,180	6.5598	1.7324	5.4349	6.5616	7.6636
BTM	4,842	1,180	0.7163	1.4089	0.2750	0.4783	0.7940
LEV	4,842	1,180	0.1709	0.1813	0.0007	0.1240	0.2798
LANACOV	4,842	1,180	3.2840	1.2880	2.7081	3.5264	4.1589
DISPERSION	4,842	1,180	0.2764	0.5656	0.0573	0.1230	0.2609
TRADEVOL	4,842	1,180	0.4736	0.9480	0.0114	0.5870	1.0829
QTRRET	4,842	1,180	0.0742	0.6730	-0.2599	-0.0254	0.2578
SA	4,842	1,180	-1.0216	1.1491	-1.5291	-0.4810	-0.1501
DEDI	4,842	1,180	0.0773	0.0979	0.0035	0.0499	0.1195
STDEARN	4,842	1,180	112.5649	563.3968	5.7630	16.7317	56.5812
IDIOSYN	4,842	1,180	0.0616	0.0294	0.0428	0.0562	0.0734
BIG4	4,842	1,180	0.6491	0.4773	0	1	1
ASVI	1,712	492	0.0205	0.3980	-0.0632	0.0025	0.0746

Panel B: The probability of informed trading (*PIN*) sample

Variables	No. of obs.	No. of firms	Mean	Std. dev.	25th	Median	75th
PIN	4,021	1,175	0.1417	0.0884	0.0874	0.1176	0.1693
SIZE	4,021	1,175	6.6128	1.7226	5.4756	6.6130	7.7216
BTM	4,021	1,175	0.6842	1.4524	0.2674	0.4619	0.7630
LEV	4,021	1,175	0.1686	0.1802	0.0006	0.1207	0.2758
LANACOV	4,021	1,175	3.2802	1.2846	2.7081	3.4965	4.1589
DISPERSION	4,021	1,175	0.2731	0.5664	0.0565	0.1216	0.2589
TRADEVOL	4,021	1,175	0.4622	0.9412	0.0014	0.5720	1.0615
QTRRET	4,021	1,175	0.0890	0.7106	-0.2588	-0.0212	0.2746
SA	4,021	1,175	-1.0210	1.1456	-1.5169	-0.4836	-0.1533
DEDI	4,021	1,175	0.0775	0.0963	0.0040	0.0499	0.1197
STDEARN	4,021	1,175	108.9865	565.5128	5.6945	16.7153	56.0598
IDIOSYN	4,021	1,175	0.0606	0.0296	0.0420	0.0553	0.0723
BIG4	4,021	1,175	0.6478	0.4777	0	1	1
ASVI	1,712	767	0.0610	0.5580	-0.0559	0.0332	0.1244

Notes: Panels A and B of the table present the descriptive statistics for the variables used in the multivariate tests in the stock liquidity (*LOG_SPREAD*) and the probability of informed trading (*PIN*) sample, respectively, before the propensity-score matching. The samples cover the period 2006-2011. All the variables are defined in Appendix A.

TABLE 2 Propensity-score-matching specification

Panel A: A logistic regression on the determinants of derivatives usage for the pre-matched samples

Variables	(1) *LOG_SPREAD* Sample Dependent Variable = $TREAT_i$	(2) *PIN* Sample Dependent Variable = $TREAT_i$
$SIZE_t$	0.5422***	0.5131***
	(5.835)	(4.981)
BTM_t	0.1411*	0.1582*
	(1.854)	(1.756)
SA_t	-0.5455***	-0.4939***
	(-3.651)	(-3.080)
LEV_t	3.9574***	4.1954***
	(7.817)	(7.400)
$DEDI_t$	-0.4634	-0.1133
	(-0.563)	(-0.120)
$STDEARN_t$	-0.0011*	-0.0007*
	(-1.845)	(-1.728)
$IDIOSYN_t$	-7.8452**	-10.7676**
	(-2.057)	(-2.331)
Intercept	-3.2132**	-2.9482*
	(-2.073)	(-1.858)
Industry×year	included	included
No. of observations	3,306	2,901
Pseudo R-squared	0.3642	0.3669

Panel B: Tests of covariate balance between compliers and non-users

Stock liquidity (*LOG_SPREAD*) sample

Variables	Un(matched)	Mean *TREAT*=1 (N=1,663)	Mean *TREAT*=0 (N=1,663)	t-stat.	Standardized Bias (%)
SIZE	U	7.4618	5.8546	32.94***	100.3
	M	7.4649	7.5256	-1.15	-3.8
BTM	U	0.7266	0.6660	2.19**	14.1
	M	0.7029	0.8095	-2.49**	-8.2
SA	U	-1.6984	-0.4563	-40.08***	-121.5
	M	-1.6987	-1.6321	-1.72*	-6.5
LEV	U	0.2204	0.0941	25.51***	77.6
	M	0.2202	0.2194	0.14	0.5
DEDI	U	0.0833	0.0677	5.55***	16.9
	M	0.0833	0.0800	1.12	3.6
STDEARN	U	193.7700	33.8790	10.18***	30.8
	M	193.8500	156.5500	2.17	7.2
IDIOSYN	U	0.0512	0.0682	-17.63***	-53.8
	M	0.0512	0.0518	-0.73	-1.9

TABLE 2 Panel B (Continued)

The probability of informed trading (*PIN*) sample

Variables	Un(matched)	Mean *TREAT*=1 (N=1,517)	Mean *TREAT*=0 (N=1,517)	t-stat	Standardized Bias (%)
SIZE	U	7.4840	5.9078	27.81***	97.9
	M	7.4881	7.5768	-1.43	-5.5
BTM	U	0.6951	0.6108	1.87*	6.6
	M	0.6638	0.6884	-0.63	-1.9
SA	U	-1.6561	-0.4462	-34.00***	-119.6
	M	-1.6565	-1.6047	-1.17	-5.1
LEV	U	0.2169	0.0915	22.21***	78.1
	M	0.2167	0.2108	0.91	3.7
DEDI	U	0.0865	0.0660	6.30***	22.2
	M	0.0865	0.0873	-0.20	-0.8
STDEARN	U	185.0000	33.7880	7.95***	27.9
	M	185.1100	164.6500	0.99	3.8
IDIOSYN	U	0.0498	0.0662	-14.34***	-50.5
	M	0.0498	0.0479	2.00**	6.0

Notes: Panel A presents the results from the regressions of derivatives usage on its determinants before the propensity-score matching. The dependent variable is the indicator variable, *TREAT*, which equals 1 for a derivative-using firm that complies with SFAS 161, and 0 for a non-derivative-user. *t*-statistics in parentheses are based on robust standard errors clustered by firm. Industry dummies (constructed from the first two digits of SIC codes) and year dummies are included but are not reported for simplicity. Each treatment firm is matched, with replacement and within the caliper of 1%, with a control firm that has the closest propensity score. Panel B reports the results from testing the covariate balance between complier group (*TREAT*=1) and non-user group (*TREAT*=0) in the stock liquidity (*LOG_SPREAD*) sample and the probability of informed trading (*PIN*) sample, respectively. For both the unmatched (U) and matched (M) samples, the *t*-statistics from the two-sample tests of mean and the standardized bias are calculated to check the covariate balance between the complier group and non-user group. The sample period covers the years 2006-2011. All the variables are defined in Appendix A. *, **, and *** indicate the two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 3 Tests of the parallel trends assumption

Panel A: Univariate tests of the parallel trends assumption

Year	Annual Growth Rates in *LOG_SPREAD*			Annual Growth Rates in *PIN*		
	Mean (*TREAT*=0)	Mean (*TREAT*=1)	Mean Differences (t-stat)	Mean (*TREAT*=0)	Mean (*TREAT*=1)	Mean Differences (t-stat)
2006	0.0582	0.0411	0.0170	-0.0574	-0.0576	0.0002
			(1.577)			(0.004)
2007	-0.0029	-0.0195	0.0166	0.0465	0.0978	-0.0513
			(1.604)			(-0.491)
2008	-0.0641	-0.0552	-0.0088	-0.0687	-0.1138	0.0451
			(-1.399)			(1.266)

Panel B: Multivariate tests of the parallel trends assumption

Stock liquidity (*LOG_SPREAD*) sample

Variables	Dependent Variable = LOG_SPREAD_t		
	(1) 2005 vs. 2006	(2) 2006 vs. 2007	(3) 2007 vs. 2008
$\boldsymbol{TREAT_i \times POST_t}$	**0.1313**	**-0.0267**	**0.0474**
	(1.225)	**(-0.377)**	**(1.046)**
Industry×year dummies	included	included	included
No. of observations	324	658	1,152
Adjusted R-squared	0.8773	0.8183	0.8594

The probability of informed trading (*PIN*) sample

Variables	Dependent Variable = PIN_t		
	(1) 2005 vs. 2006	(2) 2006 vs. 2007	(3) 2007 vs. 2008
$\boldsymbol{TREAT_i \times POST_t}$	**0.0009**	**-0.0089**	**0.0012**
	(0.083)	**(-1.031)**	**(0.198)**
Industry×year dummies	included	included	included
No. of observations	356	726	928
Adjusted R-squared	0.8189	0.7287	0.7589

Notes: This table presents the results from testing the parallel trends assumption. Panel A reports the univariate results comparing the average annual growth rates in stock liquidity (*LOG_SPREAD*) and the probability of informed trading (*PIN*) of the treatment firms with those of the control firms for the pre-SFAS 161 sample period (i.e., 2006-2008). The treatment indicator variable, $TREAT_i$, equals 1 for a derivative-using firm that complies with SFAS 161, and 0 for a non-derivative-user. Two-sample t-tests are performed to compare the mean differences. Columns (1), (2), and (3) of Panel B report the results of the multivariate tests, which use 2005 and 2006, 2006 and 2007, and 2007 and 2008 as the pre- and post-treatment periods, respectively, for the estimation of DID regression models (3) and (4). For sake of brevity, only the coefficients for the interaction terms, $TREAT_i \times POST_t$, are reported. t-statistics in parentheses are based on robust standard errors clustered by firm. Other variables, inclusive of the interacted year and industry dummies (constructed from the first two digits of SIC codes), are included but are not reported for simplicity. All the variables in the tables are defined in Appendix A. *, **, and *** indicate the two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 4 The impact of SFAS 161 on information asymmetry between informed and uninformed investors

Variables	Predicted Sign	(1) Dependent Variable= LOG_SPREAD_t	(2) Dependent Variable= PIN_t
Intercept	?	-3.9336***	0.3153***
		(-10.359)	(6.358)
$TREAT_i$	?	0.0239	0.0054
		(0.996)	(1.621)
$POST_t$	?	-0.6096	0.1242*
		(-1.159)	(1.804)
$\boldsymbol{TREAT_i \times POST_t}$	**?**	**-0.0926*** **	**-0.0131*** **
		(-2.961)	**(-3.033)**
$SIZE_t$	-	-0.3500***	-0.0247***
		(-33.855)	(-16.732)
BTM_t	-	-0.0108	-0.0027***
		(-1.640)	(-2.833)
LEV_t	+	-0.1411***	-0.0006
		(-3.143)	(-0.095)
$LANACOV_t$	-	-0.0601***	-0.0016
		(-5.403)	(-1.003)
$DISPERSION_t$	+	0.0251*	0.0022
		(1.669)	(1.050)
$TRADEVOL_t$	-	-0.4067***	-0.0363***
		(-36.759)	(-23.162)
$QTRRET_t$	+	0.0838***	0.0032**
		(7.017)	(2.057)
SA_t	+	-0.0893***	-0.0077***
		(-8.032)	(-4.846)
$DEDI_t$	-	-0.0639	-0.0424***
		(-0.910)	(-3.810)
$IDIOSYN_t$	+	8.1633***	0.2049***
		(21.176)	(3.906)
Industry×year dummies		included	included
No. of observations		3,326	3,034
Adjusted R-squared		0.8620	0.6385

Notes: This table reports the results of difference-in-differences tests for the impact of SFAS 161 on information asymmetry between informed and uninformed investors. The sample period covers the years 2006-2011. The dependent variable is stock illiquidity (LOG_SPREAD_t) in Column (1) and the probability of informed trading (PIN_t) in Column (2). The group indicator variable, $TREAT_i$, equals 1 if a firm complies with SFAS 161 by providing tabular disclosures of designated and non-designated hedges, and 0 if a firm reports no derivatives in the sample period. The time indicator variable, $POST_t$, equals 1 (0) if a firm is in the post-SFAS 161 (pre-SFAS 161) period (i.e., 2009-2011 (2006-2008)). The interaction term, $TREAT_i \times POST_t$, is the variable of interest, capturing the treatment effect of SFAS 161 on relative effective spreads and the probability of informed trading for compliers (*TREAT*=1) relative to non-users (*TREAT*=0). All the variables are defined in Appendix A. The interacted industry dummies (constructed from the first two digits of SIC codes) and year dummies are included in both regressions but not reported for simplicity. The t-statistics reported in parentheses are estimated based on the robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.

TABLE 5 Placebo tests: rule out the potential confounding effect of financial crisis

Panel A: Comparisons between the post-crisis (pre-crisis) period and crisis period

Variables	2009-2010 vs. 2011-2012		2005-2006 vs. 2007-2008	
	(1)	(2)	(3)	(4)
	LOG_SPREAD_t	PIN_t	LOG_SPREAD_t	PIN_t
Intercept	-3.7414***	0.2999***	-4.2407***	0.2884***
	(-8.749)	(5.715)	(-12.205)	(7.023)
$TREAT_i$	-0.0666**	-0.0086***	-0.0391	0.0111**
	(-2.494)	(-2.584)	(-0.862)	(2.242)
$POSTCRISIS_t$	0.7414	0.1244*		
	(1.234)	(1.732)		
$\boldsymbol{TREAT_i \times POSTCRISIS_t}$	**-0.0525**	**0.0086**		
	(-1.386)	**(1.322)**		
$CRISIS_t$			-0.7388	0.0190
			(-1.537)	(0.347)
$\boldsymbol{TREAT_i \times CRISIS_t}$			**0.0329**	**-0.0070**
			(0.650)	**(-1.221)**
$SIZE_t$	-0.4283***	-0.0197***	-0.2824***	-0.0226***
	(-32.939)	(-9.943)	(-20.267)	(-12.427)
BTM_t	0.0377***	-0.0101***	0.0044	0.0053***
	(4.460)	(-7.167)	(0.607)	(3.557)
LEV_t	0.0166	-0.0116	0.1061*	0.0234***
	(0.286)	(-1.349)	(1.952)	(3.396)
$LANACOV_t$	-0.0484***	-0.0072***	-0.0939***	-0.0071***
	(-3.219)	(-3.371)	(-6.707)	(-3.968)
$DISPERSION_t$	0.0005	-0.0001	0.0792***	0.0025
	(0.025)	(-0.038)	(4.011)	(0.984)
$TRADEVOL_t$	-0.3385***	-0.0354***	-0.4161***	-0.0383***
	(-23.704)	(-16.097)	(-28.710)	(-20.211)
$QTRRET_t$	0.0822***	-0.0002	0.1232***	0.0075***
	(6.244)	(-0.137)	(5.340)	(2.670)
SA_t	-0.0950***	-0.0104***	-0.0576***	-0.0024
	(-7.155)	(-4.966)	(-3.846)	(-1.231)
$DEDI_t$	-0.1775*	0.0095	-0.1761*	-0.0788***
	(-1.781)	(0.770)	(-1.771)	(-6.289)
$IDIOSYN_t$	6.0680***	0.2308***	7.6874***	0.3616***
	(13.943)	(3.741)	(11.946)	(4.404)
Industry×year dummies	included	included	included	included
No. of observations	2,618	1,820	1,600	1,346
Adjusted R-squared	0.8444	0.4998	0.8435	0.7515

Notes: This table reports the results from the placebo tests aimed at ruling out the potential confounding effect of financial crisis on information asymmetry between informed and uninformed investors. The dependent variable is stock illiquidity (LOG_SPREAD_t) in Columns (1) and (3), and the probability of informed trading (PIN_t) in Columns (2) and (4). The group indicator variable, $TREAT_i$, equals 1 if a firm complies with SFAS 161 by providing tabular disclosures of designated versus non-designated hedges, and 0 if a firm reports no derivative in the sample period. In Columns (1) and (2), the time indicator variable, $POSTCRISIS_t$, equals 1 (0) if a firm is in the post-crisis (crisis) period (i.e., 2011-2012 (2009-2010)); in Columns (3) and (4), $CRISIS_t$ equals 1 (0) if a firm is in the crisis (pre-crisis) period (i.e., 2007-2008 (2005-2006)). The interaction terms, $TREAT_i \times POSTCRISIS_t$ and $TREAT_i \times CRISIS_t$, are the variables of interest. All the variables are defined in Appendix A. The interacted year and industry dummies (constructed from the first two digits of SIC codes) are included in all the regressions but not reported for simplicity. The t-statistics reported in parentheses are estimated based on robust standard errors clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 5 (Continued)

Panel B: Exclude 2008-2009

Variables	(1) Dependent Variable = LOG_SPREAD_t	(2) Dependent Variable = PIN_t
Intercept	-3.7300***	0.3005***
	(-9.544)	(5.252)
$TREAT_i$	0.0156	0.0053
	(0.481)	(1.138)
$POST'_t$	-0.9926*	-0.0918
	(-1.855)	(-1.145)
$\boldsymbol{TREAT_i \times POST'_t}$	**-0.0939****	**-0.0126****
	(-2.316)	**(-2.059)**
$SIZE_t$	-0.3423***	-0.0239***
	(-25.803)	(-11.091)
BTM_t	0.0437***	-0.0002
	(3.952)	(-0.082)
LEV_t	-0.0553	0.0056
	(-0.961)	(0.644)
$LANACOV_t$	-0.0519***	-0.0024
	(-3.594)	(-1.092)
$DISPERSION_t$	-0.0443*	-0.0055
	(-1.886)	(-1.643)
$TRADEVOL_t$	-0.3502***	-0.0335***
	(-23.686)	(-14.494)
$QTRRET_t$	0.1008***	0.0032
	(5.286)	(1.005)
SA_t	-0.0224	-0.0078***
	(-1.571)	(-3.499)
$DEDI_t$	-0.0040	-0.0412***
	(-0.046)	(-2.629)
$IDIOSYN_t$	6.6798***	0.1122
	(15.328)	(1.560)
Industry×year dummies	included	included
No. of observations	2,138	1,922
Adjusted R-squared	0.8373	0.5804

Notes: This table reports the results from the placebo tests, which are aimed at ruling out the potential confounding effect of financial crisis on information asymmetry by excluding the years 2008-2009 from our sample period of 2006-2011. The dependent variable is stock illiquidity (LOG_SPREAD_t) in Column (1), and the probability of informed trading (PIN_t) in Column (2). The group indicator variable, $TREAT_i$, equals 1 if a firm complies with SFAS 161 by providing tabular disclosures of designated versus non-designated hedges, and 0 if a firm reports no derivative in the sample period. The time indicator variable, $POST'_t$, equals 1 (0) if a firm is in the post-SFAS 161 (pre-SFAS 161) period (i.e., 2010-2011 (2006-2007)). The coefficient on the interaction term, $TREAT_i \times POST'_t$, captures the treatment effects. All the variables are defined in Appendix A. The interacted year and industry dummies (constructed from the first two digits of SIC codes) are included in both regressions but not reported for simplicity. t-statistics in parentheses are based on robust standard errors clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 6 Firm-fixed-effects difference-in-differences regression analysis

	Dependent Variable =			
Variables	(1) LOG_SPREAD_t	(2) PIN_t	(3) LOG_SPREAD_t	(4) PIN_t
Intercept	-2.7987***	0.5059***	-5.7633***	0.2004*
	(-5.749)	(5.303)	(-10.343)	(1.907)
$TREAT_i$	-0.6793*	-0.0777	-2.1773***	0.0310
	(-1.946)	(-0.712)	(-5.300)	(0.362)
$POST_t$	-0.1684	0.0411	0.2652	0.0137
	(-0.490)	(0.573)	(0.678)	(0.168)
$\boldsymbol{TREAT_i \times POST_t}$	**-0.0838*** **	**-0.0137*** **	**-0.1341*** **	**-0.0159*** **
	(-3.536)	**(-3.202)**	**(-4.799)**	**(-3.673)**
$SIZE_t$	-0.3511***	-0.0243***		
	(-19.568)	(-6.833)		
BTM_t	0.0038	-0.0068***		
	(0.506)	(-4.643)		
LEV_t	0.0279	0.0302**		
	(0.326)	(2.084)		
$LANACOV_t$	-0.1031***	0.0015		
	(-6.442)	(0.516)		
$DISPERSION_t$	0.0342*	0.0085**		
	(1.783)	(2.540)		
$TRADEVOL_t$	-0.2002***	-0.0222***		
	(-11.179)	(-6.739)		
$QTRRET_t$	0.0896***	0.0045***		
	(9.643)	(2.807)		
SA_t	0.0603***	-0.0072*		
	(2.760)	(-1.651)		
$DEDI_t$	0.1168	-0.0346*		
	(1.016)	(-1.665)		
$IDIOSYN_t$	3.2369***	0.0465		
	(6.208)	(0.483)		
Firm-fixed effects	included	included	included	included
Industry×year dummies	included	included	included	included
No. of observations	3,326	3,034	3,326	3,034
Adjusted R-squared	0.9473	0.7871	0.9239	0.7751

Notes: This table reports the results of firm-fixed-effects difference-in-differences regression analysis of the impact of SFAS 161 on information asymmetry between informed and uninformed investors. The sample period covers the years 2006-2011. The dependent variable is stock illiquidity (LOG_SPREAD_t) in Columns (1) and (3), and the probability of informed trading (PIN_t) in Columns (2) and (4). The group indicator variable, $TREAT_i$, equals 1 if a firm complies with SFAS 161 by providing tabular disclosures of designated versus non-designated hedges, and 0 if a firm reports no derivative in the sample period. The time indicator variable, $POST_t$, equals 1 (0) if a firm is in the post-SFAS 161 (pre-SFAS 161) period (i.e., 2009-2011 (2006-2008)). The interaction term, $TREAT_i \times POST_t$, is the variable of interest, capturing the treatment effect of SFAS 161 on relative effective spreads and the probability of informed trading for compliers (*TREAT*=1) relative to non-users (*TREAT*=0). All the variables are defined in Appendix A. Firm-fixed effects and the interacted year and industry dummies (constructed from the first two digits of SIC codes) are included in all the regressions but not reported for simplicity. The t-statistics reported in parentheses are estimated based on robust standard errors clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 7 Tests of covariate balance between non-compliers and non-users

Panel A: Stock liquidity (*LOG_SPREAD*) sample

Variables	Un(matched)	Mean *NONCOMPLIER*=1 (N=1,333)	Mean *NONCOMPLIER*=0 (N=1,333)	t-stat	Standardized Bias (%)
SIZE	U	6.5343	5.8098	12.66***	45.2
	M	6.5039	6.4316	1.10	4.5
BTM	U	0.8073	0.6731	2.35**	8.0
	M	0.7571	0.7142	0.77	2.6
SA	U	-1.0407	-0.4349	-18.84***	-65.4
	M	-1.0124	-0.9568	-1.32	-6.0
LEV	U	0.2232	0.0905	22.40***	78.6
	M	0.2194	0.2261	-0.88	-4.0
DEDI	U	0.0800	0.0671	3.82***	13.5
	M	0.0800	0.0717	2.23**	8.6
STDEARN	U	157.6900	32.8720	5.59***	18.6
	M	95.2780	85.9470	0.83	1.4
IDIOSYN	U	0.0593	0.0707	-10.55***	-38.7
	M	0.0596	0.0600	-0.43	-1.4

Panel B: The probability of informed trading (*PIN*) sample

Variables	Un(matched)	Mean *NONCOMPLIER*=1 (N=958)	Mean *NONCOMPLIER*=0 (N=958)	t-stat	Standardized Bias (%)
SIZE	U	6.4969	5.9009	9.25***	37.0
	M	6.4683	6.5317	-0.83	-3.9
BTM	U	0.8339	0.6184	3.16***	11.7
	M	0.7046	0.7687	-1.32	-3.5
SA	U	-1.0027	-0.4448	-15.68***	-60.6
	M	-0.9732	-0.9885	0.31	1.7
LEV	U	0.2241	0.0894	20.32***	79.4
	M	0.2195	0.2175	0.23	1.2
DEDI	U	0.0801	0.0660	3.81***	15.1
	M	0.0806	0.0729	1.82*	8.3
STDEARN	U	158.8000	33.3730	4.87***	17.6
	M	89.4550	104.5300	-1.07	-2.1
IDIOSYN	U	0.0590	0.0694	-8.35***	-34.8
	M	0.0594	0.0599	-0.43	-1.7

Notes: Panels A and B of the table report the results from the tests of covariate balance between the non-complier group (*NONCOMPLIER*=1) and non-user group (*NONCOMPLIER*=0) in the stock liquidity (*LOG_SPREAD*) sample and the probability of informed trading (*PIN*) sample, respectively. For both the unmatched (U) and matched (M) samples, the t-statistics from the two-sample tests of mean and the standardized bias are calculated to check the covariate balance between the non-complier group and non-user group. The sample period covers the years 2006-2011. All the variables are defined in Appendix A. *, **, and *** indicate the two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 8 The impact of SFAS 161 on information asymmetry: comparison between non-compliers and non-users

Variables	Predicted Sign	(1) Dependent Variable= *LOG_SPREAD$_t$*	(2) Dependent Variable= *PIN$_t$*
Intercept		-3.4931***	0.2693***
		(-15.317)	(5.198)
NONCOMPLIER$_i$	?	-0.0087	-0.0035
		(-0.201)	(-0.903)
POST$_t$	?	0.2639**	-0.0572
		(2.036)	(-0.806)
NONCOMPLIER$_i$×POST	**?**	**-0.0891**	**0.0061**
		(-1.599)	**(1.162)**
SIZE$_t$	-	-0.3909***	-0.0230***
		(-12.227)	(-12.318)
BTM$_t$	-	-0.0144	-0.0008
		(-1.255)	(-0.538)
LEV$_t$	+	0.0195	-0.0040
		(0.227)	(-0.523)
LANACOV$_t$	-	-0.1069***	-0.0044**
		(-3.993)	(-2.429)
DISPERSION$_t$	+	0.0323	0.0032
		(1.213)	(1.520)
TRADEVOL$_t$	-	-0.4088***	-0.0389***
		(-14.765)	(-20.083)
QTRRET$_t$	+	0.1192***	0.0001
		(5.336)	(0.048)
SA$_t$	+	-0.1676***	-0.0052**
		(-5.137)	(-2.354)
DEDI$_t$	-	-0.3174**	-0.0160
		(-2.125)	(-1.208)
IDIOSYN$_t$	+	8.0817***	0.2204***
		(7.552)	(3.263)
Industry×year dummies		included	included
No. of observations		2,666	1,916
Adjusted R-squared		0.8750	0.6498

Notes: This table reports the results for the difference-in-differences regression analysis of the impact of SFAS 161 on information asymmetry, comparing between non-compliers and non-users. The sample period covers the years 2006-2011. The dependent variable is stock illiquidity (*LOG_SPREAD$_t$*) in Column (1) and the probability of informed trading (*PIN$_t$*) in Column (2). The group indicator variable, *NONCOMPLIER$_i$*, equals 1 (0) for a non-complier (non-user). The time indicator variable, *POST$_t$*, equals 1 (0) if a firm is in the post-SFAS 161 (pre-SFAS 161) period (i.e., 2009-2011 (2006-2008)). The interaction term, *NONCOMPLIER$_i$×POST$_t$*, is the variable of interest, capturing the treatment effect of SFAS 161 on relative effective spreads and the probability of informed trading for non-compliers (*NONCOMPLIER*=1) relative to non-users (*NONCOMPLIER*=0). All the variables are defined in Appendix A. The interacted year and industry dummies (constructed from the first two digits of SIC codes) are included in both regressions but not reported for simplicity. The t-statistics reported in parentheses are estimated based on robust standard errors clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 9 The moderating effect of firm visibility: evidence from firm size

Variables	(1) Dependent Variable = *LOG_SPREAD$_t$*		(2) Dependent Variable = *PIN$_t$*	
Firm Size (*SIZE*)	**SMALL**	**LARGE**	**SMALL**	**LARGE**
Intercept	-2.6840***	-4.1682***	0.3098***	0.2042***
	(-6.306)	(-11.788)	(7.266)	(4.761)
TREAT$_i$	-0.0518	0.0079	-0.0013	0.0059
	(-1.079)	(0.311)	(-0.234)	(1.259)
POST$_t$	-0.2286	-0.8123*	0.0261	0.1896***
	(-0.406)	(-1.825)	(0.560)	(3.548)
TREAT$_i$×POST$_t$	**-0.0843**	**-0.1005*** **	**-0.0117**	**-0.0147** **
	(-1.349)	**(-3.096)**	**(-1.630)**	**(-2.571)**
SIZE$_t$	-0.5448***	-0.2234***	-0.0262***	-0.0144***
	(-21.371)	(-15.929)	(-9.424)	(-6.527)
BTM$_t$	-0.0136*	-0.0484	-0.0028***	-0.0038
	(-1.714)	(-1.528)	(-2.670)	(-0.619)
LEV$_t$	-0.1849**	0.2130***	-0.0251**	0.0318***
	(-2.004)	(4.396)	(-2.388)	(3.846)
LANACOV$_t$	-0.0726***	-0.0357**	-0.0066***	-0.0073***
	(-3.747)	(-2.551)	(-2.751)	(-3.427)
DISPERSION$_t$	0.0699***	0.0207	0.0033	-0.0039
	(2.663)	(1.249)	(1.125)	(-1.295)
TRADEVOL$_t$	-0.4232***	-0.2821***	-0.0439***	-0.0256***
	(-20.108)	(-20.087)	(-17.743)	(-11.133)
QTRRET$_t$	0.1555***	0.0544***	0.0009	0.0011
	(5.667)	(5.724)	(0.355)	(0.397)
SA$_t$	-0.1525***	-0.0068	-0.0073**	-0.0043**
	(-4.518)	(-0.519)	(-2.143)	(-2.115)
DEDI$_t$	-0.5128***	0.3209***	-0.0635***	-0.0016
	(-2.740)	(4.108)	(-3.076)	(-0.139)
IDIOSYN$_t$	6.7092***	5.9523***	0.3266***	0.5534***
	(9.509)	(16.639)	(4.409)	(5.477)
Industry×year dummies	included	included	included	included
No. of observations	1,014	2,338	1,444	1,514
Adjusted R-squared	0.8329	0.7948	0.5983	0.5985

Notes: This table reports the results of the subsample tests examining the moderating effect of firm visibility. The sample period covers the years 2006-2011. The dependent variable is stock illiquidity (*LOG_SPREAD$_t$*) in Column (1) and the probability of informed trading (*PIN$_t$*) in Column (2). The moderator variable is firm size (*SIZE*). Difference-in-differences tests are run separately in the small-size subsample and large-size subsample, which are split based on the sample median of *SIZE*. The group indicator variable, *TREAT$_i$*, equals 1 if a firm complies with SFAS 161 by providing tabular disclosures of designated versus non-designated hedges, and 0 if a firm reports no derivative in the sample period. The time indicator variable, *POST$_t$*, equals 1 (0) if a firm is in the post-SFAS 161 (pre-SFAS 161) period (i.e., 2009-2011 (2006-2008)). The interaction term, *TREAT$_i$×POST$_t$*, is the variable of interest. All the variables are defined in Appendix A. The interacted year and industry dummies (constructed from the first two digits of SIC codes) are included in all the regressions but not reported for simplicity. The t-statistics reported in parentheses are estimated based on robust standard errors clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 10 The moderating effect of investor attention: evidence from Google Trends' Search Volume Index (SVI)

Variables	(1) Dependent Variable = *LOG_SPREAD_t*		(2) Dependent Variable = *PIN_t*	
Investor Attention (*ASVI*)	**LOW**	**HIGH**	**LOW**	**HIGH**
Intercept	-4.8280***	-3.8434***	0.3084***	0.0707
	(-12.940)	(-9.362)	(7.233)	(1.506)
$TREAT_i$	-0.0465	0.0206	0.0182**	0.0006
	(-0.662)	(0.285)	(2.261)	(0.078)
$POST_t$	-0.3278	-1.8218***	0.0401	-0.0214
	(-0.648)	(-3.261)	(0.773)	(-0.429)
$TREAT_i \times POST_t$	**-0.0899**	**-0.3278*** **	**-0.0066**	**-0.0155***
	(-1.100)	**(-3.608)**	**(-0.684)**	**(-1.681)**
$SIZE_t$	-0.3153***	-0.2390***	-0.0280***	-0.0217***
	(-16.272)	(-10.146)	(-8.755)	(-7.046)
BTM_t	-0.0283	-0.0635*	-0.0154***	0.0078**
	(-0.924)	(-1.764)	(-3.843)	(2.520)
LEV_t	-0.0393	-0.0640	-0.0040	0.0129
	(-0.397)	(-0.510)	(-0.312)	(0.965)
$LANACOV_t$	0.0788***	-0.1029***	0.0069*	0.0055*
	(2.756)	(-3.284)	(1.925)	(1.741)
$DISPERSION_t$	0.0654	0.1531***	0.0179***	-0.0176***
	(1.394)	(2.657)	(3.220)	(-2.617)
$TRADEVOL_t$	-0.4615***	-0.4891***	-0.0432***	-0.0523***
	(-15.974)	(-13.128)	(-12.104)	(-15.771)
$QTRRET_t$	0.1259***	-0.0103	0.0011	-0.0000
	(3.518)	(-0.569)	(0.473)	(-0.008)
SA_t	-0.0001**	-0.0001***	-0.0087**	-0.0008
	(-2.127)	(-3.497)	(-2.463)	(-0.226)
$DEDI_t$	0.4982***	0.3135**	-0.0196	0.0657***
	(2.787)	(2.096)	(-0.881)	(3.870)
$IDIOSYN_t$	13.5934***	11.2768***	0.4242***	0.5095***
	(11.363)	(10.658)	(3.752)	(4.223)
Industry×year dummies	included	included	included	included
No. of observations	696	718	532	526
Adjusted R-squared	0.9068	0.8650	0.7648	0.8102

Notes: This table reports the results of the subsample tests examining the moderating effect of investor attention. The sample period covers the years 2006-2011. The dependent variable is stock illiquidity (*LOG_SPREAD_t*) in Column (1) and the probability of informed trading (*PIN_t*) in Column (2). The moderator variable is investor attention (*ASVI*), constructed based on the Google Trends' daily Search Volume Index (SVI) data. Difference-in-differences tests are run separately in the low-attention subsample and high-attention subsample, which are split based on the sample median of *ASVI*. The group indicator variable, *$TREAT_i$*, equals 1 if a firm complies with SFAS 161 by providing tabular disclosures of designated versus non-designated hedges, and 0 if a firm reports no derivative in the sample period. The time indicator variable, *$POST_t$*, equals 1 (0) if a firm is in the post-SFAS 161 (pre-SFAS 161) period (i.e., 2009-2011 (2006-2008)). The interaction term, *$TREAT_i \times POST_t$*, is the variable of interest. All the variables are defined in Appendix A. The interacted year and industry dummies (constructed from the first two digits of SIC codes) are included in all the regressions but not reported for simplicity. The t-statistics reported in parentheses are estimated based on robust standard errors clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 11 Tests of covariate balance between compliers and non-compliers

Panel A: Stock liquidity (*LOG_SPREAD*) sample

Variables	Un(matched)	Mean *COMPLIER*=1 (N=1,652)	Mean *COMPLIER*=0 (N=1,652)	t-stat	Standardized Bias (%)
SIZE	U	7.4277	6.5319	14.64***	53.4
	M	7.3989	7.3975	0.02	0.1
BTM	U	0.6896	0.8145	-2.10**	-7.4
	M	0.6924	0.8378	-1.75*	-8.6
LEV	U	0.2165	0.2226	-0.90	-3.3
	M	0.2164	0.2142	0.34	1.2
LANACOV	U	3.6773	3.2539	9.58***	34.7
	M	3.6722	3.6627	0.23	0.8
DEDI	U	0.0863	0.0797	1.72*	6.3
	M	0.0865	0.0876	-0.28	-1.0
STDEARN	U	163.2800	156.4000	0.27	0.9
	M	160.3600	190.8600	-1.54	-4.2
IDIOSYN	U	0.0533	0.0594	-6.75***	-24.7
	M	0.0536	0.0536	-0.03	-0.1
BIG4	U	0.7192	0.6289	5.32***	19.3
	M	0.7197	0.7252	-0.35	-1.2

Panel B: The probability of informed trading (*PIN*) sample

Variables	Un(matched)	Mean *COMPLIER*=1 (N=1,504)	Mean *COMPLIER*=0 (N=1,504)	t-stat	Standardized Bias (%)
SIZE	U	7.4742	6.4427	15.04**	62.2
	M	7.4480	7.5108	-1.04	-3.8
BTM	U	0.7041	0.7589	-0.77	-3.1
	M	0.6735	0.6217	1.36	3.0
LEV	U	0.2156	0.2218	-0.82	-3.3
	M	0.2155	0.2293	-2.07**	-7.4
LANACOV	U	3.6642	3.1881	9.58***	38.9
	M	3.6563	3.7061	-1.20	-4.1
DEDI	U	0.0872	0.0807	1.52	6.3
	M	0.0874	0.0875	-0.01	0.0
STDEARN	U	141.4000	78.1740	6.00***	25.5
	M	134.3500	155.1600	-1.92*	-8.4
IDIOSYN	U	0.0527	0.0591	-6.18***	-25.8
	M	0.0529	0.0526	0.37	1.3
BIG4	U	0.7174	0.6054	5.83***	23.8
	M	0.7194	0.7068	0.77	2.7

Notes: Panels A and B of the table report the results for the tests of covariate balance between the complier group (*COMPLIER*=1) and non-complier group (*COMPLIER*=0) in the stock liquidity (*LOG_SPREAD*) sample and the probability of informed trading (*PIN*) sample, respectively. For both the unmatched (U) and matched (M) samples, the t-statistics from the two-sample tests of mean and the standardized bias are calculated to check the covariate balance between the complier group and non-complier group. The sample period covers the years 2006-2011. All the variables are defined in Appendix A. *, **, and *** indicate the two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 12 The impact of SFAS 161 on information asymmetry: comparison between compliers and non-compliers

Variables	Predicted Sign	(1) Dependent Variable= LOG_SPREAD_t	(2) Dependent Variable= PIN_t
Intercept	?	-4.1439***	0.3034***
		(-10.850)	(30.140)
$COMPLIER_i$	?	-0.0087	0.0036
		(-0.385)	(1.244)
$POST_t$	?	0.6100	-0.0054
		(1.143)	(-1.182)
$\boldsymbol{COMPLIER_i \times POST_t}$	**?**	**-0.0603****	**-0.0117*****
		(-2.077)	**(-3.008)**
$SIZE_t$	-	-0.3946***	-0.0221***
		(-37.350)	(-15.072)
BTM_t	-	0.0127***	0.0021*
		(3.367)	(1.872)
LEV_t	+	-0.3162***	-0.0083
		(-6.613)	(-1.337)
$LANACOV_t$	-	-0.0417***	-0.0068***
		(-3.741)	(-4.536)
$DISPERSION_t$	+	0.0421***	0.0002
		(2.786)	(0.105)
$TRADEVOL_t$	-	-0.3761***	-0.0351***
		(-30.827)	(-22.328)
$QTRRET_t$	+	0.1399***	0.0043***
		(10.998)	(2.726)
SA_t	+	-0.1577***	-0.0087***
		(-14.139)	(-5.626)
$DEDI_t$	-	-0.2760***	-0.0439***
		(-4.149)	(-4.892)
$IDIOSYN_t$	+	8.4894***	0.3101***
		(22.006)	(6.080)
Industry×year dummies		included	included
No. of observations		3,304	3,008
Adjusted R-squared		0.8522	0.6171

Notes: This table reports the results for the difference-in-differences regression analysis of the impact of SFAS 161 on information asymmetry, comparing between compliers and non-compliers. The sample period covers the years 2006-2011. The dependent variable is stock illiquidity (LOG_SPREAD_t) in Column (1) and the probability of informed trading (PIN_t) in Column (2). The group indicator variable, $COMPLIER_i$, equals 1 (0) for a complier (non-complier). The time indicator variable, $POST_t$, equals 1 (0) if a firm is in the post-SFAS 161 (pre-SFAS 161) period (i.e., 2009-2011 (2006-2008)). The interaction term, $COMPLIER_i \times POST_t$, is the variable of interest, capturing the treatment effect of SFAS 161 on relative effective spreads and the probability of informed trading for compliers (*COMPLIER*=1) relative to non-compliers (*COMPLIER*=0). All the variables are defined in Appendix A. The interacted year and industry dummies (constructed from the first two digits of SIC codes) are included in both regressions but not reported for simplicity. The t-statistics reported in parentheses are estimated based on robust standard errors clustered by firm. *, **, and *** indicate the two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.