Off the Hook: Does the Supreme Court's Scheme Liability Ruling Benefit Firms in Litigation-Prone Industries?

Candra Chahyadi Eastern Illinois University

Menghistu Sallehu Eastern Illinois University

This study measures the impact of the U.S. Supreme Court's 2008 ruling Stoneridge Investment Partners vs. Scientific-Atlanta on the cumulative abnormal returns and changes in bid–ask spread of firms in litigation-prone industries (computer, electronic, pharmaceutical/biotech, and retail industries). Although we find, in general, positive CARs around the event, we posit and find that the conditional probability that a firm will commit an accounting misstatement affects both CAR and bid–ask spread. The results show that firms with a higher probability of committing financial misstatements experience lower returns around the court's ruling. That is, the ruling increases information asymmetry and uncertainty, and thus costs increase for firms that are more likely to commit financial misstatements, as reflected in a widening of the bid–ask spread.

INTRODUCTION

To maximize the shareholder wealth of a firm, a manager must manage both financial and nonfinancial risks. One important nonfinancial risk is litigation risk. Whether the litigation case against the firm is legitimate and frivolous, shareholders bear the costs of every lawsuit. Firms in some industries (e.g., pharmaceutical industry) can be the target of class action lawsuits from their investors who incur investment losses. Investors may file the class action lawsuits to coerce financial settlements from the defendants who do not wish to engage in extended litigation process.

To limit litigants' ability to sue a firm for their investment losses from securities fraud and to protect firms from abusive class action lawsuits, Congress passed the Private Securities Litigation Reform Act of 1995 (PSLRA). This new legislation is controversial and far from being widely accepted by the public. On the one hand, PSLRA can benefit firms in litigation-prone industries by reducing the probability that a firm must financially settle with the plaintiffs in frivolous class action lawsuits. On the other hand, PSLRA can encourage firms to commit frauds as the new ruling provides firms with greater protection against even meritorious lawsuits.

The impact of the PSLRA on firms in litigation-prone industries is mixed. Johnson, Kasznik, and Nelson (2000) find that PSLRA is wealth-increasing and that firms with greater risk of being sued in a securities class action lawsuit have a more positive market reaction at the time of the passing of PSLRA. Ali and Kallapur (2001), on the other hand, argue that the timing of multiple confounding events related to PSLRA—including three sets of full House and Senate votes, the presidential veto, and subsequent

House override—cloud the true impact of PSLRA on firms. In fact, news of the presidential veto and the House override of the veto were released on the same day and the two events had opposite effects on PSLRA.

We examine the impact of a very influential and highly scrutinized Supreme Court ruling in case of *Stoneridge Investment Partners vs. Scientific-Atlanta* (2008) on firms in litigious industries (the Supreme Court ruled that third parties including investment banks, accounting firms, and suppliers are protected from liability if those parties have a business relationship with firms that engage in securities fraud). This litigation case is perhaps the most important litigation case in years in regards to the investor rights—the *Roe vs. Wade* of securities law. This ruling also sets a new precedence for many other much bigger litigation cases, including the most recent lawsuit against Facebook and its underwriters as well as the pending \$40 billion class action lawsuit filed by Enron shareholders against investments banks that advised the company. Considering that the financial impact of PSLRA on firms in litigious industries is unclear, this recent Supreme Court ruling provides us with a fresh opportunity to examine how limiting investors' ability to file a class action lawsuit (whether meritorious or frivolous lawsuits) affects firms specifically and the integrity of the financial market in general.

Using the sample of firms in four litigation-prone industries (computer, electronic, pharmaceutical/biotech, and retail industries), we measure the impact of the *Stoneridge Investment Partners vs. Scientific-Atlanta* (2008) ruling on stock returns of the firms and on the change of the bid-ask spread 90 days before and 90 days after the ruling. We find that the average cumulative abnormal return (CAR) for the full sample is 1.46%, which means that stock prices of firms in industries with a high number of litigation cases are higher on the announcement of the Supreme Court's ruling. We also find a stronger positive market reaction for firms in the retail industry (CAR = 3.84%) than firms in nonretail industry (CAR = 0.92%).

Furthermore, we also use a cross-sectional regression to test the impact of the F_Score (the ratio of conditional probability that a firm will commit accounting misstatement and its unconditional probability) and other accounting quality and control variables on the three-day CAR. In general, we find a negative relation between the F_Score and CAR, which means that firms with a higher F_Score (e.g., firms that are more likely to commit accounting misstatement than average firms) experienced lower stock returns on the Supreme Court's ruling. However, surprisingly, firms in retail industry have a positive relation between F_Score and their CARs. Our results indicate that investors react differently to the ruling depending on the firm's F_Score.

In regards to the impact of the ruling on changes in the bid–ask spread, we find that by protecting third parties from any fraud-related liabilities the ruling increases the uncertainty and consequently increases the bid–ask spread. We run robustness checks using several measures of CAR (over one-day, two-day, and three-day event windows) and by using the Fama–French (1993) three-factor model augmented by momentum factor. We also broaden the window of the bid–ask spread (-120 to +120 days and -150 to +150 days around the ruling). The results remain consistent.

Our study contributes to the literature in several significant ways. First, given the current financial market environment of distrust following several major accounting scandals, third-party liability is a very important issue for firms as well as for the credibility, integrity, and the efficiency of the financial market. We add new evidence that indicates that investors of firms with higher ex-ante probability of committing financial misstatements are concerned with limiting firm liability. That is, investors take the probability that a firm will commit financial misstatements into their investment decision-making process and price the risk accordingly. Second, our results, which provide evidence of the effect of limiting liability, are free from the multiple confounding events that hamper previous event studies that focus on the passage of PSLRA. Third, we utilize the Bayesian approach to examine the impact of the ruling conditioned on the likelihood that a firm will have material financial misstatements. Given that the Supreme Court's ruling affects all firms differently, we provide empirical evidence that this difference is mainly driven by the likelihood that a firm will have higher ex-ante probability to commit financial misstatements. That is, firms with a higher probability of committing financial misstatements experienced lower returns around the court's ruling. The ruling increases information asymmetry and uncertainty, and thus costs increase

for firms that are more likely to commit financial misstatements, as reflected in a widening of the bid-ask spread.

The remainder of the study is organized as follows. Section 2 discusses the research design including the sample selection and methodologies. Section 3 presents the empirical results, and Section 4 concludes.

RESEARCH DESIGN

Sample Selection

Following prior research, we use a sample of firms operating in litigation-prone industries. Francis, Philbrick, and Schipper (1994) identify biotech (SIC 2833–2836 and 8731–8734), computer (SIC 3570–3577 and 7370–7374), electronic (SIC 3600–3674), and retail (SIC 5200–5961) industries as industries with high number of litigation cases. Peng and Roell (2008) report that the percentages of companies that were targets of shareholder lawsuits during 1996–2002 in the telecommunication, computer and software, healthcare and drug, and retail industries were 40%, 34%, 27%, and 15%, respectively. A recent PriceWaterhouseCoopers (2010) report on shareholder litigations during 2005–2009 shows that high-tech, healthcare, and retail industries account for 26%, 16%, and 4%, respectively, of shareholder lawsuits.¹ Volatility of operations and stock prices due to disruptive innovation, intense competition, and reliance on intangibles of firms in these industries make their stock prices susceptible to significant drops following earnings disappointments and subsequent lawsuits (Lev, 2012).²

We construct our data set by collecting daily stock return data of firms in the four litigation-prone industries from the Center for Research in Security Prices (CRSP) database for one year before through 90 days after the event date. We also require the firms in our sample to have accounting data from Compustat. After this screening, our sample consists of 1,057 firms: 349 (33%), 268 (25%), 244 (23%), and 196 (19%) firms in computer, electronics, pharmaceutical/biotech and retail industries, respectively.³ Our sample for our alternative test, in which we regress cumulative abnormal returns (CARs) on firm characteristics, decreases by six firms, reducing the total number of firms to 1,051.⁴

Event Window, Empirical Models and Measurement of Variables

We base our tests on the securities price consequences of the ruling and accounting information available at the time of the ruling. We begin with the determination of abnormal returns on the announcement of the ruling. The Supreme Court handed down the ruling on January 15, 2008; however, wide dissemination of ruling's outcome occurred in the following days. For example, the *Financial Times* reported the ruling in its January 16, 2008 and January 17, 2008 editions. The *Wall Street Journal* and the *New York Times* carried the story in the January 16, 2008 and January 15, 2008 editions, respectively. To allow time for dissemination and analysis, we base our tests on abnormal returns for three days around the ruling (0,+2). For our tests of change in spread following the ruling, we examine the change in spread during the 90 days after the ruling relative to the spread during the 90 days before the ruling (-90,+90).

Market Reaction and Portfolio Returns

To mitigate cross correlation of abnormal returns, we use the portfolio method suggested by Sefcik and Thompson (1986) to test the market reaction to the ruling. Following prior studies (Ali and Kallapur, 2001; Baber, Kumar, and Verghese, 1995; Karpoff and Malatesta, 1989), we use the following model to compute abnormal returns:

$$R_{pt} = \alpha_p + \sum_{j} \gamma_{pj} \text{Event}_{jt} + \beta_{1p} \text{Event} \times \text{F}_{\text{Score}_{pt}} + \beta_{2p} \text{F}_{\text{Score}} + \beta_{3} R_{mt} + \varepsilon_{pt}, \qquad (1)$$

where R_{pt} is the daily return of a portfolio of high litigation firms, R_{mt} is the value-weighted market index, Event_{jt} is a dummy variable that equals 1 when the day corresponds to event date *j*, and zero otherwise. The coefficient $\sum_{j} \gamma_{pj}$ represents the average abnormal returns of high litigation firms during the event window.

F_Score is the logistic probability from Dechow, Ge, Larson, and Sloan (2011), scaled by the unconditional probability of having accounting manipulations. Dechow et al. estimate the predicted probability as

Manipulation = $-8.252 + 0.665 \times RSST$ Accruals $+ 2.457 \times \Delta$ Accounts Receivable

+ $1.393 \times \Delta$ Inventories + $2.011 \times \%$ Soft Assets + $0.159 \times \Delta$ Cash Sales - $1.029 \times \Delta$ ROA + $0.983 \times$ Issuance of Shares - $0.15 \times$ Abnormal Change in Employees + $0.419 \times$ Existence of Operating Lease,

where RSST accruals are the change in noncash net operating assets; Δ Accounts Receivable is Δ Accounts Receivables (RECT)/Average Total Assets; Δ Inventories is Δ Inventory (INVT)/Average Total Assets; Δ Cash Sales is percentage change in cash sales [Sales(SALE) – - Δ Accounts Receivables (RECT)]; Δ ROA is [Earnings_t (IB_t)/Average Total Assets_t] – [IB_{t-1}/Average Total Assets_{t-1}]; Issuance is an indicator variable that equals 1 if the firm has issued new debt or equity during the time period; %Soft Assets is soft assets (i.e., assets other than property, plant, and equipment and cash) as a percentage of total assets (AT – CHE – PPENT)/AT; Abnormal Change in Employees is the percentage change in the number of employees (EMP) minus the percentage change in assets (AT); and Existence of Operating Leases is an indicator variable that is coded 1 if future operating lease obligations are greater than zero, and zero otherwise.

An F_Score of 1 indicates that the firm has the same probability of manipulation as the unconditional expectation. An F_Score smaller (greater) than 1 indicates a lower (higher) conditional probability of manipulation than that of the unconditional expectation of misstatement. We determine the unconditional probability of misstatement based on the total number of misstatements during 1997–2006, as reported by the U.S. Government Accountability Office (GAO) database. Among the firms in litigious industries, 545 firms restated their financial statements during the period.

Market Reaction and Individual Firm Abnormal Returns

We determine abnormal returns of day t as the difference between actual returns and expected returns based on the following market model:

$$\mathbf{R}\mathbf{q} = \beta_{i} \mathbf{R}_{i} \quad \underset{\text{fit}}{\boldsymbol{\varepsilon}} + \underset{\text{it}}{\boldsymbol{\varepsilon}}$$
(2a)

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt}), \qquad (2b)$$

where R_{it} and R_{mt} refer to daily return for firm *i* on day *t* and market return for firms listed on NYSE, Amex, and NASDAQ, respectively. Parameters are estimated using returns during *t*-252 days and *t*-30 days. $\hat{\alpha}_i$ and $\hat{\beta}_i$ refer to the intercept and beta estimates from Eq. 2a.

Next we assess whether investors view the litigation as a reduction of insurance or a deterrence of nuisance litigation. On one hand, if investors view the reduction as an elimination of deterrence, we would observe an overall negative reaction. On the other hand, if investors believe that the ruling protects firms from liability, especially frivolous lawsuits, we should see an overall positive reaction, with attenuated reaction for firms with likelihood of fraud. We use three-day CARs as the dependent variable in the following equation to examine how investors react to firms' F_Score and other firm characteristics:

$$CAR\gamma = + {}_{0}\gamma F_{s}Core + \gamma \sigma_{2} \circ_{opCashFlow}\gamma AV_{3}SGR + \gamma LogTot alAssets_{i} + \gamma Leverage_{i} + \gamma_{6}BTM_{i} + \gamma_{7}Settle_{i} + \gamma_{8}R_{T}Times_{i} + \gamma_{9}Big4_{i} + \varepsilon,$$
(3)

where CAR is the CARs during the three-day event period (0,+2) subsequent to the ruling date based on the market model; F_Score is the scaled predicted probability of misstatement as previously defined; σ_{op} $C_{ashFlows}$ is the standard deviation of operating cash flows over *t*-4 and *t*; AV_SGR is the mean of sales growth over *t*-4 and *t*, Log Total Assets (size) is the natural log of total assets; leverage is total liabilities divided by total assets; BTM is the book value of equity divided by market value of equity; Settle is an indicator variable that equals to 1 if the firm settled a litigation over the last five years, and zero otherwise; R_T imes is the number of times the firm restated its financial statements (based on the GAO restatement database); and Big4 is an indicator variable that is coded 1 if the firm is a client of one of the Big Four audit firms, and zero otherwise.

Change in Bid–Ask Spread

The Supreme Court ruling establishes the need for an explicit causal connection between the defendant's misrepresentation and a plaintiff's injury for liability to attach. As a result, the new legal environment allows third parties to escape liability as long as they avoid public statements irrespective of their culpability (Klock, 2010; Sinai, 2008). However, limiting the liability of participants in fraud may cultivate behavior that has adverse effects on the stability and development of capital markets (Cooter, 2005; Klock, 2010), which require investor protection from fraud and remedy for injury if fraud occurs. In other words, the integrity of capital markets partly depends on the expectation that no form of fraud is tolerated and that strong remedies exist if it does occur (Donaldson, Levitt, and Goldschmid, 2007). If implied private cause of action available to injured investors is effectively dissolved by the ruling, subsequent risk and transaction cost are likely to increase.

Third parties that assist a company to mislead its investors are now immune from liability if they do not make public statements on which investors rely in their decisions. As disclosure is crucial for establishing liability, the ruling potentially triggers a shift from reporting based on the full disclosure principle to one that is based on caveat emptor (Matricianni, 2009). That is, it provides incentive to firms to limit disclosure that may potentially link the firm to fraudulent activities of other firms. For example, information concerning current and future relationships with suppliers, customers, and other business partners is crucial to forecast future cash flows. However, managers may curtail such disclosures as a preemptive defense against potential lawsuits involving fraud by business partners. Even if firms do not limit disclosure, investors are more likely to be skeptical of corporate disclosure due to the potential for such omissions.

We posit that the ruling creates increased information asymmetry or uncertainty relative to the period before the ruling. Prior research shows that an increase in information asymmetry is associated with an increase in bid–ask spread (Amihud and Mendelson, 1988; Diamond and Verrecchia, 1991). Recent research also reports that the quality and quantity of information made available to investors affects the cost of capital (Easley and O'Hara, 2004). Disclosure of information and accounting quality crucially affect asset prices and cost of capital (Botosan, 1997; Francis, LaFond, Olsson, and Schipper, 2004). In addition, the ruling reduces the amount that investors can recover from involved third parties without reducing the risk of fraud. Thus, we posit that the bid–ask spread subsequent to the ruling is likely to be higher relative to that of before the ruling. In particular, we expect that the increase in bid ask–spread to be more pronounced for firms with higher F Score.

To estimate the change in the bid–ask spread, we test the impact of F_Score. We augment Chang, Chen, Liao, and Mishra's (2006) model by including F_Score and an interaction term between Event and $F_Score.as$ follows:

Spread_{it}=
$$\beta + \beta I_{r}$$
ogVolume $+ \beta R$ eturnVolatility $+ \beta R$

+
$$\beta_5 F_Score_{it} + \beta_6 Settle_{it} + \beta_7 R_time_{it} + \beta_8 ESent$$
 ettle_{it} + $\beta_5 Event \times R_t$ = Times + $\beta_6 R_t$, it

where Spread is $2\times(Ask - Bid)/(Ask + Bid)$; Return Volatility is the square of stock returns, a proxy for return variability; Log Volume is the log of the total number of shares of the company; Event is an indicator variable that is coded 1 if the day lies in the event window (0,+89) and zero if it lies in event window (-90, -1).

We expect that investors will in general take measures to price protect themselves in the face of heightened information asymmetry and uncertainty. We also expect a positive coefficient for β_3 . In addition, we expect the subsequent increase in the bid–ask spread to be greater for firms with higher F_Score. Finally, we consider whether the firm settled a lawsuit in the three years prior to the ruling

(Settle) and the number of times the firm restated its financial statements during 1997–2006 (R_Times) based on the GAO restatement database.⁵

EMPIRICAL RESULTS

Descriptive Statistics

Table 1 shows the descriptive statistics of variables used in Eqs. 2, 3, and 4. The mean three-day CARs for the full sample is 1.46%. For the same event window, the CAR for firms in nonretail (retail) industries is 0.92% (3.84%).⁶ The mean F_Score for the full sample is 0.6396, suggesting that the average firm is less likely to commit fraud. An F_Score of 1 indicates that a firm's propensity to misstate its financial statements, given the predictor variables, is similar to the unconditional expectations (Dechow et al., 2011); an F_Score greater than 1 suggests that the likelihood of misstatement is higher than the unconditional expectations. The mean F_Score for nonretail (retail) industries is 0.6560 (0.5683), suggesting that the likelihood of misstatement by the average firm is not greater than the unconditional probability.

	Full S	Sample	Firms in nonr	etail industries	Firms in ret	ail industries
	(n - 1)	1,057)	(<i>n</i> –	801)	(<i>n</i> =	190)
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
CAR	0.0146	0.0672	0.0092	0.0660	0.0384	0.0674
F_Score	0.6396	0.4972	0.6560	0.5259	0.5683	0.3372
$\sigma_{\rm op. \ cash \ flows}$	0.0812	0.0862	0.0887	0.0923	0.0481	0.0362
Av_SGR	0.3673	1.7856	0.4205	1.9747	0.1353	0.1551
Log Total Assets	5.6738	1.9867	5.4727	1.9894	6.5510	1.7230
Leverage	0.3853	0.2008	0.3628	0.1990	0.4833	0.1783
BTM	0.4189	0.2698	0.4135	0.2721	0.4424	0.2587
Settle	0.3844	0.4867	0.3637	0.4814	0.4745	0.5006
R Times	0.3264	0.6056	0.2573	0.5554	0.6276	0.7154
BIG4	0.7231	0.4477	0.7018	0.4578	0.8163	0.3882
Spread	0.0500	0.0366	0.0505	0.0372	0.0480	0.0337
Return Volatility	0.0012	0.0026	0.0013	0.0026	0.0012	0.0025
Log Volume	12.1865	2.2988	12.1132	2.2736	12.5056	2.3795

 TABLE 1

 DESCRIPTIVE STATISTICS OF SELECTED VARIABLES

Notes: CAR = cumulative abnormal returns during the three day event period (0,+2) subsequent to the ruling date based on the market model: $R_{it}=\alpha_i+\beta \times R_{mt}+\epsilon_{it}$. $\sigma_{op. \ cash \ flows}$ = standard deviation of operating cash flows over *t*-4 and *t*. AV_SGR= the mean of sales growth over *t*-1 and *t*. Log Total Assets = the log of total assets. Leverage = total liabilities divided by total assets. BTM = book value of equity divided by market value of equity. Settle = an indicator variable that equals 1 if the firm settled a litigation over the last five years, and zero otherwise. R_Times = the number of times the firm restated its financial statements (based on the GAO restatement database). Big4 = an indicator variable that is coded 1 if the firm is a client of one of the Big Four Auditors, and zero otherwise. Spread=2×(ask – bid)/(ask + bid). Return Volatility = square of stock returns, a proxy for return variability. Log Volume = the log of the total number of shares of the company. F-Score = scaled predicted probability from plugging firm characteristics into the following logistic model using estimated coefficients from Dechow et al. (2011).

Thirty-eight percent of the sample settled at least one lawsuit during the three years prior to the ruling. Settlement total is determined based on settlements reported on Compustat. These amounts include settlements related to securities litigation and other types of litigation. Thus the percentage of firms that reported settlements is higher than settlements related to securities litigation. For example, the percentage of retail firms that reported settlements constitute 47.45%, which is relatively higher than the percentage

of litigation reported in other studies (shown in the sample distribution section). Overall, the size (Log Total Assents), book-to-market (BTM), leverage, number of times firms restated financial statements (R_Times), percentage of firms audited by Big Four auditors (Big4), return volatility, and volume (Log Volume) are similar for retail and nonretail subgroups.

TABLE 2	
CORRELATION MATRIX FOR INDEPENDENT	VARIABLES

				Log Total					
	F_Score	$\sigma_{op. cash flows}$	Av_SGR	Assets	Leverage	BTM	Settle	R_Times	Big4
F_Score	1.000								
$\sigma_{op. cash flows}$	-0.055^{*}	1.000							
Av_SGR	-0.009	0.228^{***}	1.000						
Log Total Assets	0.054^{*}	-0.382^{***}	-0.106***	1.000					
Leverage	0.143***	-0.008	-0.034	0.235^{***}	1.000				
BTM	0.013	-0.152^{***}	-0.109***	-0.054^{*}	-0.179***	1.000			
Settle	-0.016	-0.098^{***}	-0.072**	0.180^{***}	0.045	0.051^{*}	1.000		
R_Times	-0.025	-0.104^{***}	-0.018	0.164^{***}	0.151***	-0.012	0.207^{***}	1.000	
Big4	-0.062^{**}	-0.143***	-0.063**	0.480^{***}	0.101***	-0.078^{**}	0.069**	0.028	1.000

Notes: $\sigma_{op. \ cash \ flows}$ = standard deviation of operating cash flows over *t*-4 and *t*. AV_SGR= the mean of sales growth over *t*-1 and t. Log Total Assets = the log of total assets. Leverage = total liabilities divided by total assets. BTM = book value of equity divided by market value of equity. Settle = an indicator variable that equals 1 if the firm settled a litigation over the last five years, and zero otherwise. R_Times = the number of times the firm restated its financial statements (based on the GAO restatement database). Big4 = an indicator variable that is coded 1 if the firm is a client of one of the Big Four Auditors, and zero otherwise. Return Volatility = square of stock returns, a proxy for return variability. Log Volume = the log of the total number of shares of the company. F-Score = scaled predicted probability from plugging firm characteristics into the following logistic model using estimated coefficients from Dechow et al. (2011).

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

In Table 2, we show correlation coefficients between any two variables of interest. The F_Score is positively correlated with leverage and negatively correlated with Big4. The negative correlation between F_Score and Big4 is consistent with the view that a higher quality audit reduces the likelihood of accounting manipulation (Becker, DeFond, Jiambalvo, and Subramanyam, 1998). However, the positive correlation between leverage and F_Score supports the finding that firms use accounting maneuvers to prevent the likelihood of violating debt covenants (DeFond and Jiambalvo, 1994; Sweeney, 1994). Both AV_SGR and BTM are strongly correlated with $\sigma_{op. cash flows}$, showing that firms with higher growth have more volatile cash flows from operations. The negative association of Log Total Assets with AV_SGR and $\sigma_{op. cash flows}$ shows that bigger firms have lower sales growth and operating cash flows volatility. In contrast, the positive association of Log Total Assets with Settle and Big4 suggests that bigger firms in litigious industries are audited by Big4 firms. It also shows that bigger firms settle lawsuits more often. However, we interpret these results with caution as the correlations are univariate.

Portfolio and Individual Firm Returns

We follow prior research and use the portfolio approach to test whether investors view the ruling as good news or bad news. The court agreed with the argument that permitting private cause of action for scheme liability extends liability to the whole marketplace in which a firm does business (*Stoneridge v. Scientific Atlanta*, 2007). Such liability creates an obstacle particularly in partnerships between U.S. companies and their suppliers (Chamber of Commerce, 2007). If investors interpret curtailment of third-party liability in such a manner, we would expect a positive market reaction to the ruling. In contrast, opponents argue that limiting liability provides too much immunity to corporate officers who are less than forthcoming in disclosure and thus increases uncertainty (Ali and Kallapur, 2001; Lev, 1995). In addition, opponents also argue that absolving fraud participants from liability undercuts the deterrence effect of

litigation, damages investor confidence, and, with it, market integrity (Donaldson et al., 2007). These arguments suggest that the market would react negatively to the ruling.

Rather than considering the ruling as wholly good or bad news, we posit that investors react based on the likelihood that the firm commits fraud. If well-governed firms have the misfortune of dealing with a bad company, they may be dragged into assisting fraud and the consequent litigation. For such firms, the ruling represents elimination of potential future nuisance litigation or litigation from plaintiffs that target firms with deep pockets. If the likelihood that a firm commits fraud is higher, the deterrence effect of litigation as well as recovery of loss will be diminished as a result of the ruling. We expect investors to react differentially based on firms' proclivity to commit fraud.⁷ Therefore, in the first set of tests we augment the portfolio model used in prior studies with our F_Score variable.

Columns 1 through 5 of Table 3 show that the market reaction is, in general, positive, suggesting that investors generally view the ruling as relief from potentially nuisance litigations. The amount by which the three-day CAR is higher ranges from 0.4% (t stat= 2.13) to 0.9% (t-stat = 3.72). While the general market reaction is positive, the CAR for the event window is lower at higher level of F_Score. The coefficient of EVENT × F_Score is negative and significant (t-stat= -3.56) for the full sample. For individual industries, the effect of F_Score is generally negative. Contrary to our expectation, the CAR for firms with higher F_Score in the retail industry is higher. These results, in general, show that investors interpret elimination of third-party liability depending on the likelihood that the firm will commit fraudulent activities.

The results in Table 3 suggest that the impact of F_Score for the retail industry differs slightly while its impact is generally similar for the other industries. As a result, we present our results for the retail industry separately from the other industries.⁸ In Table 4, we show our results for the full sample, the nonretail subsample, and the retail subsample after partitioning observations into top and bottom quintiles based on F_Score.⁹ For the nonretail industries, the CAR for firms in the bottom quintile of F_Score is higher than that of the top quintile F_Score across different event windows. The three-day (0, +2) CAR for firms in the top quintile is 0.17% (*t*-stat = 2.27) compared to 1.14% (*t*-stat = 4.41) for firms in the bottom quintile of F_Score. Similarly, the proportion of positive returns across different event windows is higher for firms in the bottom quintile (54% for the top quintile vs. 59% for the bottom quintile). Similar to the results in the portfolio method (Table 3), the results for the retail industry show that firms in the top quintile have higher CAR (5%, *t*-stat= 8.11) than those in the bottom quintile (0.8%, *t*-stat= 1.08). We observe this difference across different event windows and in terms of the percentage of firms realizing positive abnormal returns (e.g., 75% for the top quintile vs. 55% for the bottom quintile for the three-day event window).

TABLE 3 CUMULATIVE ABNORMAL RETURNS FOR THE THREE DAYS AROUND THE RULING DATE (0, +2)

			I	ndustry	
				Pharmaceuticals /	/
	Full Sample	Computers	Electronics	Biotech	Retail
Event	0.0085***	0.0043**	0.0054**	0.0089***	0.0078^{***}
	(8.56)	(2.13)	(2.55)	(3.72)	(2.58)
Event \times F Score	-0.0044***	-0.0026	-0.0055**	-0.0037	0.0143***
_	(-3.56)	(-1.23)	(-2.36)	(-1.09)	(3.06)
F Score	0.0003**	0.0001	0.0004	0.0008^{*}	-0.0004
_	(2.02)	(0.18)	(1.11)	(1.87)	(-0.67)
R _m	0.8855***	0.8897^{***}	0.9067***	0.6906***	1.0911***
	(141.81)	(79.10)	(73.18)	(44.55)	(73.20)
Intercept	-0.0010****	-0.0006**	-0.0009****	-0.0012***	-0.0011***
1	(-7.59)	(-2.15)	(-3.08)	(-4.27)	(-3.08)
Industry Fixed Effects	Yes	No	No	No	No
Adj. R^2	0.097	0.103	0.112	0.050	0.150
No. of firms	1,057	349	268	244	196
$\gamma_p + \beta_{1p}$:					
Coefficient	0.0041	0.0017	0.0001	0.0052	0.0221
F-Statistic	30.31***	1.78	0.00	5.99**	70.81***

using observations during t-90 to t + 90.

 $R_{pt} = \alpha_p + \sum_{i} \gamma_{pj} \bullet Event_{jt} + \beta_{1p} Event \times F _ Score_{pt} + \beta_{2p} F _ Score + R_{mt} + \varepsilon_{pt}$

Notes: Event = an indicator variable that is coded 1 if the day lies in the event window (0,+2), and zero otherwise. F-Score = scaled predicted probability from plugging firm characteristics into the following logistic model using estimated coefficients from Dechow et al. (2011). Market = Market factor: value weighted return on all NYSE, Amex and NASDAQ stocks.

Manipulation = $-8.252 + 0.665 \times RSST$ Accruals $+ 2.457 \times \Delta$ Accounts Receivable $+ 1.393 \times \Delta$ Inventories

+ 2.011 × % Soft Assets+ $0.159 \times \Delta Cash Sales - 1.029 \times \Delta Return on Assets + 0.983 \times$ Issuance of Shares $-0.15 \times$ Abnormal Change in Employees $+0.419 \times$ Existence of

Operating Lease,

See Table 1 for model variable definitions. t-stats are in parentheses.^{*}, ^{**} and ^{***} denote significance at 10%, 5% and 1% levels, respectively.

Tests using both the portfolio approach (Table 3) and the market model (Table 4) show that the threeday CAR is generally positive, suggesting that investors view the ruling as good news. The results also show that investors' reaction is moderated by firms' proclivity to misstate their financial statements (F Score). For firms in nonretail industries, the CAR for firms with a higher F Score is lower than that of firms with a lower F Score.¹⁰ However, the retail subsample shows a higher CAR for firms in the top quintile of F Score. We interpret the results as evidence that investors generally view the ruling as good news. At the same time, investors show concern about dissolving third-party liability for firms with the tendency to misstate financial statements (high F Score). Nonetheless, this concern does not appear to dominate the generally positive reaction to the ruling.

$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		AR(0)	%	CAR(0,+1)	%	CAR(0,+2)	%	CAR(0,+3)	%
$ \begin{array}{llllllllllllllllllllllllllllllllllll$		(Patel's <i>t</i> -stat)	Positive CAR						
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	Full Sample	0.0006	0.48	0.0099	0.41	0.0144	0.40	0.0149	0.41
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	4	(0.71)		(10.27)		(13.33)		(12.51)	
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Top Quintile	0.0028	0.58	0.0114	0.62	0.0107	0.58	0.013	0.59
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	I	(2.60)		(5.99)		(5.57)		(4.87)	
Firms in Nonretail Industries (2.06) (3.11) (4.50) (3.36) Full Sample 0.0014 0.48 0.0069 0.43 0.0081 0.45 Full Sample 0.0014 0.88 0.0007 0.58 0.00017 0.54 0.0029 0.52 Top Quintile 0.0019 0.58 0.0017 0.54 0.0029 0.53 0.52 Bottom Quintile 0.0010 0.61 0.011 0.58 0.0141 0.59 0.0069 0.53 Firms in Retail Industry (4.09) (4.09) (4.48) (2.27) (1.68) 0.53 Full Sample -0.003 0.52 0.0229 0.32 0.0379 0.28 0.0449 0.53 Full Sample -0.003 0.52 0.0229 0.32 0.0379 0.28 0.0449 0.28 Full Sample -0.003 0.52 0.0229 0.32 0.0379 0.28 0.0449 0.24 Top Quintile 0.0071 0.55 0.0229 0.32 0.0379 0.28 0.0449 0.24 Top Quintile 0.0071 0.55 0.0407 0.8 0.0095 0.75 0.0169 0.50 Bottom Quintile -0.009 0.38 -0.005 0.43 0.0084 0.55 0.0169 0.50 Full Sample -0.003 0.38 -0.0229 0.037 0.037 0.0365 0.90 Top Quintile -0.003 0.55 0.0407 0.56 0.0169	Bottom Quintile	0.0045	0.57	0.0081	0.55	0.0131	0.58	0.0088	0.53
Firms in Nonretail IndustriesFull Sample 0.0014 0.48 0.0069 0.43 0.0091 0.43 0.0081 0.45 Full Sample 0.0014 0.28 0.0046 0.58 0.0017 0.54 0.0081 0.45 Top Quintile 0.0019 0.58 0.0017 0.54 0.0029 0.52 Bottom Quintile 0.0076 0.61 0.011 0.58 0.0141 0.59 0.0069 0.53 Bottom Quintile 0.0076 0.61 0.011 0.58 0.0141 0.59 0.0069 0.53 Full Sample -0.003 0.52 0.0011 0.58 0.0141 0.59 0.0049 0.53 Full Sample -0.003 0.52 0.0229 0.32 0.0379 0.28 0.0449 0.24 Top Quintile 0.0071 0.55 0.0407 0.80 0.0495 0.75 0.0449 0.24 Bottom Quintile 0.0091 0.38 -0.005 0.43 0.0379 0.75 0.0499 0.76 Bottom Quintile -0.009 0.38 -0.005 0.43 0.0364 0.50 0.0169 0.50 Potom Quintile -0.009 0.38 -0.005 0.43 0.1695 0.77 0.0169 0.50 Potom Quintile -0.009 0.38 -0.005 0.43 0.0169 0.50 0.0169 0.50 Potom Quintile -0.009 0.38 -0.005 0.43 0.0169 <		(2.06)		(3.11)		(4.50)		(3.36)	
$ \begin{array}{llllllllllllllllllllllllllllllllllll$	Firms in Nonretail Indust	ries							
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Full Sample	0.0014	0.48	0.0069	0.43	0.0091	0.43	0.0081	0.45
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	ĸ	(1.34)		(6.08)		(7.46)		(6.41)	
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Top Quintile	0.0019	0.58	0.0046	0.58	0.0017	0.54	0.0029	0.52
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(2.10)		(2.88)		(2.27)		(1.68)	
Firms in Retail Industry (3.28) (4.09) (4.48) (2.83) Full Sample -0.003 0.52 0.0229 0.32 0.0379 0.28 0.0449 0.24 Full Sample -0.003 0.52 0.0229 0.32 0.0379 0.28 0.0449 0.24 Top Quintile (-1.16) 0.55 0.0407 0.80 0.0495 0.75 0.0965 0.90 Top Quintile -0.009 0.38 -0.005 0.43 0.0495 0.55 0.0169 0.50 Bottom Quintile -0.009 0.38 -0.005 0.43 0.0084 0.55 0.0169 0.50 (-2.07) (-1.34) (-1.08) (1.08) (1.41) (-1.41) (-1.41)	Bottom Quintile	0.0076	0.61	0.011	0.58	0.0141	0.59	0.0069	0.53
Firms in Retail Industry Full Sample -0.003 0.52 0.0229 0.32 0.0379 0.28 0.0449 0.24 Top Quintile (-1.16) (11.13) (15.33) (15.62) (15.62) Top Quintile 0.0071 0.55 0.0407 0.80 0.0495 0.75 0.0565 0.90 Bottom Quintile -0.009 0.38 -0.005 0.43 0.0495 0.55 0.0169 0.50 (-2.07) (-1.34) (1.08) (1.01) (1.41)		(3.28)		(4.09)		(4.48)		(2.83)	
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Firms in Retail Industry								
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Full Sample	-0.003	0.52	0.0229	0.32	0.0379	0.28	0.0449	0.24
Top Quintile 0.0071 0.55 0.0407 0.80 0.0495 0.75 0.0565 0.90 (1.63) (1.63) (7.83) (7.83) (7.14) (7.74) Bottom Quintile -0.009 0.38 -0.005 0.43 0.0084 0.55 0.0169 0.50 (-2.07) (-1.34) (-1.08) (1.08) (1.41)		(-1.16)		(11.13)		(15.33)		(15.62)	
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Top Quintile	0.0071	0.55	0.0407	0.80	0.0495	0.75	0.0565	0.90
Bottom Quintile -0.009 0.38 -0.005 0.43 0.0084 0.55 0.0169 0.50 (-2.07) (-1.34) (1.08) (1.41)		(1.63)		(7.83)		(8.11)		(7.74)	
(-2.07) (-1.34) (1.08) (1.41)	Bottom Quintile	-00.00	0.38	-0.005	0.43	0.0084	0.55	0.0169	0.50
		(-2.07)		(-1.34)		(1.08)		(1.41)	
	liability). Abnormal retur	ns are determined	as						

CLIMIT ATIVE ABNORMAL RETTIRNS (CAR) FOR VARIOUS EVENT WINDOWS LINDED THE MARKET MODEL **TABLE 4**

 $R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon$

where R_{it} and R_{mt} refer to daily return for firm i on day to and value return market return for firms listed on NYSE, Amex and NASDAQ, respectively. Parameters are estimated using returns during t-252 days and t-30 days.

 $AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt}) ,$

where \hat{a}_i and $\hat{\beta}_i$ refer to the intercept and beta from the market model above.

Regression Results for Cross-Sectional Analysis

We also use a cross-sectional regression specification (Eq. 3) to test the impact of the F_Score and other accounting quality and control variables on the three-day CAR. In Table 5, we first show the impact of F_Score on CAR after controlling for operating and general firm characteristics variables. Columns 1 through 3 show the impact of the ruling after controlling for size (Log Total Assets), book-to-market ratio (BTM), and financial leverage (Leverage). Consistent with our prediction and results in the previous section, the coefficient of F_Score is negative and significant for the nonretail subsample (*t*-stat = -2.56). In addition, $\sigma_{op. \ cash \ flows}$ has a negative and significant coefficients, suggesting that the CAR is chiefly affected by the event (ruling) and firms' propensity to commit fraud.¹¹ More important, the result shows that the impact of F_Score is significant and negative after we control for firm operating and general characteristics. Similar to our findings shown in Tables 3 and 4, the F_Score has a significant and positive coefficient (*t*-stat = 2.78) for the retail industry. For this industry subsample, the coefficients of Log Total Assets and Leverage have significant coefficients in the expected direction. Likewise, the result for retail industry after controlling for general and operating characteristics variables is similar to the results previously reported in Tables 3 and 4.

Table 5, columns 4 through 6, provides our results after controlling for past questionable accounting practices (R Times and Settle) and auditor size (Big4). The impact of F Score on CAR remains similar to the results shown in columns 1 through 3. Specifically, the coefficient of F Score is negative and significant (t-stat = -2.41) for the nonretail subsample and positive and significant (t-stat = 2.67) for the retail subsample. The coefficients of control variables are also similar to those in columns 1 through 3. Furthermore, the coefficients of the additional control variables are not significant, indicating that these variables do not impact CAR. The control variables are significantly associated with CAR to the extent that investors use these variables to interpret the new information with respect to these characteristics. The result in the previous and this section show that investors use F Score to interpret the impact of the ruling. Results also provide weak evidence that size and leverage are important in decoding the impact. Large firms are usually targets of litigation due to their large budgets, generous insurance coverage, and large number of investors (Lev 2012).¹² The ruling partly eliminates exposure of large firms to such types of litigation; therefore, the market reaction (CAR) is positively associated with size. On the other hand, the negative association between leverage and CAR is consistent with prior research that shows that firms use accounting manipulation to avert default (DeFond and Jiambalvo, 1994, Sweeney, 1994).¹³ Thus, the finding suggests that investors responded negatively to the ruling that limited recovery from firms that may distort accounting amounts.

TABLE 5 CROSS-SECTIONAL REGRESSION OF CUMULATIVE ABNORMAL RETURNS (CARS) OF FIRM CHARACTERISTICS

 $CAR = \gamma_0 + \gamma_1 F _Score + \gamma_2 \sigma_{op \ CashFlow} + \gamma_3 AV _SGR + \gamma_4 LogTotalAssets + \gamma_5 Leverage + \gamma_6 BTM$

, on						
	Full	Firms in	Firms in	Full	Firms in	Firms in
	Sample	Non-Retail	Retail	Sample	Non-Retail	Retail
		Industries	Industry		Industries	Industry
F_Score	-0.0067	-0.0112^{**}	0.0425^{***}	-0.0059	-0.0106**	0.0435***
	(-1.59)	(-2.56)	(2.78)	(-1.40)	(-2.41)	(2.67)
σ _{op. cash flows}	-0.0443^{*}	-0.0601^{**}	0.1305	-0.0448^{*}	-0.0603**	0.1193
	(-1.66)	(-2.21)	(0.87)	(-1.67)	(-2.21)	(0.82)
AV_SGR	0.0015	0.0016	-0.0158	0.0016	0.0016	-0.0126
	(1.32)	(1.34)	(-0.53)	(1.37)	(1.36)	(-0.40)
Log Total Assets	0.0037^{***}	0.0019	0.0140^{***}	0.0027^{**}	0.0010	0.0115^{***}
	(3.19)	(1.53)	(4.63)	(2.06)	(0.71)	(3.53)
Leverage	-0.0185^{*}	-0.0117	-0.0641**	-0.0192^{*}	-0.0128	-0.0671^{**}
	(-1.70)	(-0.98)	(-2.09)	(-1.75)	(-1.08)	(-2.14)
BTM	0.0066	0.0086	-0.0109	0.0067	0.0087	-0.0117
	(0.83)	(0.98)	(-0.43)	(0.84)	(0.98)	(-0.46)
Settle				0.0038	0.0033	0.0066
				(0.89)	(0.70)	(0.70)
R_Times				0.0031	0.0062	-0.0035
				(0.87)	(1.49)	(-0.53)
Big4				0.0065	0.0050	0.0225
				(1.25)	(0.89)	(1.57)
Intercept	0.0056	0.0116	-0.0460	0.0037	0.0102	-0.0471
	(0.58)	(1.13)	(-1.59)	(0.38)	(0.99)	(-1.65)
Industry Fixed Effect	Yes	Yes	No	Yes	Yes	No
No. of firms ^a	1,051	855	196	1051	855	196
Adj. R^2	0.057	0.032	0.127	0.057	0.033	0.128
-						

 $+\gamma_7 Settle + \gamma_{8R} _{Times+v_{\infty}} Big4 + \varepsilon$

^aThe number of firms decreases by 6 due to $\sigma_{op. cash flows and AV SGR variables}$ that require five years data.

CAR = cumulative abnormal returns during the three day event period (0,+2) subsequent to the ruling date based on the market model: Returns_{it} = α_i + β ×Market_t + ε_{it} . F_Score = scaled predicted probability from plugging firm characteristics into the following logistic model using estimated coefficients from Dechow et al. (2011). $\sigma_{op. \ cash \ flows}$ = standard deviation of operating cash flows over *t*-4 and *t*. AV_SGR = the mean of sales growth over *t*-4 and *t*. Log Total Assets = the log of total assets. Leverage= total liabilities divided by total assets. BTM = book value of equity divided by market value of equity. Settle = an indicator variable that equals 1 if the firm settled a litigation over the last five years, and zero otherwise. R_Times = the number of times the firm restated its financial statements (based on the GAO restatement database). Big4 = an indicator variable that is coded 1 if the firm is a client of one of the Big Four Auditors, and zero otherwise.

Manipulation = -8.252 + 0.665 × RSST Accruals + 2.457 × ΔAccounts Receivable + 1.393 × ΔInventories + 2.011 × % Soft Assets+ 0.159 × ΔCash Sales - 1.029 × ΔReturn on Assets + 0.983 × Issuance of Shares -0.15 × Abnormal Change in Employees + 0.419 × Existence of Operating Lease,

See Table 1 for model variable definitions.

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

Results of Bid–Ask Spread Estimation

We present the results of bid–ask spread regression in Table 6. In Section 3, we predict that the postruling regime is, to some extent, characterized by increased uncertainty and information asymmetry. In particular, the tendency to reduce the extent of disclosure to limit potential lawsuit where a firm is a party in a potentially fraudulent transaction is likely for firms with a higher F_Score. To test this hypothesis, we begin by examining whether the bid–ask spread widens after the ruling. Column 1 of Table 6, Panel A, shows that the coefficient of Event is positive and significant (*t*-stat = 39.88), suggesting that investors price-protect themselves after the ruling. We next examine whether the increase in bid–ask spread is exacerbated at higher F_Scores; as we expect, the effect of the ruling is greater for firms with a higher F_Score, as shown in column 2. The coefficient of Event × F_Score is positive and significant (*t*-stat = 3.69).¹⁴

TABLE 6REGRESSION RESULTS OF BID-ASK SPREAD

Panel A. Regression Results of Bid–Ask Spread	
---	--

 $Spread = \beta_0 + \beta_1 LogVolume + \beta_2 \operatorname{Re} turnVolatility + \beta_3 Event + \beta_4 Event \times F_Score + \beta_5 F_Score + \beta_6 Settle$

				Firms in	
	Full	Full	Full	nonretail	Firms in
	sample	sample	sample	industries	retail industries
Return Volatility	8.6338***	8.6327***	8.6110***	8.5814***	8.6824***
	(344.57)	(344.54)	(343.75)	(305.21)	(85.63)
Log Volume	-0.0006***	-0.0006^{***}	-0.0005^{***}	-0.0006***	0.0002***
	(-21.21)	(-21.23)	(-18.28)	(-21.52)	(3.10)
Event	0.0052***	0.0046^{***}	0.0048^{***}	0.0046***	0.0042***
	(39.88)	(22.78)	(20.33)	(17.97)	(5.99)
Event \times F Score		0.0009^{***}	0.0008^{***}	0.0007^{***}	0.0046***
_		(3.61)	(3.42)	(2.78)	(4.89)
F Score		-0.0013***	-0.0013***	-0.0020***	0.0020****
_		(-5.80)	(-5.83)	(-8.34)	(3.52)
Settle			-0.0026***	-0.0033***	0.0007^{*}
			(-13.40)	(-15.15)	(1.89)
R_Times			-0.0002	-0.0002	0.0003
			(-1.16)	(-1.21)	(1.19)
Event × Settle			-0.0003	-0.0005	-0.0001
			(-1.24)	(-1.62)	(-0.13)
Event \times R_Times			0.0001	-0.0001	-0.0003
	***	***	(0.23)	(-0.40)	(-0.76)
Intercept	0.0434	0.0441	0.0444	0.0476	0.0298
	(130.85)	(123.17)	(122.01)	(116.03)	(29.96)
Industry Fixed Effects	Yes	Yes	No	Yes	No
Adj. R^2	0.394	0.394	0.396	0.390	0.437
No. of firms	1,057	1057	196	861	196

 $^{+\}beta_7 R_time + \beta_8 Event \times Settle + \beta_9 Event \times R_Times + \varepsilon$

Table 6 continues

Table 6 (*continued*)

Panel B. Regression Results of Bid-Ask Spread for bottom and top quintiles of F_Score.

 $Spread = \beta_0 + \beta_1 LogVolume + \beta_2 ReturnVolatility + \beta_3 Event + \beta_4 Event \times F_5 Core + \beta_5 F_5 Core + \beta_6 Settle$

	Bottom two	Top two
	quintiles of F Score	quintiles of F Score
Return Volatility	8.2004***	8.6984***
2	(209.06)	(217.33)
Log Volume	0.0003***	-0.0009***
-	(6.96)	(-22.34)
Event	0.0104***	0.0021***
	(16.62)	(4.68)
Event \times F Score	-0.0107***	0.0019***
_	(-5.69)	(6.13)
F Score	-0.0179***	0.0028***
_	(-11.57)	(8.16)
Settle	-0.0018***	-0.0013***
	(-5.48)	(-4.34)
R Times	0.0019***	-0.0009***
_	(6.92)	(-3.69)
Event × Settle	-0.0012****	0.0013***
	(-2.75)	(2.98)
Event \times R Times	-0.0011****	0.0007*
—	(-3.06)	(1.94)
Intercept	0.0406***	0.0452***
-	(61.04)	(67.56)
Industry Fixed Effects	Yes	Yes
Adj. R^2	0.409	0.398
No. of firms	411	411
$\overline{\beta_3 + \beta_4}$:		
Coefficient	0.0004	0.004
F-Statistic	0.03	204.83***

 $+\beta_7 R_Times + \beta_8 Event \times Settle + \beta_9 Event \times R_Times + \varepsilon$

Notes: Spread = $2 \times (ask - bid)/(ask + bid)$. Return Volatility = square of stock returns, a proxy for return variability. Log Volume= the log of the total number of shares of the company. Event = an indicator variable that is coded 1 if the day lies in the event window (0,+89), and zero if it lies in event window (-90, -1). Settle = an indicator variable that equals 1 if the firm settled a litigation over the last five years, and zero otherwise. R_Times = the number of times the firm restated its financial statements (based on the GAO restatement database). F-Score = scaled predicted probability from plugging firm characteristics into the following logistic model using estimated coefficients from Dechow et al. (2011).

Manipulation = -8.252 + 0.665 × RSST Accruals + 2.457 × ΔAccounts Receivable + 1.393 × ΔInventories + 2.011 × % Soft Assets+ 0.159 × ΔCash Sales - 1.029 × ΔReturn on Assets + 0.983 × Issuance of Shares -0.15 × Abnormal Change in Employees + 0.419 × Existence of Operating Lease,

See Table 1 for model variable definitions.

t-stats are in parentheses. ^{*}, ^{***} and ^{****} denote significance at 10%, 5% and 1% levels, respectively.

To explore further how past legal encounter and reporting behavior interact with post-ruling bid-ask spread, we conduct two additional tests. First, we include F_Score and other reporting behavior characteristics and partition the sample into nonretail and retail industries. In columns 3 to 5 of Table 6, Panel A, we include past legal encounter (Settle) and reporting behavior (R_Times) along with an interaction term with Event for each variable. The variables of interest in this panel are Event (β_3) and Event × F_Score (β_4). Consistent with our prediction, we find that the in bid–ask spread increases as the F Score increases. The coefficient of the interaction term (β_4) is positive and significant for the full

sample (*t*-stat = 3.42), nonretail subsample (*t*-stat = 2.78), and the retail subsample (*t*-stat = 4.89). Overall, these results suggest that investors are wary of shielding third parties and that the concern increases if the firm's history shows a higher propensity to commit fraud (high F_Score). Except for the coefficient of Settle, the other variables do not have significant coefficients. This lack of significance is in part because a firm's F Score affects investors' response, a relation that we examine in the following discussion.

Second, the results in Panel A of Table 6 show that the bid–ask spread increases with the extent of F_Score. To further examine how the bid-ask spread changes at lower and higher levels of F_Score, we partition out the sample into two subsamples based on firm's F_Score ranking. We classify firms in the lowest two quintiles as bottom F_Score and the top two quintiles as top F_Score firms. The bottom quintile of F_Score shows a lower likelihood of misstatement while the top quintile of F_Score shows a higher likelihood of misstatement. The mean F_Score for the bottom (top) F_Score firms is 0.3137(0.9879). For each subsample, we examine the impact of F_Score and the other variables post-ruling bid–ask spread.

Column 1 of Table 6, Panel B, shows our results for the bottom F_Score firms. As in Panel A, the key variables of interest are Event (β_3) and Event × F_Score (β_4), and we test whether $\beta_3 + \beta_4$ is significant. Our test of the joint effect shows that $\beta_3 + \beta_4$ is not significantly different from zero for the bottom quintile F_Score. Specifically, the test shows an *F* statistic of 0.03(*p*-value = 0.86). A similar test for the top quintile F_Score firms shows an *F* statistic of 204.84 (*p*-value < 0.001). Likewise, the past reporting behavior on bid–ask spread is different depending on whether the subsample is the bottom or top quintile F_Score. For the bottom quintile F_Score firms, the coefficient of Settle × F_Score and R_Times× F_Score is negative and significant (*t*-stat = -2.75 and *t*-stat = -3.06, respectively). In contrast, the coefficients of Settle×F_Score and R_Times× F_Score firms. These results suggest that the increase in bid–ask spread after the ruling is concentrated in the top quintile F_Score firms. That is, the results suggest that shielding third parties from liability for fraud and recoverable amounts increases uncertainty that results in an increase in the bid–ask spread.

Additional Tests

We perform several tests to ensure that our results are robust to alternative specifications. First, to evaluate robustness of results in Tables 3 and 4, we measure CAR over one-day, two-day, and three-day event windows. The untabulated results are consistent with those reported in Tables 3 and 4. In addition, we follow prior research and use the market model augmented for F_Score. We check the robustness of our results in Table 3 using the Fama–French (1993) three-factor model augmented by a momentum factor (Carhart, 1997). The untabulated results are qualitatively similar to the results in Table 3. In addition, based on prior studies, we concentrate on litigation-prone industries. As a robustness check, we perform our tests for firms in all industries with the required variables. The untabulated results show that the CAR and the impact of F_Score on the CAR are similar to those reported in Table 3.

Second, we check the robustness of our results in Table 6 by changing the event window to -120 to +120 days and -150 to +150 days around the event date. In addition, we classify firms in the lowest (highest) quintile as bottom (top) F_Score firms instead of those in the lowest (highest) two quintiles. Untabulated results are consistent with those reported in Table 6, Panels A and B.

Finally, we report results based on variables winsorized at 1% level and 99% levels. We also perform our tests after winsorizing variables at 5% and 95% levels as well as after deleting outliers.¹⁵ Our results are, in general, qualitatively similar except that results become weaker for the portfolio-based CAR test when we delete outliers using 5% and 95% levels as thresholds.

SUMMARY

Using the sample of firms in four litigation-prone industries (computer, electronic, pharmaceutical/biotech, and retail industries), we measure the impact of the Supreme Court's ruling in the case of *Stoneridge Investment Partners vs. Scientific-Atlanta* (2008) on stock returns of the firms in

litigious industries and on those firms' change of the bid–ask spread 90 days before and 90 days after the ruling. We find that, in general, the stock price reaction is positive, indicating that the market favors the ruling. However, firms with a higher F_Score (the ratio of conditional probability that a firm will commit accounting misstatement and its unconditional probability) and firms with a higher likelihood of having material misstatements experience significantly lower stock price reaction to the ruling. We report this reaction using both a portfolio approach and a market model. Furthermore, the market reaction is positive for firms with more resources (measured by total assets) and significantly negative for firms that may face financial constraints (indicated by higher leverage). We also use a cross-sectional regression to test the impact of F_Score and other accounting quality and control variables on the three-day CAR. In general, we find a negative relation between the F_Score and CAR, which means that firms with a higher F_Score (e.g., firms that are more likely to commit accounting misstatement than average firms) experience lower stock return on the Supreme Court's ruling. However, surprisingly, firms in retail industry have a positive relation between F_Score and their CARs. Our results indicate that investors react differently to the ruling depending on the firm's F Score.

In regards to the impact of the ruling on the change of the bid–ask spread, we find that by protecting third parties from any fraud-related liabilities, the ruling increases the uncertainty and, consequently, increases the bid–ask spread. We run robustness checks using several measures of CAR (over one–day, two–day, and three–day event windows) and by using the Fama–French (1993) three-factor model augmented by momentum factor (Carhart, 1997). We also broaden the window of the bid–ask spread (to – 120 to +120 and –150 to +150 days around the ruling). The results are still consistent with the original results in Tables 3 and 4. We expect that the increased uncertainty and the wider bid–ask spread causes third parties to reduce disclosure as the ruling protects the third parties as long as they do not make public statements that investors can rely on to make their investment decisions. In the long run, this reduction in available information increases information asymmetry and thus extends the bid–ask spread.

Prior to the ruling, investors had better access to class-action lawsuits to recover financial damages that result from financial fraud. However, innocent firms were also more susceptible to costs related to investors' frivolous lawsuits and settlements made to avoid undesirable prolonged financial litigation cases. After the ruling, which stripped investors of their ability to sue third parties and reduced third parties' disclosure demands, investors are now less willing to pay as much for securities of firms in litigious industries due to exposure to higher information asymmetry. Therefore, legislators need to continue to weigh carefully the balance between protecting shareholders' rights and protecting firms from frivolous lawsuits in setting legislations in the future.

ENDNOTES

- These percentages are higher than the incidences in other industries except for the financial services industry. The incidence of litigation in financial services industry increased significantly in 2008 and 2009 due to the financial crisis. We do not include firms in the financial services industry for two reasons. First, the increase in incidence of litigation in 2008 and 2009 is an aberration rather than a systematically higher incidence of litigation. Second, our variable of interest, F_Score, cannot be meaningfully calculated for the financial services industry due to the distinct nature of the industry's accrual process.
- 2. Ali and Kallapur (2001) and Johnson et al. (2000) focus in these industries in their analyses of shareholder reaction to the passage of PSLRA.
- 3. The distribution of our sample is similar to prior studies. For example, the maximum (minimum) number of firms in the computer, electronics, pharmaceuticals/biotech, and retail industries in Ali and Kallapur (2001) is 492(579), 430(484), 74(79) and 441(450), respectively. Similarly, Johnson et al. (2000) use a sample of 191, 128, and 170 firms from pharmaceuticals, hardware, and software industries, respectively. Ali and Kallapur (2001) have more firms because they do not require accounting information for their sample firms.

- 4. We drop six firms because we require five years of data to calculate mean sales growth and standard deviation of operating cash flows.
- 5. We include these variables because we expect that investors utilize firms' past litigation experience or misstatement in their current decisions. Past misstatement or settlement may either signal that the firms' behavior is currently problematic or may suggest that their behavior going forward is improved. As a result, we do not provide directional prediction for these variables.
- 6. Our tests for market reaction and change in bid-ask spread show that reactions are different for the retail industry. Therefore, we divide the sample into nonretail and retail industries. Results for firms in retail industries are similar in direction magnitude for the other three industries.
- 7. If firms intentionally collaborate with another firm, those firms may possibly defraud their own investors.
- 8. In untabulated results, we also test our hypothesis for individual industries. Results are qualitatively similar to the results for tabulated. In other words, the impact of F_Score is similar for all industries other than retail.
- 9. We determine CAR using the market model for this purpose.
- 10. Even though the CAR at high F_Score is lower than that of lower F_Score, the CAR does not become negative even at the highest level. Our joint test of the Event and Event × F_Score shows that CAR is not negative for higher F_Scores.
- 11. It could be argued that variables showing firm characteristics or F_Score contain information that in the public domain and therefore the CAR should be unrelated to these variables. We include these variables to test whether the interpretation of the event depends on its past behavior. In particular, we include the F_Score variable to examine whether investors incorporate compensation in the event of fraud in their pricing decisions.
- 12. Firms with a large number of investors are targets of lawsuits because large firm size is usually associated with big plaintiff class action suits and substantial damage estimates (Lev, 2012).
- 13. The negative association between CAR and leverage suggests limiting liability of firms with high leverage, especially if a link is found between higher leverage and accounting manipulation or involvement in fraud.
- 14. Our maintained assumption is that firms with high F_Score are more likely to engage in assisting others structure fraudulent transaction.
- 15. We deleted outliers for both 1% (99%) and 5%(95%) levels.

REFERENCES

Ali, A., & Kallapur, S. (2001). Securities price consequences of the private securities litigation reform act of 1995 and related events. *Accounting Review*, 76(3), 431–460.

Amihud, Y., & Mendelson, H. (1988). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 17(2), 223–249.

Baber, K., Kumar, K., & Verghese, T. (1995). Client security price reaction to the Laventhol and Howarth bankruptcy. *Journal of Accounting Research*, 33(2), 385–395.

Botosan, C. (1997). Disclosure level and the cost of capital. Accounting Review, 72(3), 323-349.

Becker, C., DeFond, M., Jiambalvo, J., & Subramanyam, K. (1998). The effect of audit quality on earnings management. *Contemporary Accounting Research*, 15(1), 1–24.

Carhart, M.M (1997). On persistence in mutual fund performance. Journal of Finance, 52(1), 57-82.

Chang, H., Chen, J., Liao, W.M., & Mishra, B.K. (2006). CEOs'/CFOs' swearing by the numbers: Does it impact share price of the firm? *Accounting Review*, *81*(1), 1–27.

Chamber of Commerce. (2007). On writ of certiorari to the United States Court of Appeals for the Eighth Circuit: Brief of the Chamber of Commerce of the United States of America as amicus curiae in support of respondents. Washington, DC: Supreme Court of the United States.

Cooter, R. (2005). Innovation, information, and the poverty of nations. *Florida State Law Review 33*(2), 373–386. http://www.law.fsu.edu/journals/lawreview/downloads/332/cooter.pdf>

Dechow, P., Ge, W., Larson, C.R., & Sloan, R.G. (2011). Predicting material accounting misstatements. *Contemporary Accounting Research*, 28(2), 17–82.

DeFond, M.,& Jiambalvo, J. (1994). Debt covenant violation and manipulation of accruals. *Journal of Accounting and Economics*, 17(1–2), 145–176.

Diamond, D., & Verrecchia, R. (1991). Disclosure, liquidity and the cost of capital. *Journal of Finance*, 46(1), 1325–1360.

Donaldson, W.H., Levitt, A., & Goldschmid (2007). On writ of certiorari to the United States Court of Appeals for the Eighth Circuit: Motion for leave to file brief out of time and brief amici curiae of former SEC commissioners in support of the petitioner. Washington, DC: Supreme Court of the United States.

Fama, E.F., & French, K.R. (1993). Common risk factors in returns on bonds and stocks. *Journal of Financial Economics*, 33(1), 3–56.

Francis, J., Philbrick, D., & Schipper, K (1994). Shareholder litigation and corporate disclosures. *Journal of Accounting Research*, 32(2), 137–164.

Francis, J., LaFond, R., Olsson, P.M., & Schipper, K. (2004). Cost of equity and earnings attributes. *Accounting Review*, *79*(4), 967–1010.

Johnson, M. F., Kaznick, R., & Nelson, K.K. (2000). Shareholder wealth effects of private securities litigation reform act of 1995. *Review of Accounting Studies*, *5*(3) 217–233.

Karpoff, J., & Malatesta, P. (1989). The wealth effects of second-generation state takeover legislation. *Journal of Financial Economics*, 25(2), 291–322.

Klock, M. (2010). What will it take to label participation in a deceptive scheme to defraud buyers of section 10(b)? The disastrous result and reasoning of Stoneridge. *Kansas Law Review*, 58(2), 309–354. http://www.law.ku.edu/publications/lawreview/pdf/2 Klock Final.pdf>

Lev, B. (1995). Disclosure and shareholder litigation. California Management Review 37(3), 8-28.

Lev, B. (2012). Winning investors over: Surprising truths about honesty, earnings guidance, and other ways to boost your stock price. Boston: Harvard Business Review Press.

Matricianni, A.J. (2009). Stoneridge Investment Partners, LLC v. Scientific-Atlanta, Inc.: Substitution of congressional intent with caveat emptor. *Journal of Business and Technology law*, 4(1), 187–199.

Peng, L., & Roell, A. (2008). Executive pay and shareholder litigation. *Review of Finance*, 12(1), 141–184.

PriceWaterhouseCoopers. (2010). 2009 Securities litigation study. New York. http://10b5.pwc.com/PDF/NY-10-0559%20SEC%20LIT%20STUDY V7%20PRINT.PDF>

Sefcik, S.E., & Thompson, R. (1986). An approach to statistical inference in cross-sectional models with security abnormal returns as dependent variable. *Journal of Accounting Research*, 24(2), 316-334.

Spiess, K & Tkak, P. (1997). The Private Securities Litigation Reform Act of 1995: The stock market casts its vote. *Management and Decision Economics*, *18*(7-8), 545-561.

Sinai, S. (2008). Stoneridge—Escape from securities liability notwithstanding active, intentional, deceptive conduct. *Journal of Business and Securities Law, 9*(1), 171–187.

Sweeney, A. (1994). Debt-covenant violations and managers' accounting responses. *Journal of Accounting and Economics*, 17(3), 281–308.