The Effect of Litigation Risk on Management Earnings Forecasts*

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Abstract

We examine the effect of litigation risk on managers' decision to issue earnings forecasts. We use a new *ex ante* measure of litigation risk, namely, the Directors and Officers liability insurance premium. This choice bypasses significant problems associated with the estimation of *ex ante* litigation risk in prior studies. By using this measure of litigation risk, our results are more intuitively appealing. We find that when faced with *ex ante* litigation risk, managers with bad news are more likely to issue an earnings warning. For good news firms, we do not see this effect. We also examine three forecast characteristics: forecast horizon, extent of news revealed and forecast precision. Firms with higher litigation risk tend to issue earnings forecasts earlier if they have bad news but not so when they have good news. They also reveal less news in the forecasts if they have good news. As litigation risk increases, bad news earnings forecasts become more precise. Good news earnings forecasts, however, tend to become less precise relative to bad news forecasts. This differential effect of litigation risk on management earnings forecasts, based on the direction of news, has not been documented by previous studies.

Key words: litigation risk, voluntary disclosure, management earnings forecasts, directors and officers insurance

JEL Classification: G39; K22; K41; M41

1. Introduction

Earnings forecasts by managers affect stock prices. This is shown in studies by Patell 1976, Jaggi 1978, Nichols and Tsay 1979, Penman 1980, Ajinkya and Gift 1984 and Waymire 1984, all of whom document significant stock price reaction to the release of earnings forecasts by managers. After analyzing the evidence, King, Pownall, and Waymire (1990) conclude that earnings forecasts are primarily issued by managers to adjust expectations of market participants about their company's prospects. The price reaction varies with the biases in the forecasts, which in turn depends on the forecasting incentives of the managers (Rogers and Stocken 2005). Given the varying price relevance to different forecast incentives such as litigation risk and labor market disciplinary forces, a study of the incentives to forecast earnings is of particular interest to all market participants in that it can help them to better interpret the information contained in these forecasts.

One important incentive involves litigation risk faced by the managers. The Jenkins Committee Report from the American Institute of Certified Public Accountants [AICPA (1994)] identifies "fear of litigation" as an important obstacle to providing forward looking information. Breeden (1995), Securities Exchange Commission (1994) and Conference Report (1995) are other documented instances of this view. This "fear of litigation" view appears justifiable since a company facing litigation does experience a significant drop in value. Bhagat, Bizjak, and Coles (1998) present large sample evidence that, on the date a lawsuit is filed, corporate defendants lose nearly one percent of their value. For any filing pertaining to violation of securities laws, the losses are much higher with companies on average losing about 2.73% of their value at the filing date. Aside from the direct costs faced by companies, managers also face indirect costs of litigation. Managers appear to suffer significant reputational costs when their firms get sued. For instance, Strahan (1998) finds that the probability of CEO turnover increases dramatically after class action filings.

Among these costly lawsuits, inadequate and inaccurate disclosure was most frequently at issue in shareholder claims (2002 Tillinghast-Towers Perrin survey). The survey states: *Disclosures of publicly traded companies are an area of increased underwriting concern due to the significantly higher cost of Directors and Officers' liability* claims *… such claims relate to securities trading decisions* that led to *financial loss, which were made on the basis of allegedly inadequate or inaccurate disclosure by the corporation.*

From the above facts, it is clear that managers have strong incentives to modify their behavior to avoid costly litigation pertaining to inadequate or inaccurate disclosure. Understanding whether and how managers adjust their forecast behavior in response to litigation risk is helpful to investors, as they can better interpret the price-relevant content of the forecasts provided by the managers. Besides investors, studying the effect of litigation risk on disclosure of earnings forecasts is also useful for regulators, policy makers and accounting standard setters. Legislators can bring about litigation reform by introducing new legislation aimed at changing the disclosure incentives of managers. Regulators and accounting standard setters can modify reporting and disclosure standards based on studies of managerial incentives for disclosure.

While several studies have investigated the effect of disclosure on incidence of shareholder litigation (e.g., Skinner 1994; Francis, Philbrick, and Schipper 1994; Field, Lowry, and Shu 2005), there have been far fewer studies providing direct evidence on the reverse effect, that is, the effect of litigation risk on managers' decisions to make earnings forecasts and the characteristics of these disclosures. Intuitively, we expect the likelihood of making bad news forecasts to increase with litigation risk since these disclosures can reduce the likelihood that managers are sued for not releasing information in a timely fashion. In contrast, we do not expect the proclivity of issuing good news forecasts to increase with litigation risk because the litigation environment is overwhelmingly asymmetric with managers rarely getting sued for withholding good news. However, the results from existing cross-sectional studies in the U.S. are conflicting and somewhat counter-intuitive. For example, Johnson, Kasznik, and Nelson (2001), for a sample of high technology firms, report that litigation risk (the reduction of which is proxied by the passage of Private Securities Litigation Reform Act 1995 (PSLRA)), is negatively associated with both good news and bad news forecasts. In contrast, Brown, Hillegeist, and Lo (2005) find the opposite result. Specifically, they show that, cross-sectionally, litigation risk is positively associated with the likelihood of issuing both good and bad news forecasts.

In this study, we use a new measure of litigation risk, namely, the directors' and officers' (D&O) liability insurance premiums to study the effect of litigation risk on management earnings forecasts. In the U.S., firms routinely purchase D&O insurance coverage (or "D&O limit amount") for their directors and officers for reimbursement of defense costs and settlements arising from litigations. The D&O insurance premium is the price a firm pays for getting such coverage. Conceptually, it incorporates richer information than a single litigation risk proxy that is derived from *ex post* litigation incidence or frequency as used by prior literature (e.g., Johnson, Kasznik, and Nelson 2001; Rogers and Stocken 2005; Brown, Hillegeist, and Lo 2005). It aggregates both the expected magnitude of loss or damage recovery amount (through the choice of a D&O insurance limit) and the expected likelihood of such losses (through the pricing of the chosen limit). It also effectively distinguishes between frivolous and meritorious lawsuits, as the former are expected to be dismissed more often than not with defense costs being the only reimbursement. In other words, frivolous lawsuits affect D&O premium to a minimal extent. Such differentiation is critical, as shown in Field, Lowry, and Shu 2005, whose preliminary results on the association between disclosure and litigation risk change when they exclude *ex post* dismissed lawsuits. Furthermore, the use of D&O insurance premium, which is determined largely by a competitive D&O underwriting market, dispenses with the need to estimate a model that links the *ex post* probability of being sued with underlying economic determinants of litigation risk. Hence, as discussed in detail in Section 2, it bypasses econometric problems such as in-sample estimation and incorrect specification of dependent variables. The promise of D&O insurance premiums as a litigation risk proxy measure has also been recognized in the legal literature recently. For example, based on in-depth interviews with D&O insurance underwriters, Baker and Griffith (2007) explicitly state that D&O premiums are the only place to look if one wants to find "the annualized present value of shareholder litigation risk" for any particular firm.

Using this new litigation risk proxy, our results are more intuitively appealing when compared with earlier studies. Specifically, we find that managers with bad news, facing higher *ex ante* litigation risk, are more likely to issue a bad news earnings forecast. This is consistent with the finding in Brown, Hillegeist, and Lo 2005, but is opposite to the finding in Johnson, Kasznik, and Nelson 2001 that bad news disclosures increase with the lowering of litigation risk. In contrast, firms with good news are not more likely to disclose such information in the presence of greater litigation risk. This is opposite to the finding in Brown, Hillegeist, and Lo 2005 that good news disclosures increased with increasing litigation risk. In addition to the likelihood of issuing forecasts, we also examine the effect of litigation risk on three forecast characteristics: forecast horizon, extent of news revealed in a forecast and forecast precision. We find that firms with higher litigation risk tend to issue earnings forecasts earlier during bad news periods as consistent with Brown, Hillegeist, and Lo 2005. However, they do not tend to behave differently with respect to forecast horizon in good news periods, in contrast to findings in prior studies (Baginski, Hassell, and Kimbrough 2002; Brown, Hillegeist, and Lo 2005). Firms also tend to reveal less news in good news forecasts relative to bad news forecasts when litigation risk is higher. With respect to forecast precision, our results suggest that when faced with greater litigation risk, companies are more precise (i.e., switching from qualitative forecasts to open-range, closed-range or point forecasts) with bad news forecasts. However, they tend to become less precise with good news forecasts relative to bad news forecasts. This contrast between the bad news and good news scenarios has not been documented by earlier studies (e.g., Brown, Hillegeist, and Lo 2005).

This study complements prior studies on the effect of litigation risk on forecasts in non-cross-sectional contexts. For example, Baginski, Hassell, and Kimbrough (2002) have a unique setting that exploits cross-country differences in litigation risk. They compare management forecasts across two litigation regimes – U.S. and Canada. They argue that, in Canada, companies face lower litigation risk than in the U.S. It is worth noting that Baginski, Hassell, and Kimbrough (2002), similar to the present study, also bypass the empirical estimation of *ex ante* litigation risk by using an indicator variable of country for legal regime (U.S. or Canada) to proxy for changing litigation risk. They find more good news forecasts and more bad news forecasts in the lower litigation risk regime (i.e., Canada). Our finding that the relationship between forecast likelihood and litigation risk differs between bad news and good news cases is in direct contrast to their results. A potential reason for the difference in results is as follows. Although Baginski, Hassell, and Kimbrough (2002) strengthen the validity of their litigation risk proxy by documenting similarities between the U.S. and Canada, cross-country non-litigation differences can still exist and significantly affect management forecast decisions. Such differences are less of an issue in this study.

In summary, this paper makes two contributions. First, it advances the extant literature by providing more intuitive results about the effect of litigation risk on voluntary disclosure compared to earlier studies in cross-sectional or cross-country context (e.g., Brown, Hillegeist, and Lo 2005; Baginski, Hassell, and Kimbrough 2002). Second, from a methodological perspective, this study introduces D&O insurance premium as an *ex ante* measure of litigation risk and thus mitigates the potential problems inherent in earlier studies that use *ex post* lawsuits to derive a firm's litigation risk.[1]

The rest of the paper proceeds as follows. Section 2 describes the typical research approach to measuring litigation risk and how the use of D&O insurance premium as a litigation risk proxy bypasses significant problems both conceptually and econometrically. Section 3 develops testable hypotheses. Section 4 presents the research design and introduces the econometric models. Section 5 discusses the empirical results and Section 6 concludes.

2. D&O insurance premium as a litigation risk proxy

A typical study of the effect of litigation risk on disclosure uses *ex post* lawsuits to get an *ex ante* measure of litigation risk.[2] In such a study, a litigation risk prediction model with the dependent variable being whether the firm got sued *ex post* is first estimated. Then, the predicted values of the probability of getting sued are used as *ex ante* measures of litigation risk in a model of voluntary disclosure. This methodology has two potential problems:[3] an inappropriate choice of the first-stage dependent variable and the use of in-sample tests.

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[1] See detailed discussion in Section 2.

[2] See, for example, Brown, Hillegeist, and Lo (2005), Johnson, Kasznik, and Nelson (2001), Rogers and Stocken (2005), and Atiase, Supattarakul, and Tse (2006). A notable exception, as discussed in the Section 1, is Baginski, Hassell, and Kimbrough 2002. By exploiting cross-country differences in litigation risk, they bypass problems with cross-sectional estimation of litigation risk.

[3] Management forecasts can themselves ultimately change litigation risk or the severity of the damages or judgments. And if they do, it is possible that insurance companies offer different premiums when managers commit to issuing forecasts. This in turn implies that the probability of issuing forecasts and the premiums for a given period should be determined using a simultaneous equation system. In our study (like most

First, the dependent variable is incorrectly specified in the first-stage estimation. Most studies that use actual lawsuits to estimate litigation likelihood ignore lawsuits filed in state courts. This can cause an underestimation of the actual litigation risk of a company. Grundfest and Perino (1997) report an increase in the number of lawsuits emerging in state courts after the passage of the PSLRA 1995. Most of the precedent-setting decisions regarding shareholder lawsuits have been taken by the judges in the state courts (especially, Delaware).[4] Besides not considering lawsuits in state courts, viewing all firms that got sued as equal treats frivolous and meritorious claims the same, potentially leading to incorrect estimation of the litigation risk model. An example of this effect can be seen in Field, Lowry, and Shu 2005, where their preliminary results on the association between disclosure and litigation risk change when all *ex post* dismissed claims are removed from their sample. It is also a little counter-intuitive that, in these studies, the same firm is treated as having high litigation risk in the quarter it is sued and as having low risk in the adjoining quarters. Given extant laws governing the statue of limitations (time available to file a lawsuit), it is likely that the alleged act provoking litigation and the actual litigation span different quarters.

Second, most studies use an approach of in-sample testing, where the first- and second-stage models are usually estimated using the same data. For example, Rogers and Stocken (2005) estimate a probit model for lawsuits from 1995 to 2000. Subsequently, they use the fitted values in a forecast errors regression for the same period (1995 to 2000) to show that managers forecast in a self-serving fashion when faced with litigation risk. Brown, Hillegeist, and Lo (2005) follow a similar approach. They estimate a logistic model of the probability of getting sued for firm quarters between 1996 and 2002. They use the fitted values from this model in a regression of voluntary disclosure for the period 1996 to 2002 and conclude that the probability of litigation affects management's decision to issue earnings forecasts. Such an approach faces the criticism that it assumes the managers knew the litigation risk model pertaining to 2002, when they made their management forecast decisions in 1996.

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others in this research field), we have not modeled it as a simultaneous equations system since we did not have appropriate instruments. Additionally, the small sample properties of simultaneous equation system are unknown.

[4] Comments of Harvey Pitt, former chairman of the Securities and Exchange Commission, at the Yale Law School (November 2005).

A possible solution to this criticism is that the second-stage model should encompass a time period different from the first stage. However, that solution is not perfect either. The litigation environment a company operates in is dynamically changing and evolving. There are changes in legislation, the performance of the economy, the way judges adjudicate and create precedence, and shareholder activism including but not limited to institutional activism. The dynamic nature of the litigation environment can be seen from the Tillinghast Survey 2002, which reports that in 1991 less than 20% of all shareholder-initiated claims were disclosure related. This changed in 2002 to nearly 50%. Another related problem is that a lawsuit is a relatively low probability event. For example, in the Brown, Hillegeist, and Lo 2005 sample, over a seven year period, there were only 972 firm-quarters with a lawsuit compared to 128,269 firm-quarters without a lawsuit. A lawsuit, being a low probability event, necessitates the use of a long enough estimation period in the first stage, which compounds the problems discussed above.

In this paper, we use the D&O liability insurance premium to measure *ex ante* litigation risk. In the U.S., firms routinely purchase D&O insurance coverage for their directors and officers for reimbursement of defense costs and settlements arising from litigations.[5] A typical D&O insurance policy[6] combines up to three types of insurance coverage: (1) personal coverage ("Side A" coverage), which provides direct payment to directors and officers when a firm cannot provide indemnification payments;[7] (2) corporate reimbursement coverage ("Side B" coverage), which reimburses the company when it indemnifies directors and officers for the costs of defending the lawsuits; and (3) entity coverage ("Side C" coverage), which has been available for many years to nonprofits and in recent years to for-profit companies, encompassing at least some claims against the organization directly, including those that name no insured individuals. The personal and corporate reimbursement coverage limits are usually the same. Entity coverage for direct

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[5] A possible criticism of the use of D&O insurance premium as a proxy for litigation risk is that managers' disclosure decisions themselves can be affected by whether they have insurance or not. However, as suggested by the Tillinghast 2002 Survey data, more than 97% of publicly listed firms in the survey have D&O insurance. As such, the taking or not of D&O insurance does not appear to be a decision variable for managers anymore.

[6] This description of a typical D&O Insurance policy draws upon the Tillinghast 2002 D&O survey report, Core 2000 and Baker and Griffith 2007.

[7] U.S. law allows indemnification against most claims. However, defense costs in certain shareholder derivative lawsuits where the directors and officers are sued by a party on behalf of the firm are not indemnifiable. Additionally, firms may be unable to bear the costs due to financial distress.

company liabilities usually carries a separate premium and retention. In this study, we focus on the aggregate insurance coverage of the first two types.

The D&O insurance premium, the price a firm pays the insurance carrier to get the coverage, is an *ex ante* litigation risk measure that incorporates information on both the expected magnitude of loss or damage recovery amount (through the choice of a D&O insurance limit) and the expected likelihood of such losses for the policy period (through the pricing of the chosen limit). It can bypass the aforementioned estimation problems associated with the use of *ex post* litigation incidence in the following ways. First, as D&O insurance policies are usually renewed on an annual basis, the D&O premium can be viewed as a timely measure of litigation risk. It thus dispenses with the need for a first-stage estimation of litigation risk and avoids associated problems such as in-sample testing and relying on events with low probability. Second, D&O insurance premiums, *ex ante,* should be able to differentiate between frivolous and meritorious claims as the former are likely to be dismissed and only have a minimal impact on the premium and consequently, on our estimate of litigation risk. The premium should also encompass expectation about both federal- and state-level claims. Finally, we are more comfortable with a litigation risk measure that is determined in a reasonably efficient market[8] than in an econometrically estimated measure. Despite the above advantages, not many studies use D&O insurance variables largely due to unavailability of firm-level data.

The use of D&O insurance premium, for all its advantages, is itself not without caveats. First, D&O insurance covers all types of claims, not just disclosure-related ones initiated by shareholders, even though these are the most frequent types of claims in shareholder litigation and incur significantly higher litigation costs (Tillinghast Survey 2002). Second, D&O policies normally exclude claims against directors and officers for actions made in bad faith, being fraudulent, or involving personal gain. If these claims have the greatest deterrence effect on management disclosure choices, using the D&O premium likely biases against

[8] Unlike the 1980s, the current market for D&O insurance is very liquid with several underwriters. The 2002 Tillinghast annual survey identifies five underwriters with at least 8% of the D&O insurance market by premium and ten underwriters with at least 2% of the market. In 2002, Arthur J Gallagher, a leading D&O insurance broker estimated that there were at least 47 underwriters competing in the marketplace ("The buyer's perception of D&O realities and latest trends", speech by Philip Norton, Arthur J Gallagher & Co., Tillinghast Executive Seminar 2004). These statistics point to the insurance pricing being reasonably efficient.

finding a link between the two by understating the true litigation risk. However, shareholder plaintiffs normally have little incentive to characterize claims into such a category, as it invalidates the primary source of payouts, the D&O insurance coverage (Romano 1990). Moreover, in a case that is so egregious that shareholders are determined to pursue D&O's personal wealth by claiming actual fraud, it is not clear whether *ex ante* a concern about litigation plays an important role in managers' forecast decisions. Finally, the D&O premium depends critically on the insurance limits chosen.[9] As such, we need to tease out the effect of any "abnormal limit" (the limit amount that cannot be explained by litigation risk factors) on the insurance premium before using the premium as an *ex ante* measure of litigation risk. We describe the model below.

We model the D&O insurance pricing using a two-stage approach similar to Core 2000 and Cao and Narayanamoorthy 2006. It is pertinent to point out that this two-stage model yields consistent estimates only under the assumption that there is no information asymmetry between insurers and managers.[10] Given the extensive scrutiny of the company and its directors and officers at every insurance renewal,[11] it is reasonable to assume minimal asymmetry between the company and the insurance carrier. Alexander (1991) suggests that D&O policies typically contain exclusions for active and deliberate dishonesty and improper personal benefit that protect the insurer from adverse information asymmetry. Such observation is also confirmed by Knepper and Bailey 1998. There are some exceptions to this assumption. For example, Chalmers, Dann, and Harford (2002) report that typically there are huge increases in insurance limits (or coverage is initiated) and premiums around the time a company makes an IPO. It is possible that, at this time, there may be some information asymmetries. As described later in Section 4, we have exercised caution in eliminating companies with significant potential information asymmetries.

[9] There is almost no variation in the deductibles (Tillinghast Surveys 2001 and 2002).
[10] For a detailed discussion of this point, see Core 2000.
[11] Based on in-depth interviews with D&O professionals including underwriters, brokers, actuaries, risk managers, lawyers, etc., Baker and Griffith (2007) provide insights into underwriters' thoroughness in the pricing of premiums.

Cao and Narayanamoorthy (2006), while investigating the determinants of litigation risk for U.S. firms, estimate a variant of the two-stage model developed by Core 2000. Following that study, we write the following equation for the insurance premium:

Premium = f (limit, deductible, litigation risk)

As suggested by the Tillinghast surveys, deductible for personal coverage is largely zero and is usually two percent of the limit on the corporate coverage portion. The absence of a menu of deductible options reinforces our belief that information asymmetries in this business are limited. Assuming that the above equation without the deductible is multiplicative, we can estimate it in logarithmic form as follows.

$$Log(premium) = a_0 + a_1\ Litigation\ Risk + a_2\ log\ (limit) + err \qquad (1)$$

When purchasing the D&O insurance, typically firms first choose the limit amount based on the litigation risk they face and then pay the corresponding premium agreed with the insurance company. Hence, we can rewrite *log(limit)* as follows:

$$Log(limit) = b_0 + b_1\ Litigation\ Risk + xlimit \qquad (2)$$

where *xlimit* is the residual term in equation (2). We call this variable *abnormal limit*, as it captures the limit taken over and above the amount that can be explained by litigation risk proxies.

Substituting (2) in (1) yields

$$Log\ (premium) = a_0 + b_0a_2 + (a_1+b_1a_2)\ Litigation\ Risk + a_2\ xlimit + err, \qquad (3)$$

which is estimated in its reduced form as:

$$Log(premium) = c_0 + c_1\ Litigation\ Risk + c_2\ xlimit + err \qquad (4)$$

From equation (4), we can see that in order to use the insurance premium as a litigation risk proxy in a regression of forecast choices, we also need to include *xlimit* to control for the effect of abnormal limit on the total premium.[12] When using equation (2) to arrive at an estimate for *xlimit*, we follow Cao and

[12] It is worth noting that if *xlimit* absorbs the effect of those litigation risk factors omitted from equation (2) on *log(limit)*, this will bias against finding a link between D&O insurance premium and managerial forecast decisions.

Narayanamoorthy 2006 and include three sets of litigation-risk-related factors as independent variables: business risk, corporate governance risk, and PSLRA risk.[13] We do deviate from Cao and Narayanamoorthy 2006 in one way. That study shows that risk variables related to quality of accounting are a significant determinant of litigation risk. However, one can argue against the inclusion of accounting related litigation risk in a study of voluntary disclosure since it is not clear that accounting irregularity related risks are relevant variables that are likely to influence managers' disclosure choices (Field, Lowry, and Shu 2005). In that case, the correct approach would be to include the accounting quality risk variables in both equation (2) and equation (4). We show that our base-case results on forecast likelihood are robust to this alternative specification in Section 5. In our tests of forecast characteristics, we have not included the quality of earnings in the limit regression to determine *xlimit* since the use of accounting quality risk variables such as the Dechow and Dichev 2002 quality of earnings measure (see Appendix 1 for definition) requires accounting data over a long time period and significantly reduces our sample size.

3. Hypotheses development

In this section, we discuss the implications of litigation risk for management's earnings forecasts and develop several testable hypotheses. We focus on the effect of litigation risk on the likelihood of issuing a forecast and on management's choice on three forecast characteristics: precision, horizon and the amount of earnings news released in the forecast. We develop our hypotheses by relying on the framework proposed by King, Pownall, and Waymire 1990. In their framework, the decision to issue a forecast or not is a stage A decision. The choice of public or selective disclosure is a stage B decision. This decision is no longer an issue after the promulgation in 2000 of Regulation Fair Disclosure ("Reg FD") which severely restricts selective disclosure. The characteristics of the forecast are stage C decisions and there is acute self-selection at this stage: the characteristics of forecasts are a relevant variable only for firms that choose to make a forecast. In our research design, we explicitly control for this self-selection by including the inverse Mills ratio estimated from the regressions for Stage A choices.

The effect of litigation risk on likelihood of management earnings forecasts

[13] We provide detailed discussion on these variables in Section 5.

Institutional arrangements penalize managers *ex post* for actions contrary to shareholder interests. Specifically, the stock exchanges require firms to immediately disclose any information expected to have a material effect on their stock prices. The anti-fraud provisions of the federal securities law provide substance to stock exchanges' timely disclosure rules. In particular, Rule 10b-5 of the Securities and Exchange Act of 1934 establishes liability for fraudulent practices in securities transactions. The scope of actionable conduct under this rule includes: … (3) disclosure misrepresentation, either overtly or in certain circumstances in maintaining silence (King, Pownall, and Waymire 1990). This part of the rule is the one most likely to affect management's forecasts.

King, Pownall, and Waymire (1990) first model management making earnings forecasts or not as a Stage A decision. In this context, several studies have examined the determinants, both litigation-risk-related and non-litigation-risk-related, of the likelihood of making management forecasts. For example, Nagar, Nanda and Wysocki (2003) investigate the incentives arising out of stock-based compensation while controlling for the level of litigation risk. Among litigation risk related studies, Baginski, Hassell, and Kimbrough (2002), comparing across different litigation regimes, find a greater forecast frequency of management earnings disclosure in Canada relative to the U.S. and attribute the finding to the difference in litigation risk across these regimes. In contrast, Brown, Hillegeist, and Lo (2005) find that firms, whether they have good news or bad news, are more likely to make earnings forecasts when faced with higher litigation risk. In light of this mixed evidence, and to facilitate comparison with studies of the determinants of management earnings forecasts, in the first hypothesis (hypothesis 1), we explicitly investigate the effect of litigation risk on the overall likelihood of management earnings forecasts irrespective of whether these were good news forecasts or bad news forecasts.

The likelihood of issuing an earnings forecast also depends on whether the forecast contains good news or bad news relative to the market's expectation. For better or worse, the litigation risk faced by managers is overwhelmingly asymmetric to whether the forecast has good news or bad news. Prior research has documented that litigations alleging non-disclosure of bad news far outweigh those alleging non-disclosure of good news (Palmiter 2002). Thus, in the presence of litigation risk, if the managers have bad news, they are more likely to voluntarily disclose this information via an earnings forecast in the face of high litigation risk. This can reduce the likelihood of being sued for not releasing the information in a timely fashion (Francis, Philbrick, and Schipper 1994; Skinner 1994). The voluntary disclosure can also reduce the expected settlement amount or damage award in the event of a successful lawsuit because the release of the information marks the end of the class period used to compute damages (Skinner 1997). As a result, we predict a positive relationship between litigation risk and the proclivity of managers to issue a bad news forecast (hypothesis 1a).[14] In contrast, if the forecast is going to be about good news, there is a possibility that it could initiate a lawsuit if subsequently managers fail to deliver the promised earnings. The aforementioned asymmetry suggests that shareholder litigation seldom target managers who have withheld good news. Hence, we expect managers to be more reluctant to issue a good news forecast when they face higher litigation risk (hypothesis 1b). We summarize the hypotheses on the relationship between forecast likelihood and litigation risk as follows:

HYPOTHESIS 1(Null Form). *The likelihood of issuing an earnings forecast is not associated with litigation risk.*

HYPOTHESIS 1a. *The likelihood of issuing a bad news forecast frequency is positively associated with litigation risk after controlling for the amount of underlying bad news.*

HYPOTHESIS 1b. *The likelihood of issuing a good news forecast is negatively associated with litigation risk after controlling for the amount of underlying good news.*

The effect of litigation risk on forecasts characteristics

Forecast horizon

Firms with bad news forecasts are likely to disclose earlier (thereby increasing forecast horizon) to avoid subsequent lawsuits alleging untimely disclosures, and to avoid costly settlements. Disclosing bad news early preempts allegations that managers withheld negative information (Skinner 1997). Additionally, the class period in a lawsuit typically ends on the news release date (Francis, Philbrick, and Schipper 1994;

[14] Note that a voluntary bad news forecast itself may precipitate shareholder lawsuits rather than providing deterrence or basis of dismissal (Francis, Philbrick, and Schipper 1994; Skinner 1997) if the firm operates in a highly litigious environment. In this light, it is likely that firms with higher litigation risk want to withhold the information and make less voluntary disclosure with the hope of turning things around eventually. However, we believe that the first force normally prevails in affecting the proclivity of managers to issue a bad news forecast.

Skinner, 1997), thereby decreasing potential liability. For good news forecasts, on the other hand, management incentives could be different as these forecasts have a greater chance of turning out optimistic with longer horizons since uncertainty increases with horizon. Thus, we expect bad news forecast horizon to increase with litigation risk (hypothesis 2a) and good news forecast horizon to decrease with litigation risk . It is possible that the empirical testing of these two separate hypotheses does not yield accurate results because of unknown correlated omitted variables that affect managers' forecast choices. As a logical extension of the litigation asymmetry assumption, we also test a corollary that if we use bad news forecasts as a benchmark, firms facing higher litigation risk tend to choose shorter forecast horizons for good news (corollary 2c). We summarize the testable hypotheses on forecast horizon below:

HYPOTHESIS 2a. *The horizon of bad news forecast is positively associated with litigation risk once managers decide to issue a forecast.*

HYPOTHESIS 2b. *The horizon of good news forecast is negatively associated with litigation risk once managers decide to issue a forecast.*

COROLLARY 2c. *Once managers decide to issue a forecast, the horizon of a good news forecast is shorter than that of a bad news forecast.*

Amount of earnings news disclosed in the forecasts

Disclosing all bad news promptly likely reduces the litigation probability by preempting allegations of untimely disclosures and by reducing the settlement amounts in the event of a successful lawsuit. This implies that firms are likely to disclose all bad news promptly when faced with litigation risk. Consistent with this theory, Soffer, Thiagarajan, and Walther (2000) find that bad news pre-announcements contain almost all the firms' bad news. On the other hand, it is also known that sharp stock price drops trigger lawsuits (Grundfest and Perino 1997). Gradual release of bad news can potentially ease the negative shock to the stock price and argues against complete release of all bad news. Taken together, however, we believe that the deterrence effect of full disclosure of bad news is still dominant and expect a positive relation between litigation risk and the amount of news released in an earnings forecast in the case of bad news (hypothesis 3a). For a good news case, complete release of such news leaves the possibility of a lawsuit in the event of *ex post* inability to meet forecasts. Thus, when faced with litigation risk, managers have incentives to only partially release the good news (hypothesis 3b). Given the directional prediction made above, it also follows that there is a lower association between earnings news released and litigation risk for good news forecasts relative to bad news forecasts (corollary 3c).[15] We present the hypotheses below.

HYPOTHESIS 3a. *There is a positive association between litigation risk and the amount of earnings news disclosed in a bad news forecast once managers decide to issue a forecast.*

HYPOTHESIS 3b. *There is a negative association between litigation risk and the amount of earnings news released in a good news forecast once managers decide to issue a forecast.*

COLLORARY 3c. *Once managers decide to issue a forecast, the association between the amount of earnings news released and litigation risk is lower for good news forecasts relative to bad news forecasts.*

Forecast precision

A more precise forecast for both good and bad news can open the door to subsequent litigation if the forecast turns out *ex post* optimistic (King, Pownall, and Waymire 1990). Issuing a forecast that encompasses a broad range of possible earnings numbers thus appears to benefit managers facing high litigation risk in both bad news (Hughes and Pae 2004; Hutton, Miller, and Skinner 2003; Skinner 1994) and good news cases. However, a more precise forecast for bad news can substantiate the firm's argument that it did not deliberately withhold information (Brown, Hillegeist, and Lo 2005). As such, we hypothesize that litigation risk will be positively related to forecast precision when firms have bad news (hypothesis 4a). On the other hand, when firms have good news, the asymmetry in shareholder lawsuits suggests that managers tend to make their forecasts less precise and thus less likely to turn out to be a negative surprise. We hypothesize a negative association between litigation risk and the precision of a good news forecast (hypothesis 4b). Based on the above arguments, we also predict that the association between litigation risk and forecast precision is greater for bad news forecasts relative for good news forecasts (corollary 4c).[16] Specifically, we test the following hypotheses:

[15] News is revealed even if a company reiterates that it agrees with the analysts' current consensus because the discount rate can be decreased due to reduced uncertainty of outcome. Under our model, we treat this setting as a zero-news case. However, we believe that in most cases such a setting would still convey less news than when the difference is significantly different from zero.

[16] Similar to the argument made before, another logical way to test the asymmetric effect of good and bad news is to examine whether firms tend to be more precise with bad news relative to good news in the face of higher litigation risk. This prediction is tested as a corollary of the hypotheses 4A and 4B: Once

HYPOTHESIS 4a. *There is a positive association between litigation risk and the precision of a bad news forecast once managers decide to issue a forecast.*

HYPOTHESIS 4b. *There is a negative association between litigation risk and the precision of a good news forecast once managers decide to issue a forecast.*

COROLLARY 4c. *Once managers decide to issue a forecast, the association between litigation risk and forecast precision is lower for good news forecasts relative to bad news forecasts.*

4. Research design

Litigation risk and likelihood of management earnings forecasts

We use a multivariate logistic regression model to test our hypotheses on the relation between litigation risk and the likelihood of management earnings forecasts. Besides litigation risk, managers have other incentives, including reputation costs associated with earnings surprises (Lowengard 1997; Tucker 2005) and contracting between managers and shareholders (Watts and Zimmerman 1986) that influence their disclosure decisions. In addition, there are other costs of voluntary disclosure such as the release of proprietary information (Verrecchia 1983; Dye 1985). These incentives are likely to be relatively less dynamic than the litigation environment. In our econometric design, we control for these additional incentives by using the lagged measure of the disclosure variable. Firms' disclosure decisions tend to be persistent (Field, Lowry, and Shu 2005) and are likely a result of decisions based on all these incentives. As such, Field, Lowry, and Shu (2005) argue that lagged disclosure is unlikely to affect a firm's current litigation risk. Cao and Narayanamoorthy (2006) provide empirical evidence confirming such an argument by showing that previous disclosures do not affect the pricing of D&O insurance.

Specifically, the model we use for the management earnings forecast likelihood is as follows.

$$
\begin{aligned}
Logit(Pr\{dfcast_{i,t} = 1\}) = b_0 + b_1\, log\_premium_{i,t} &+ b_2\, xlimit_{i,t} + b_3\, dfcast\_lag_{i,t} \\
&+ b_4\, log\_ana\_resid_{i,t} + b_5\, regulated_{i,t} + b_6\, retail\_ind_{i,t} \\
&+ b_7\, tech\_ind_{i,t} + \varepsilon_{i,t} \qquad (5)
\end{aligned}
$$

managers decide to issue a forecast, forecast precision is higher for bad news forecasts than good news forecasts.

In equation (5), *dfcast* is a dummy variable that equals one if there is at least one management earnings forecast (annual or quarterly) in the year covered by the insurance contract[17] and zero otherwise. Our litigation proxy, *log_premium,* is the natural logarithm of D&O insurance premium paid by a firm for a given policy year. *Xlimit* is the abnormal limit estimated using equation (2). An important control variable we include in the above regression is the dynamic information environment in which a firm operates. Most controls for the information environment are related to firm size. Our challenge was to find a proxy without incorporating the effect of firm size in the regression (e.g., directly using firm size as an independent variable), as size is a significant determinant of litigation risk (Cao and Narayanamoorthy 2006). We use an approach similar to Hong, Lim, and Stein 2000 to remove the effect of size from analyst coverage by estimating a regression of analyst coverage (*log_analyst*, defined as one plus the natural logarithm of number of analysts issuing earnings forecasts for a firm) on firm size (*log_mv*, measured as the natural logarithm of market value of equity). We then use the residual term (*log_ana_resid*) from that regression to proxy for the information environment.[18] We expect the likelihood of earnings forecasts to increase with *log_ana_resid*. We also included three dummy variables for retail, technology and regulated industries, as prior research (e.g., Field, Lowry, and Shu 2005) have suggested that the information environment for these firms is different than those in other industries. Specifically, *regulated* is defined as an indicator for whether a firm is in a regulated industry (2-digit SIC code is 49 or 1-digit SIC code is 6); *tech_ind* is an indicator for whether a firm is in the technology industry (SIC code in 2833-2836, 3570-3577, 3600-3674, 7371-7379 or 8731-8734); and *retail_ind* is an indicator for whether a firm is in the retail industry (SIC code between 5200 and 5961). Finally, we use *dfcast_lag*, a dummy variable for whether a firm issued at least one earnings forecast (annual or quarterly) in the preceding year, to control for any persistence in the pattern of forecast likelihood that can be attributable to non-litigation-risk determinants not explained by *log_ana_resid*, *regulated*, *tech_ind*, and *retail_ind*.[19]

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[17] The "year" refers to the one-year period starting from the effective date of a D&O insurance contract. It does not necessarily correspond to a firm's fiscal year.

[18] In estimating the analyst coverage regression, all the data take values on dates immediately preceding the effective date of a D&O insurance contract period. Hence, *log_ana_resid* predates forecast decisions, which are made during the year covered by a D&O insurance contract.

[19] Field, Lowry, and Shu (2005) argue that lagged management forecast(s) can be used purely as a control for managerial behavior. However, we note that this variable can also be determined by prior-period litigation risk that persists into the current period. Since that probability might not zero, the lagged forecast

We estimate two variants of equation (5) to test hypotheses on good news and bad news scenarios separately as follows.

$$Logit(Pr\{dbadnews_{i,t}=1\}) = b_0 + b_1\, log\_premium_{i,t} + b_2\, xlimit_{i,t} + b_3\, dfcast\_lag_{i,t} + b_4\, neps\_chg\_neg_{i,t} + b_5\, log\_ana\_resid_{i,t} + b_6\, regulated_{i,t} + b_7\, retail\_ind_{i,t} + b_8\, tech\_ind_{i,t} + \varepsilon_{i,t} \qquad (5a)$$

$$Logit(Pr\{dgoodnews_{i,t}=1\}) = b_0 + b_1\, log\_premium_{i,t} + b_2\, xlimit_{i,t} + b_3\, dfcast\_lag_{i,t} + b_4\, neps\_chg\_pos_{i,t} + b_5\, log\_ana\_resid_{i,t} + b_6\, regulated_{i,t} + b_7\, retail\_ind_{i,t} + b_8\, tech\_ind_{i,t} + \varepsilon_{i,t} \qquad (5b)$$

In equation (5a), *dbadnews* is an indicator variable that equals one if a firm made as least one "bad news" forecast (annual or quarterly) during the year covered by the insurance contract and zero otherwise. Similarly, in equation (5b) *dgoodnews* is an indicator variable that equals one if a firm made as least one "good news" forecast during the year. A forecast is said to contain "good news" if First Call views the forecast as a positive surprise and "bad news" if First Call does not qualify the forecast as a positive surprise. As a robustness check against potential bias in First Call's classification, we also use an alternative definition to categorize the nature of news. We compute the cumulative abnormal return (adjusting for CRSP value-weighted index return) for day [-2, 0] around the forecast date. We classify a forecast as having good news if the abnormal return is greater than zero and as having bad news if such return is non-positive. Accordingly, we call the two forecast-likelihood indicator variables defined along this dimension *dgoodnews_mkt* and *dbadnews_mkt*, respectively. Our methodology here is slightly different from the prior literature (e.g., Baginski, Hassell, and Kimbrough 2002; Brown, Hillegeist, and Lo 2005) in that we define our dependent variables based on the nature of the forecasted news and use two specifications (i.e., equations (5a) and (5b)) to separately address the good news and bad news scenarios. Previous studies, in contrast, normally use one general specification with the dependent variable being an indicator equal to one if managers issued a forecast during a given period, regardless of whether that forecast is consistent with the direction of underlying news or not.

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variable will likely absorb some effect of litigation risk on forecast decisions and bias against finding a significant coefficient on *log_premium*, our main proxy for *ex ante* litigation risk.

As the propensity to issue a bad (good) news forecast should be associated with the amount of underlying bad (good) news, we control for such news in both of the above equations. In equation (5a), we measure the incidence/magnitude of underlying bad news that can prompt a bad news forecast by *neps_chg_neg*, the number of non-positive seasonal changes (current-year number minus previous-year number, both split-adjusted) in quarterly earnings for the year in which the insurance contract is in effect. Similarly, in equation (5b) we define *neps_chg_pos* as the number of positive seasonal changes in quarterly earnings for the year.[20] Consistent with equation (5), we also control for non-litigation risk factors that can affect disclosure choices. Specifically, we include *dfcast_lag*, *log_ana_resid*, *regualted*, *tech_ind*, and *retail_ind* as control variables, all of which have been defined before.

Litigation risk and forecast properties

Forecast horizon

We use the following empirical model to test the implications of litigation risk on forecast horizon.

$$\begin{aligned} log\_horizon_{j,\tau} = {} & b_0 + b_1\, log\_premium_{j,\tau} + b_2\, goodnews_{j,\tau}{*}log\_premium_{j,\tau} + b_3\, goodnews_{j,\tau} \\ & + b_4\, d\_lag_{j,\tau} + b_5\, d\_lag_{j,\tau}{*}log\_horizon\_lag_{j,\tau} + b_6\, xlimit_{j,\tau} + b_7\, mills_{j,\tau} \\ & + b_8\, d\_annual_{j,\tau} + b_9\, log\_ana\_resid_{j,\tau} + b_{10}\, regulated_{j,\tau} + b_{11}\, retail\_ind_{j,\tau} \\ & + b_{11}\, tech\_ind_{j,\tau} + \varepsilon_{j,\tau} \qquad (6) \end{aligned}$$

In the above model, *log_horizon* is the natural logarithm of one plus the days between forecast date and actual report date for an annual or quarterly earnings forecast *j* made during the one-year period *t* covered by a D&O insurance contract. *Log_premium* is the natural logarithm of D&O premium a firm paid to obtain insurance coverage for the year. *Goodnews* is a dummy variable that equals one if First Call characterized the forecast as a positive earnings surprise and zero otherwise.[21] The coefficient on *log_premium* (b_1) tells us how litigation risk is related to forecast horizon in the bad news scenario, while the sum of coefficients

[20] The reason for using *neps_chg_pos* and *neps_chg_neg* are twofold. First, seasonal random-walk model produces reasonable estimates of earnings expectations (Kasznik and Lev 1995; Baginski, Hassell, and Kimbrough 2002). Second, we expect the likelihood of having a positive (non-positive) change in annual earnings increases with the number of positive (non-positive) changes in quarterly earnings.

[21] There could be concern that the nature of the news about earnings, *goodnews*, is also a forecast characteristic and should be jointly determined with forecast horizon, news amount revealed and precision. Following the King, Pownall, and Waymire (1990) framework, however, we have treated these as sequential decisions and leave the simultaneous treatment of these decisions to future research.

on *log_premium* and *goodnews*log_premium* ($b_1 + b_2$) indicates such relationship in the good news scenario. Coefficient b_3 reveals whether there is any difference across the two cases. *D_annual* is a dummy variable that equals one if the forecast is for annual earnings and zero for interim earnings. *D_lag* is an indicator variable that equals one if there is an earnings forecast regarding a similar fiscal period in the year covered by the preceding insurance contract period.[22] *Log_horizon_lag* is the natural logarithm of one plus the average horizon of lagged forecast(s) regarding a fiscal period end similar in nature.[23] As consistent with our research design for likelihood of issuing earnings forecasts, in addition to controls for information environment (proxied by *log_ana_resid*, *regulated*, *retail_ind* and *tech_ind*), we use the two lag variables, *d_lag* and *d_lag*log_horizon_lag* mainly as controls for all non-litigation risk related determinants of management earnings forecasts characteristics. For forecasts without lagged counterparts, the regression reduces to a version without *d_lag* and *log_horizon_lag*. We control for the first-stage self-selection by including in the regression the inverse Mills ratio (*mills*) computed from a probit regression of the likelihood of issuing a forecast on litigation risk similar to equation (5). The remaining variables, including *xlimit*, *log_ana_resid*, *regulated*, *retail_ind* and *tech_ind,* have been defined before.

Amount of earnings news disclosed

We use the following empirical model to test the implications of litigation risk on extent of news revealed in management earnings forecasts.

$$\begin{aligned} fcast\_diff_{j,\tau} = {} & b_0 + b_1\, log\_premium_{j,\tau} + b_2\, goodnews_{j,\tau}{*}log\_premium_{j,\tau} + b_3\, goodnews_{j,\tau} \\ & + b_4\, act\_diff_{j,\tau} + b_5\, d\_lag_{j,\tau} + b_6\, d\_lag_{j,\tau}{*}fcast\_diff\_lag_{j,\tau} + b_7\, xlimit_{j,\tau} \\ & + b_8\, mills_{j,\tau} + b_9\, d\_annual_{j,\tau} + b_{10}\, log\_ana\_resid_{j,\tau} + b_{11}\, regulated_{j,\tau} \\ & + b_{12}\, retail\_ind_{j,\tau} + b_{13}\, tech\_ind_{j,\tau} + \varepsilon_{j,\tau} \end{aligned} \tag{7}$$

[22] For example, for an annual earnings forecast made for the fiscal period ending on December 31, 2001during the 2001 insurance contract period, its lagged counterpart refers to an annual forecast made during the 2000 insurance contract period regarding the fiscal period ending on December 31, 2000. Also, earnings forecasts (made before a fiscal period end) and earnings preannouncements (made after a fiscal period end but before actual earnings report date) are treated as being different. *D_lag* should also be differentiated from *dfcast_lag* used in the forecast likelihood regressions (equations (5), (5a) and (5b)), as the latter is a general indicator of whether managers made *any* earnings forecast in the year covered by the insurance contract.

[23] In all of our definitions of lagged forecast characteristics, if for a given forecast there are more than one lagged counterparts, the lagged forecast characteristic variable takes the average value of all the lagged counterparts.

In the above model, *fcast_diff* is the split-adjusted difference between forecasted value (a point estimate or the mean of a range estimate) and the I/B/E/S consensus estimate. *Act_diff* is the split-adjusted difference between actual reported earnings and the I/B/E/S consensus estimate. *Fcast_diff* and *act_diff* capture the revealed (dependent variable) and underlying (control variable) differences between the true earnings number and the market expectation of earnings, respectively.[24] Similar to equation (6) on forecast horizon, we include *fcast_diff_lag* as a control variable, which is defined as the average *fcast_diff* for the forecast(s) made in the preceding year of insurance coverage regarding a similar fiscal period end. *Log_premium*, *goodnews*, *d_annual*, *d_lag* , *xlimit*, *mills*, *log_ana_resid*, *regulated*, *retail_ind* and *tech_ind* are included to control for non-litigation risk factors and have been defined before.

Forecast precision

We use the following two models to examine the effect of litigation risk on forecast precision.

$$\begin{aligned} Logit(Pr\{Precision\ (0/1)_{j,\tau} = 1\}) = {} & b_0 + b_1\, log\_premium_{j,\tau} + b_2\, goodnews_{j,\tau} * log\_premium_{j,\tau} \\ & + b_3\, goodnews_{j,\tau} + b_4\, d\_lag_{j,\tau} + b_5\, d\_lag_{j,\tau} * precision\_lag_{j,\tau} \\ & + b_6\, xlimit_{j,\tau} + b_7\, mills_{j,\tau} + b_8\, d\_annual_{j,\tau} \\ & + b_9\, log\_ana\_resid_{j,\tau} + b_{10}\, regulated_{j,\tau} + b_{11}\, retail\_ind_{j,\tau} \\ & + b_{12}\, tech\_ind_{j,\tau} + \varepsilon_{j,\tau} \qquad (8a) \end{aligned}$$

$$\begin{aligned} Precision\ (1\text{- to-}4)_{j,\tau} = G(& log\_premium_{j,\tau}, goodnews_{j,\tau} * log\_premium_{j,\tau}, goodnews_{j,\tau}, \\ & d\_lag_{j,\tau}, d\_lag_{j,\tau} * precision\_lag_{j,\tau}, xlimit_{j,\tau}, mills_{j,\tau}, d\_annual_{j,\tau}, \\ & log\_ana\_resid_{j,\tau}, regulated_{j,\tau}, retail\_ind_{j,\tau}, tech\_ind_{j,\tau}) \qquad (8b) \end{aligned}$$

In the first model (i.e., equation (8a)), we rely on a logistic regression with the dependent variable being binary. Specifically, *precision (0/1)* equals one if a forecast is quantitative (i.e., a point, open-range or closed-range estimate) and zero if qualitative. The assumption is that in general quantitative forecasts are more precise than forecasts that use qualitative terms to describe the earnings. In the second model (i.e.,

[24] Brown, Hillegeist, and Lo (2005) measure the "news amount revealed" as the difference between forecast value and consensus estimate, scaled by the difference between actual reported earnings and consensus estimate. Our original intent was also to use the ratio of these variables as a proxy for the extent of earnings news released, but we realized that the ratio becomes indeterminable when the denominator was close to zero, a rather frequent occurrence. As such, we included *act_diff* as a control variable instead of it being the denominator in a ratio.

equation (8b)), we use a multinomial logistic regression to study precision and define *precision (1-to-4)* as 1 for qualitative forecast, 2 for open-range forecasts, 3 for closed-range forecasts, and 4 for point estimates.[25] The second model on forecast precision can preserve more information without imposing a constraint of order on different precision categories. In both of the models, lagged precision (*precision_lag*) is defined in a way consistent with the dependent variable: in equation (8a) it is the lagged binary precision while in equation (8b) it is the lagged precision in a 1-to-4 scale. Other variables, including *log_premium*, *goodnews, d_annual, d_lag*, *xlimit*, *mills*, *log_ana_resid*, *regulated*, *retail_ind* and *tech_ind*, have been defined before.

To summarize, in equations (6) through (8) the main variables of interest are *log_premium* and *log_premium*good news*. A positive (negative) coefficient on *log_premium* will suggest that the forecast characteristic is increasing (decreasing) with litigation risk for bad news forecasts. A positive (negative) sum of the coefficients on *log_premium* and *log_premium*good news* will suggest that the forecast characteristic is increasing (decreasing) with litigation risk for good news forecasts. Finally, a positive coefficient on *log_premium * good news* will suggest that the forecast characteristic increases with litigation risk even more (decreases with litigation risk less) for good news forecasts than for bad news forecasts given that the coefficient on *log_premium* is positive (negative).

5. Empirical results

Sample selection

We obtain the data on D&O insurance limits and premiums from Tillinghast-Towers Perrin. The Investor Responsibility Research Center (IRRC) Directors database is our main source of the corporate governance data. We have also augmented our sample by hand collecting some corporate governance data from firms' proxy statements obtained at LexisNexis. We obtain stock return data from CRSP, institutional shareholding data from Thomson Financial, analyst forecast and coverage data from I/B/E/S, management

[25] It is pertinent to point out that sometimes a management forecast can confirm or adjust downward/upward market expectation in a non-numeric context yet convey the same information as a quantitative forecast.

earnings forecasts data from First Call and accounting data from Compustat, respectively. Appendix 2 summarizes the variable definitions and data sources.

As shown in Panel A of Appendix 3, Tillinghast D&O Insurance Surveys 2001 and 2002 cover 3169 firms altogether, among which 1236 are repeated respondents. After excluding non-publicly-traded, non-U.S. and financial firms, we get an initial sample of 552 firms. Due to confidentiality reasons, Tillinghast has withheld the names of the respondents. However, since we were furnished with survey data on revenues, assets, number of employees, after-tax loss, state of domicile and 2-digit SIC codes, we came up with a matching algorithm to identify respondents by searching in the Compustat annual database.[26] Panel B of Appendix 3 presents our matching criteria in detail. We start with a stringent matching process (Step 1) that requires a perfect match for assets, revenue, number of employees, 2-digit SIC and state code in Compustat for the year of interest and obtain 201 firms. Since the dates of Tillinghast surveys do not necessarily correspond to a respondent's fiscal year end, it is likely that when a respondent fills out the survey questions, the actual values of total assets, revenues and so on deviate from those reported at the fiscal year end. Hence, in Steps 2 through 9 we vary the matching criteria by relaxing certain group(s) of constraints. For example, in Step 2, we allow the difference between total assets reported by Compustat and Tillinghast to fall within ±10% of the value reported by Tillinghast. Similarly, in this step the constraints on revenue and number of employees are relaxed by ±10% and ±2%, respectively. This gives us another 47 unique matched firms and increases the sample size to 248. In some of the steps, the matching criterion includes the term "for both years", which means that we impose two sets of constraints on firm characteristics based on both 2001 and 2002 survey data in order to arrive at a matched identification. Performing Steps 1 9 altogether yields a matched sample of 323 unique firms.

Table 1 describes our final sample. Starting from the 552 publicly-traded non-financial U.S. firms included in Tillinghast surveys 2001 and 2002, we get 323 firms that can be successfully identified by matching with Compustat database. We then exclude firms that offered IPOs shortly before their insurance contracts took

[26] In accordance with our Data License Agreement with Tillinghast, we would like to add the following disclaimer: Tillinghast has not furnished the names of the respondents to their survey. The accuracy of the results depends on our ability to identify firms correctly.

effect. This is to reduce the incidence of any information asymmetry between the insurance carrier and the company as documented by Chalmers, Dann, and Harford 2002. Data availability constraints (CRSP, Compustat, IRRC directors database, hand collection, I/B/E/S, First Call and Thomson Financial) further reduce the sample to 203 firms. Of this final sample, 124 firms made 759 forecasts during the insurance contract periods that they report on Tillinghast surveys. For our test on the extent of news released in forecasts, we get 624 forecasts with available point or range earnings estimates to compute the variable.

Descriptive statistics

Table 2 provides summary statistics on the variables used in this study. Panel A presents the statistics on D&O insurance limit and premium, earnings forecast frequencies and other firm characteristics. The median and mean of the D&O limit amount (*totlim*) are $20 million and $37.68 million, respectively, with a standard deviation of 46.71. The mean (median) premium (*totprem*) paid for the coverage is $480,000 ($390,000). The average price of D&O insurance (*totprem/totlim*) paid for the coverage by sample firms is two cents per dollar of coverage and is lower than the average price paid by the IPO firms in Chalmers, Dann, and Harford 2002. The mean (median) size of the company, as measured by total market value (*mv*), is $3087.79 million ($652.31 million). Of the 297 firm-years, 58% contain at least one management earnings forecast and 18% (57%) contain at least one good news (bad news) forecast as defined by First Call's classification on the nature of news. There are on average more than seven analysts (*n_analyst*) issuing earnings forecasts for the sample firms, indicating a reasonable demand for information for the sample firms. Our estimation for *log_ana_resid*, the proxy for a firm's information environment net of size effect generates results comparable with Hong, Lim, and Stein 2000 and *log_ana_resid* has a median value of is 0.06 with standard deviation of 0.53.[27]

Panel B of Table 2 reports descriptive statistics on the forecast characteristics. For the 759 forecasts made by 124 firms, 95% are quantitative forecasts, 49% are forecasts of annual earnings, and the median forecast horizon is 100 days before actual earnings report date. A subset of 624 forecasts with point or range

[27] In the regression of analyst coverage on firm size, the coefficient on firm size (*log_mv*) is 0.36 and statistically significant at the 1% level (t-stat = 21.8). For comparison, in Hong, Lim, and Stein (2000) such coefficient is 0.54, with a t-stat of 52.67. The adjusted R-squared of our study is 0.665 while it is 0.610 in Hong, Lim, and Stein (2000).

estimate is used to compute the extent of news released in an earnings forecast. As discussed earlier, this variable is jointly captured by the difference between management forecast and consensus estimate (*fcast_diff*), and the underlying difference between actual earnings and consensus estimate (*act_diff*). The median value of *fcast_diff* is zero, indicating that the middle-level forecast value does not deviate from the proxy of market expectation. [28] *Act_diff* has a mean (median) of $-0.08 ($-0.02), suggesting that on average actual earnings fall below consensus estimates for the sample firms that chose to make a point or closed-range forecast. Panel C shows that the sample firms cover a broad range of industries and that manufacturing and service firms account for 51% and 31% of the sample, respectively.

Regression results

Computing the "abnormal limit" (xlimit) - Regression of D&O insurance limit on its determinants

Table 3 reports the estimation results for the regression of D&O insurance limit on its determinants (equation (2)).[29] The dependent variable is *log_limit*, the natural logarithm of D&O insurance limit for a given year. We include use three groups of litigation-risk related factors as explanatory variables and they all take values immediately preceding the effective date of the D&O insurance contract that specifies the coverage amount. First, we include variables related to business risk as follows. *Cumret* is the cumulative abnormal return (adjusted for CRSP value-weighted index return) for the preceding year. *Vol* is the standard deviation of daily stock returns for the previous year. *Turnover* is the average daily volume of shares traded as a percent of total shares outstanding for the previous year. *Lev* is total debt (debt included in current liabilities plus long-term debt) as a percentage of total assets. *Priorclaim* is a dummy variable equal to one if the company had any D&O claims in the past ten years and zero otherwise. *Risk_ind* is a dummy variable equal to one for all high risk industries identified in Francis, Philbrick, and Schipper 1994: biotechnology industry (SIC 2833-2836), computer hardware industry (SIC 3570-3577), electronics

[28] The mean of *fcast_diff* is 0.11, which seems to indicate that the average firm that chose to make a point or closed-range earnings forecast estimate did not successfully pull the market expectations down to avoid even the smallest negative surprise. However, a closer look at the data indicates that the number is largely attributable to those forecasts with *fcast_diff* in the upper 95 percentile ranging from1.04 to 3.79 (in direct contrast to the lower 95 percentile, where *fcast_diff* only ranges from -0.25 to -0.93). If we exclude these forecasts with extremely large magnitude of positive forecast bias, the mean of *fcast_diff* would decrease to 0.01.

[29] In all of the empirical results presented by Tables 3 through 7, firm size is winsorized at the levels of 1% and 99% to mitigate the influence of potential outliers as consistent with prior literature. The results are qualitatively unchanged without winsorizing.

industry (SIC 3600-3674), retailing industry (SIC 5200-5967) and computer software industry (SIC 7371-7379). *Log_mv* is the natural logarithm of market value in millions. Second, we include several variables proxying for corporate governance risk. *Ceo_cob* is a dummy variable equal to one if the Chief Executive Officer (CEO) is also Chairman of the Board and zero otherwise. *Log_ceo_exp* is the natural logarithm of one plus the number of years a CEO has served on the board. *Dir_out* is the number of outside directors as a percentage of total number of directors. *Dir_out_app* is the percentage of outside directors that start service on the board after the CEO joins the board. *Ins_value* is the percentage of inside directors' shareholding. Finally, to proxy for PSLRA related risk, we use *inst_block10*, an indicator variable equal to one if there is at least one institutional investor with shareholdings greater than ten percent.

Table 3 shows that the coefficients on *priorclaim, log_mv, lev, dir_out, dir_out_app,* and *ceo_cob* are all significantly positive. This suggests that firms purchase higher D&O insurance coverage if there has been a prior claim, if they are larger, if the chairman of the board and the CEO are the same, if the firm has higher level of debt as a percentage of total assets and if more outsiders are on the board of directors and have been appointed during the CEO's tenure on the board. This result is mostly intuitive, as these variables (except for *dir_out*) are hypothesized to be positively linked with business risk or governance risk. The positive coefficient on *dir_out* is consistent with the findings in Chalmers, Dann, and Harford 2002 and Cao and Narayanamoorthy 2006. From our discussions with D&O insurance industry participants, a potential explanation for this result is that firms tend to provide greater D&O insurance protection as a prerequisite to attract outside talent to the board. Table 3 also shows that *log_limit* is negatively related to *log_ceo_exp, vol* and *turnover*. Hence, firms choose less insurance limit if the CEO has had a long tenure on the board and if return volatility and turnover of their stocks are high.

Regressions of forecast likelihood on litigation risk

Table 4 presents the results from logistic regressions of likelihood of issuing all forecast(s), bad news forecast(s) and good news forecast(s). For each specification, we report coefficients (*coeff*), marginal effects estimated at the sample mean (*M.E.*) and z statistics (*z-stat*) based on Huber-White standard errors adjusting for firm-level clustering. The main variable of interest is litigation risk, proxied by *log_premium*.

The control for abnormal insurance limit a firm takes on, *xlimit*, comes from the regression of *log_limit* on its economic determinants reported in Table 3.

Panel A of Table 4 presents the logistic regression results on the likelihood of issuing an earnings forecast (*dfcast*). Model 1 shows that the coefficient on *log_premium* is significantly positive (coeff. = 0.36, z-stat = 2.11), suggesting that managers' general propensity of issuing an earnings forecast increases with litigation risk and thus rejecting the null form of hypothesis 1. This result remains robust after controlling for lagged forecast behavior (*dfcast_lag*) and information environment (*log_ana_resid, regulated, tech_ind* and *retail_ind*): in Model 2, the same coefficient is 0.31 and significantly positive (z-stat = 1.87). The residual analyst coverage, *log_ana_resid*, also has a significantly positive coefficient, indicating that greater information demand is related to greater likelihood of forecast disclosure.

Panels B and C of Table 4 report the regression results on the likelihood of issuing at least one bad news forecast (*dbadnews*) and the likelihood of issuing at least one good news forecast (*dgoodnews*), respectively. In both panels, Model 1 presents a base specification where *dbadnews* or *dgoodnews* is regressed upon litigation risk (*log_premium*), abnormal limit (*xlimit*) and the likelihood of forecast in the preceding year (*dfcast_lag*). In Model 2, we control for a firm's information environment by including *log_ana_resid*, *regulated*, *tech_ind* and *retail_ind,* and the underlying extent of news by including *neps_chg_neg* in Panel B and *neps_chg_pos* in Panel C, respectively. In Model 3, we check the robustness of our results by using the alternative definition of bad and good news based on abnormal returns around the forecast date. In other words, the dependent variables change to *dbadnews_mkt* in Panel B and *dgoodnews_mkt* in Panel C. In Model 4, we control for accounting risk by including the Dechow and Dichev 2002 earnings quality variable, *sresid* (see Appendix I for detailed estimation). Note that for this particular model, *sresid* is also included in the limit regression used to estimate *xlimit* (Table 3) as discussed in Section 2. The requirement for data availability to compute *sresid* reduces our sample to almost half and leads to 157 forecast observations used in Model 4.

The main finding from Panel B is that consistent with hypothesis 1a, litigation risk has a significantly positive association with the likelihood of issuing a bad news forecast after controlling for abnormal limit, past forecast behavior, information environment and underlying earnings news. Specifically, in Panel B the coefficient on *log_premium* is significantly positive in each of the models. The marginal effect for *log_premium* in Model 2 of Panel B is 0.10. This indicates that holding all explanatory variables at the level of sample mean, if premium increases by 50% (hence *log_premium* increases by 0.41), the likelihood of issuing a bad news forecast will increase by 0.41 times 0.10, which yields about four percent. This finding is robust to the alternative definition of the dependent variable (*dbadnews_mkt*, Model 3) and the inclusion of a control for accounting quality (*sresid*, Model 4). Another interesting result in Panel B is that *xlimit* is negatively associated with *dbadnews* in all of the specifications, suggesting that the likelihood of issuing a bad news forecast increases with the abnormal insurance coverage purchased by managers. A likely reason is that managers that are overly risk-averse tend to purchase coverage over and above those explained by litigation risk factors and they are also the ones who are more inclined to reveal the bad news if the firms' prospects do not look good. The proxy for information environment, *log_ana_resid* has a significantly positive association (coeff = 0.807, z-stat = 2.67 in Model 2) with the likelihood of issuing a bad news forecast, while results on other controls such as *regulated*, *retail_ind* and *tech_ind* are insignificant in the regressions. Turing to the likelihood of issuing good news forecasts, Panel C indicates that there is in general no statistically significant association between litigation risk and such likelihood. Specifically, none of the coefficients on *log_premium* is significant. Hence, hypothesis 1b is not supported by the data.

Taken together, our empirical results on forecast likelihood show that, in general, firms with higher litigation risk tend to be more likely to issue an earnings forecast. More importantly, we provide direct evidence that when faced with greater litigation risk firms are more likely to issue bad news forecasts, but are not more or less likely to issue good news forecasts.

Regressions of forecast characteristics on litigation risk

Tables 5 through 7 present the regression results on three forecast characteristics: forecast horizon, amount of news revealed and forecast precision. As discussed earlier, these characteristics are relevant only if the managers make the decision to issue an earnings forecast. Hence, this self-selection bias is corrected by including the inverse Mills ratio (*mills*) from estimating a probit model of the likelihood of issuing management earnings forecasts similar to Model 2 in Panel A, Table 4.

Table 5 reports the multivariate regression estimates for forecast horizon (*log_horizon*). The coefficient on *log_premium* is significantly positive (coeff = 0.087, t-stat = 1.80) as predicted by hypothesis 2a, suggesting that bad news forecasts are released earlier when a firm faces higher litigation risk. The F-test on the sum of coefficients on both *log_premium* and *goodnews*log_premium* (coeff = 0.145, F-test = 1.86) is insignificant. This suggest that in good news scenarios, litigation risk does not have a statistical association with managers' choice of forecast horizon. Thus, the results do not support hypothesis 2b. One possibility is that in these cases once managers decide to issue a forecast, what matters more is the forecast's content (e.g., news revealed) or format (e.g., quantitative vs. qualitative) rather than forecast horizon. The coefficient on *goodnews* log_premium* is insignificant as well, which means that firms with greater litigation risk does not reveal good news earlier or later than what they would do for bad news. The positive coefficient on *d_annual* is the expected result that forecasts for annual earnings have greater horizon than forecasts for interim earnings. Also, past horizon for similar forecasts (*d_lag*log_horizon_lag*) seems to persist into current-period choice (coeff = 0.282, t-stat = 5.338). The significant coefficient on *mills* shows the importance of correcting for self-selection. Finally, the controls for information environment are mostly significant. Specifically, firms with greater information demand (*log_ana_resid*) and in regulated industries (*regulated*) tend to issue forecasts later, while firms in the retail industry (*retail_ind*) tend to make forecasts earlier.

Table 6 presents the results for the extent of earnings news revealed in the forecast. We perform the multivariate regression for a smaller sample of 624 forecasts with point or closed-range estimates from which the dependent variable (*fcast_diff*) can be quantified. Consistent with our expectation, we find the proxy for the underlying difference between actual earnings and market expectation (*act_diff*) to be positively linked with *fcast_diff*, the proxy for revealed difference (coeff = 0.237, t-stat = 3.549). The coefficient on *log_premium* is insignificant, implying that in bad news periods firms with high litigation risk reveal more or less the same amount of earnings news as firms with low litigation risk. Hence, the results do not support hypothesis 3a. The F-test on the sum of coefficients on both *log_premium* and *goodnews*log_premium* is significant (coeff = - 0.159, F-test = 10.77), indicating that in good news periods managers reveal less news in their forecasts if they face greater litigation risk as predicted by hypothesis 3b. The coefficient on *goodnews*log_premium* is also significantly negative (coeff = -0.164, t –stat=-1.659). This suggests that bad news and good news differ significantly in their effect on the relationship between litigation risk and the amount of news released in an earnings forecast and thus confirms corollary 3c. Past forecast behavior in terms of news released, as captured by the interactive term *d_lag * fcast_diff_lag*, has a significantly positive association with *fcast_diff*. Finally, firms in the technology industry in general tend to release less news in their forecasts, as the coefficient on *tech_ind* is significantly negative.

Panel A of Table 7 reports the logistic regression of binary forecast precision (*precision 0/1*) on litigation risk. Due to multi-collinearity concerns, we have excluded the dummy for retail industries from this regression. The coefficient on *log_premium* at 0.712 is significantly positive (z-stat = 3.58). This strongly suggests that, as predicted by hypothesis 4a, firms with higher litigation risk are more likely to issue a quantitative forecast as opposed to qualitative forecast in bad news periods. When it comes to good news forecasts, the sum of coefficients on *log_premium* and *goodnews*log_premium* is negative but not significantly different from zero. This finding does not seem to support hypothesis 4b, which predicts that managers are more likely to issue a qualitative forecast when it is about good news. However, the results do support corollary 4c, as the coefficient on *goodnews*log_premium* has a value of -1.923 and statistically significant (z-stat = -3.91). This confirms our expectation that relative to bad news firms, good news firms faced with greater litigation risk would rather issue imprecise forecasts by making them qualitative. Finally, past forecast precision is positively related to current-period *precision (0/1)*, as indicated by the significantly positive coefficient on *d_lag*precision_lag*.

Panel B of Table 7 describes the multinomial logistic regression of forecast precision defined using a 1-to-4 scale. Qualitative forecasts (precision level coded as “1”) are used as a benchmark for the three sets of comparison. The results reinforce our findings in Panel C1. Except for the “*Precision 2 vs.1*” group, the coefficients on *log_premium* are significantly positive, indicating that in bad news periods firms with greater litigation risk are more likely to issue a point or closed-range forecast relative to qualitative forecast. In addition, moving from Precision 2 to Precision 4, the regression coefficient on *log_premium* becomes progressively more significant, which seems to suggest that litigation risk plays a more prominent role in prompting a switch from a qualitative forecast to a most precise type of quantitative forecast (i.e., point forecast). The three coefficients on *goodnews*log_premium* are all negative and significant. This confirms our earlier finding on the differential impact that good news scenarios (vs. bad news scenarios) can have on the relationship between litigation risk and forecast precision. In other words, as litigation risk increases, good news forecasts (relative to bad news forecasts) tend to become qualitative. Overall, the multinomial regression results validate our findings in the logistic regression. Faced with higher litigation risk, firms, with bad news, opt for more precise forecasts. Relative to bad news forecasts, firms, with good news, have less proclivity to make their forecasts more precise.

To summarize, the results in Tables 5, 6 and 7 suggest that firms with higher litigation risk tend to issue earnings forecast earlier when they have bad news. But these firms do not issue forecasts particularly earlier or later when they have good news. Firms in good news period reveal less news in the forecasts if facing higher litigation risk both in absolute sense and relative to bad news period. Finally, as litigation risk increases, earnings forecasts regarding bad news are more prone to be quantitative while earnings forecasts about good news are more likely to be qualitative. The contrast between the two scenarios is statistically significant. We also repeat the analysis on forecast characteristics by using the alternative definition of "good news" based on abnormal returns around forecast dates. The results (untabulated) are qualitatively similar.

5. Conclusion

We examine the effect of litigation risk on managers' decision to issue earnings forecasts. This effect is of interest to stock market participants, regulators and accounting standard setters. By choosing a new *ex ante* measure of litigation risk (i.e., the D&O liability insurance premiums), we bypass conceptual and econometric problems associated with using *ex post* litigation incidence to arrive at a proxy for litigation risk. Our results provide new insights into the relationship between litigation risk and management earnings forecasts. When faced with *ex ante* litigation risk, managers, with bad news, are more likely to issue an earnings warning. For firms with good news, we do not see this effect. We also examine the effect of litigation risk on three forecast characteristics: forecast horizon, extent of news revealed and forecast precision. Managers, facing litigation risk, issue bad news earnings forecasts earlier but do not issue good news forecasts particularly earlier or later. They also release less information in their good news forecasts. Finally, they tend to be more precise with bad news forecasts. They are also less precise with good news forecasts relative to bad news forecasts.

We believe that a caveat is in order regarding the forecast characteristics' results. As discussed earlier, we have not considered the interaction between the forecast characteristics. It is possible that all forecast characteristics are jointly determined. For example, it is possible that firms facing litigation risk release good news forecasts earlier and are imprecise about these forecasts, not because of litigation risk concerns, but, because they, themselves, are less certain about the forecasts. We plan to address the issue of joint determination in future research.

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Appendix 1: Computation of *sresid* using the Dechow-Dichev (2002) model

$$\Delta WC_t / \overline{TA}_t = b_0 + b_1 CFO_{t-1} + b_2 CFO_t + b_3 CFO_{t+1} + \varepsilon_t$$

where,

ΔWC =	change in working capitals (defined as change in accounts receivable + change in inventory – change in change in accounts payable + change in other operating assets (net));
CFO =	cash flow from operations scaled by average assets;
$\overline{TA}$ =	average total assets.

The above regression is estimated for each firm and each year using observations in six consecutive years on a rolling-window basis. *Sresid* is defined as the standard deviation of the six residual terms obtained from the regression. To avoid any hindsight bias, for year t, the *sresid* measure is based on the financial information available up to year t only. For example, *sresid* for 2001 is estimated by a regression linking ΔWC_{2000} with $CFO_{1999,}$ $CFO_{2000,}$ and CFO_{2001}, ΔWC_{1999} with $CFO_{1998,}$ $CFO_{1999,}$ and CFO_{2000} and so on.

Appendix 2: Variable Definition

Variables	Definition	Data Source
totlim	Total annual D&O insurance coverage limit ($Millions)	Tillinghast
totprem	Total annual D&O insurance premium ($Millions)	Tillinghast
log_limit	Natural logarithm of the D&O insurance limit (in $Millions)	Tillinghast
log_premium	Natural logarithm of the D&O insurance premium (in $Millions)	Tillinghast
xlimit	The residual term coming from a regression of *log_limit* on its determinants	-
log_mv	Natural logarithm of the market value of a firm's equity (in $Millions)	Compustat
vol	Standard deviation of daily stock returns for the previous year	CRSP
priorclaim	Indicator for whether the firm had D&O claims during the past 10 years, = 1 if yes; = 0 otherwise	Tillinghast
cumret	Cumulative abnormal returns (based on CRSP weighted index) for the previous year	CRSP
turnover	Average daily trading volume (in shares percentage) for the previous year	CRSP
lev	Total debt (debt in current liabilities plus long-term debt) as a percentage of total assets	Compustat
inst_block10	Indicator for whether there is at least one institutional investor with shareholdings greater than10%, = 1 if yes; = 0 otherwise	Thomson Financial
ins_value	Percentage of inside directors' shareholding	IRRC or Hand Collected
dir_out	Number of outside directors as a percentage of total number of directors	IRRC or Hand Collected
dir_out_app	Percentage of outside directors that start board service after the CEO joins the board	IRRC or Hand Collected
ceo_cob	Indicator for whether the CEO is also the chairman of the board, = 1 if yes; = 0 otherwise	IRRC or Hand Collected
log_ceo_exp	Natural logarithm of (1 + number of years the CEO has served on the board of directors)	IRRC or Hand Collected
risk_ind	Indicator for risky industries including biotechnology industry (SIC 2833-2836), computer hardware industry (SIC 3570-3577), electronics industry (SIC 3600-3674), retailing industry (SIC 5200-5967) and computer software industry (SIC 7371-7379); = 1 if yes; = 0 otherwise	Compustat
regulated	Indicator for whether a firm is in the regulated industry (2-digit SIC = 49 or 1-digit SIC = 6), = 1 if yes; = 0 otherwise	Compustat
tech_ind	Indicator for whether a firm is in the technology industry (SIC code in 2833-2836, 3570-3577, 3600-3674, 7371-7379 or 8731-8734), = 1 if yes; = 0 otherwise	Compustat
retail_ind	Indicator for whether a firm is in the retail industry (SIC code between 5200 and 5961), = 1 if yes; = 0 otherwise	Compustat
n_analyst	Number of analysts issuing earnings forecasts for a firm	I/B/E/S
log_ana_resid	The residual term coming from a regression of log(1+analyst coverage) on *log_mv*	I/B/E/S
sresid	Dechow and Dichev (2002) measure estimated at the firm level using six years of time-series data (see Appendix 1)	Compustat

Appendix 2 (Continued): Variable Definition

Variable	Definition	Data Source
dfcast	Indicator for whether a firm made any earnings forecasts for a given year, = 1 if yes; = 0 otherwise	First Call
dfcast_lag	Indicator for whether a firm made any earnings forecasts for the previous year, = 1 if yes; = 0 otherwise	First Call
dgoodnews	Indicator for whether a firm made at least one good news (qualified by First Call as a positive surprise) earnings forecast for a year, = 1 if yes; = 0 otherwise	First Call
dbadnews	Indicator for whether a firm made at least one bad news (not qualifying as a positive surprise) earnings forecast for a year, = 1 if yes; = 0 otherwise	First Call
goodnews	Indicator for whether an earnings forecast contains good news (qualified as a positive surprise), as defined by First Call, = 1 if yes; = 0 otherwise	First Call
dgoodnews_mkt	Indicator for whether a firm made at least one good news (with positive day [-2, 0] abnormal return) earnings forecast for a given year, = 1 if yes; = 0 otherwise	First Call, CRSP
dbadnews_mkt	Indicator for whether a firm made at least one bad news (with non-positive day [-2, 0] abnormal return) earnings forecast for a given year, = 1 if yes; = 0 otherwise	First Call, CRSP
neps_chg_pos	Number of positive seasonal changes in quarterly earnings for the year the insurance contract is in effect	Compustat
neps_chg_neg	Number of non-positive seasonal changes in quarterly earnings for the year the insurance contract is in effect	Compustat
horizon	Number of days between forecast date and actual report date	First Call
log_horizon	Natural logarithm of (1 + number of days between forecast date and actual report date)	First Call
precision (0/1)	Indicator for whether a management earnings forecast is quantitative (point, range or bound estimates)	First Call
precision (1- to-4)	=1 if a forecast is qualitative; = 2 if a forecast is open-range; = 3 if a forecast is closed-range; and = 4 if a forecast provides a point estimate.	First Call
fcast_diff	The difference between forecast value (the point estimate or the mean of a range estimate) and I/B/E/S consensus estimate	First Call & I/B/E/S
act_diff	The difference between actual reported earnings and I/B/E/S consensus estimate	First Call & I/B/E/S
d_lag	Indicator for whether there is a forecast in the preceding year regarding a similar fiscal period, = 1 if yes; = 0 otherwise	First Call
log_horizon_lag	For a given forecast, the natural logarithm of (1 + the average horizon for the forecasts made in the preceding year regarding a similar fiscal period end)	First Call
precision_lag	For a given forecast, the average *precision* for the forecasts made in the preceding year regarding a similar fiscal period end	First Call
fcast_diff_lag	For a given forecast, the average *fcast_diff* for the forecasts made in the preceding year regarding a similar fiscal period	First Call
d_annual	Indicator variable: = 1 if a forecast is regarding annual earnings; = 0 otherwise	First Call
mills	Inverse Mills ratio from a probit model on the likelihood of issuing management earnings forecasts	-

Appendix 3: Statistics on Firm Identification Process Using the Matching Algorithm

Panel A: Initial Sample:	**Number of firms**
Firms included in 2001 or 2002 Tillinghast surveys	3169
Firms included in both 2001 and 2002 Tillinghast surveys (repeated respondents)	1236
Firms publicly traded on a major stock exchange	634
U.S. firms publicly traded on a major stock exchange	596
Non-financial U.S. firms publicly traded on a major stock exchange	552

Panel B: Cumulative CUSIP Matching Results For the Initial Sample of 552 Non-Financial U.S. firms:	**Cumulative Number of Firms**
Step 1: Within ±0% assets, ±0% revenue and ±0% #employees, matching 2-digit SIC and state	201
Step 2: Within ±10% assets, ±10% revenue and ±2% #employees, matching 2-digit SIC and state	248
Step 3: Within ±20% assets, ±20% revenue and ±2% #employees, matching 2-digit SIC and state	260
Step 4: Within ±10% assets, ±10% revenue and ±2% #employees, matching 2-digit SIC and state, for both years	263
Step 5: Within ±20% assets, ±20% revenue and ±2% #employees, matching 2-digit SIC and state, for both years	263
Step 6: Within ±0% assets, ±0% revenue and ±5% #employees, matching 2-digit SIC code and state	290
Step 7: Within ±0% assets, ±0% revenue and ±5% #employees, matching 2-digit SIC code and state, for both years	294
Step 8: Within ±10% assets, ±10% revenue and ±10% #employees, matching 2-digit SIC, state, and year in business	318
Step 9: Within ±10% assets, ±10% revenue and ±10% #employees, matching 2-digit SIC, state, and after-tax loss	323

Note:
Panel A reports the initial sample we get from Tillinghast D&O Insurance Surveys 2001 and 2002. Tillinghast does not directly provide us the names of survey respondents but does furnish us with firm attributes such as total assets, revenue, number of employees, industry classifications and state code. Based on such information, we use a matching algorithm to identify each firm by searching in the Compustat annual database. As described in Panel B, we start with a stringent matching process that requires a perfect match for assets, revenue, number of employees, 2-digit SIC and state code (Step 1) in Compustat and obtain 201 firms. Since the dates of Tillinghast surveys do not necessarily correspond to a respondent's fiscal year end, it is likely that when a respondent fills out the survey questions, the actual values of total assets, revenues, etc. deviate from those reported at the fiscal year end. Hence, in Steps 2 to 9 we vary the matching criteria by relaxing certain group(s) of constraints. For example, in Step 2, we allow the difference between total assets reported by Compustat and Tillinghast to fall within ±10% of the value reported by Tillinghast. Similarly, constraints on revenue and number of employees are relaxed by ±10% and ±2%, respectively. This gives us another 47 unique matched firms and increases the sample size to 248. In some of the steps, the matching criterion includes the term "for both years", which means that we impose two sets of constraints on firm characteristics based on both 2001 and 2002 survey data in order to arrive at a matched identification. Steps 2 to 9 altogether lead to another 122 identified firms and increase the sample size to 323 firms.

Table 1 Sample Selection

	Number of Firms
Initial Sample:	
Non-financial firms included in the 2001 and 2002 Tillinghast Survey	552
Matched Sample	
Number of firms matched with SIC, assets, revenue, number of employees, state code, etc.	323
Data Availability Constraints	
Less: # of firms with IPO or without available data in Compustat, CRSP, I/B/E/S, Thomson Financial or First Call	(120)
Final Sample of Firms	**203**
Number of firms with forecast(s)	124
Number of firms without forecast(s)	79
Number of forecasts during the sample period	759
Number of forecasts with point or range estimates during the sample period	624

Note:
This table presents the sample selection criteria. Tillinghast D&O insurance surveys 2001 and 2002 cover 3169 firms, among which 1236 are repeated respondents. After excluding non-publicly-traded, non-U.S. and financial firms, we get an initial sample of 552 firms. We then perform a matching algorithm that incorporates matching criteria on assets range, revenue range, number of employees, state code, 2-digit SIC code, year in business and after-tax loss (all of which are reported by the Tillinghast survey) and get a matched sample of 323 firms (see Appendix 3 for details). Data availability constraints further reduce the sample to 203 firms (124 firms with forecasts and 79 firms without forecasts in the sample period).

Table 2 Summary Statistics

Panel A: D&O insurance and firm characteristics (297 firm-year observations)

Variable	*Q1*	*Median*	*Q3*	*Mean*	*Stdev*
totlim (in $millions)	10.00	20.00	50.00	37.68	46.71
totprem (in $millions)	0.19	0.39	0.64	0.48	0.41
totprem/totlim	0.01	0.02	0.03	0.02	0.02
log_limit	2.30	3.00	3.91	3.06	1.06
log_premium	-1.67	-0.93	-0.45	-1.09	0.90
mv (in $millions)	118.11	652.31	2288.90	3087.79	7612.73
log_mv	4.77	6.48	7.74	6.30	2.08
vol	0.03	0.06	0.08	0.06	0.03
cumret	-0.26	0.28	0.66	0.23	0.81
priorclaim	0.00	0.00	0.00	0.21	0.40
turnover	0.00	0.01	0.01	0.01	0.01
risk_ind	0.00	0.00	1.00	0.49	0.50
lev	0.00	0.04	0.25	0.14	0.19
inst_block10	0.00	0.00	1.00	0.27	0.45
dir_out	0.50	0.60	0.75	0.60	0.18
dir_out_app	0.14	0.67	1.00	0.55	0.39
ceo_cob	0.00	1.00	1.00	0.60	0.49
log_ceo_exp	1.39	1.95	2.56	1.89	0.80
ins_value	0.00	0.03	0.08	0.08	0.15
n_analyst	2.00	5.00	11.00	7.36	6.78
log_ana_resid	-0.32	0.06	0.32	0.00	0.53
regulated	0.00	0.00	0.00	0.08	0.28
tech_ind	0.00	0.00	1.00	0.48	0.50
retail_ind	0.00	0.00	0.00	0.02	0.14
dfcast	0.00	1.00	1.00	0.58	0.49
dfcast_lag	0.00	1.00	1.00	0.56	0.50
dgoodnews	0.00	0.00	0.00	0.18	0.39
dgoodnews_mkt	0.00	0.00	1.00	0.43	0.50
dbadnews	0.00	1.00	1.00	0.57	0.50
dbadnews_mkt	0.00	0.00	1.00	0.49	0.50
neps_chg_neg	1.00	2.00	3.00	2.01	1.36
neps_chg_pos	1.00	2.00	3.00	1.96	1.37

Table 2 (Continued) Summary Statistics

Panel B: Forecast Properties

Overall sample (759 forecasts for 124 firms):

Variable	*Q1*	*Median*	*Q3*	*Mean*	*Stdev*
d_annual	0.00	0.00	1.00	0.49	0.50
d_lag	0.00	0.00	1.00	0.49	0.50
goodnews	0.00	0.00	0.00	0.13	0.34
horizon	48.5	100.0	278.5	166.2	146.6
precision	1.00	1.00	1.00	0.95	0.21

precision on a 1-to-4 scale:	*Number of forecasts*	*Percentage*
1: qualitative	36	4.7%
2: open-range	34	4.5%
3: closed-range	531	70.0%
4: point	158	20.8%

Sub-sample with point or range estimates to compute news amount released (624 forecasts for 112 firms):

Variable	*Q1*	*Median*	*Q3*	*Mean*	*Stdev*
fcast_diff	-0.05	0.00	0.05	0.11	0.490
act_diff	-0.11	-0.02	0.03	-0.08	0.270

Panel C: Industry Distribution

1-Digit SIC	***Industry Name***	***D&O Insurance & Forecast Sample (297 firm-years)***		***Forecast Characteristic Sample (759 forecasts)***	
		# of obs	*% of obs*	*# of obs*	*% of obs*
1	Mining & Construction	9	3.0%	26	3.4%
2 & 3	Manufacturing	151	50.8%	280	36.9%
4	Transportation & Public Utilities	34	11.4%	161	21.2%
5	Wholesale & Retail	10	3.4%	66	8.7%
7 & 8	Services	93	31.3%	226	29.8%
		297	100.0%	759	100.0%

Note:
This table presents the descriptive statistics of the sample. Panel A presents the summary statistics on 297 firm-year observations for the 203 sample firms that meet the sample selection criteria described in Table 1. Panel B reports the summary statistics on forecast properties for 759 forecasts made by a subset of 124 firms that chose to issue at least one forecast during the sample period. It also shows the summary statistics for 624 point or range forecasts made by 112 firms during the sample period. Panel C shows the industry distribution of the sample firms. Variables are as defined in Appendix 2.

Table 3 Computing the "Abnormal Limit" (*xlimit*): Regression of D&O Insurance Limits on Economic Factors

$$log\_limit_{i,t} = b_0 + b_1\ cumret_{i,t} + b_2\, vol_{i,t} + b_3\, turnover_{i,t} + b_4\, inst\_block10_{i,t} + b_5\, lev_{i,t}$$

$$+ b_6\, log\_ceo\_exp_{i,t} + b_7\, priorclaim_{i,t} + b_8\, risk\_ind_{i,t} + b_9\, log\_mv_{i,t} + b_{10}\, ceo\_cob_{i,t}$$

$$+ b_{11}\, dir\_out_{i,t} + b_{12}\, dir\_out\_app_{i,t} + b_{13}\, ins\_value_{i,t} + \varepsilon_{i,t}$$

Independent Variable	***coefficient***	***t-stat***
Intercept	1.451***	[4.765]
cumret	0.045	[1.171]
vol	-7.721***	[-3.660]
turnover	-13.119***	[-2.730]
inst_block10	-0.033	[-0.395]
lev	0.647**	[2.542]
log_ceo_exp	-0.266***	[-3.337]
priorclaim	0.176*	[1.938]
risk_ind	-0.072	[-0.842]
log_mv	0.312***	[13.065]
ceo_cob	0.220***	[2.657]
dir_out	0.496*	[1.839]
dir_out_app	0.328*	[1.921]
ins_value	0.136	[0.501]
Adj. R-squared	0.719	
# observations	297	

Notes:

This table presents the regression of D&O limits on economic factors. The residual term ε from this regression is called "abnormal limit", or *xlimit*. It captures the limit taken over and above the amount that can be explained by litigation risk proxies and is used as a control variable in the subsequent analysis.

The sample includes 297 firm-year observations with available data on D&O insurance characteristics and economic factors for 203 firms that meet the sample selection criteria described in Table 1.

Variables are as defined in Appendix 2. The values of the independent variables are measured immediately before the effective date of the D&O insurance contract.

***, **, and * denote significance at the 1%, 5%, and 10% levels of a two-tailed t-test, respectively. The statistics are based on Huber-White standard errors adjusting for firm-level clustering.

Table 4 Logistic regressions of likelihood of issuing forecasts, good news forecasts and bad news forecasts on litigation risk (hypotheses 1)

Panel A: Logistic regressions of likelihood of issuing forecasts on litigation risk

Model 1: $Logit(Pr\{dfcast_{i,t} = 1\}) = b_0 + b_1\, log\_premium_{i,t} + b_2\, xlimit_{i,t} + b_3\, dfcast\_lag_{i,t} + \varepsilon_{i,t}$

Model 2: $Logit(Pr\{dfcast_{i,t} = 1\}) = b_0 + b_1\, log\_premium_{i,t} + b_2\, xlimit_{i,t} + b_3\, dfcast\_lag_{i,t} + b_4\, log\_ana\_resid_{i,t} + b_5\, regulated_{i,t}$

$+ b_6\, retail\_ind_{i,t} + b_7\, tech\_ind_{i,t} + \varepsilon_{i,t}$

		Model 1			Model 2		
	Predicted Sign	***coeff***	***M.E.***	***z-stat***	***coeff***	***M.E.***	***z-stat***
Intercept		-0.407		-1.38	-0.265		-0.73
log_premium	+/- (H1)	0.355**	0.08	2.11	0.309*	0.07	1.87
xlimit		-0.465	-0.11	-1.61	-0.511*	-0.13	-1.71
dfcast_lag		2.154***	0.33	7.65	1.984***	0.32	7.00
log_ana_resid					0.742**	0.16	2.54
regulated					0.744	0.16	0.89
retail_ind					-0.069	-0.02	-0.07
tech_ind					-0.311	-0.08	-1.02
Likelihood ratio (p-value)		82.287 (<0.0001)			94.215 (<0.0001)		
Pseudo Adj. R^2		0.325			0.366		
# of obs		297			297		

Table 4 (Continued) Logistic regressions of likelihood of issuing forecasts, good news forecasts and bad news forecasts on litigation risk (hypotheses 1)

Panel B: Logistic regressions of likelihood of issuing bad news forecasts on litigation risk

Model 1: $Logit(Pr\{dbadnews_{i,t} = 1\}) = b_0 + b_1\, log\_premium_{i,t} + b_2\, xlimit_{i,t} + b_3\, dfcast\_lag_{i,t} + \varepsilon_{i,t}$

Model 2: $Logit(Pr\{dbadnews_{i,t} = 1\}) = b_0 + b_1\, log\_premium_{i,t} + b_2\, xlimit_{i,t} + b_3\, dfcast\_lag_{i,t} + b_4\, neps\_chg\_neg_{i,t} + b_5\, log\_ana\_resid_{i,t}$

$+ b_6\, regulated_{i,t} + b_7\, retail\_ind_{i,t} + b_8\, tech\_ind_{i,t} + \varepsilon_{i,t}$

Model 3: $Logit(Pr\{dbadnews\_mkt_{i,t} = 1\}) = b_0 + b_1\, log\_premium_{i,t} + b_2\, xlimit_{i,t} + b_3\, dfcast\_lag_{i,t} + b_4\, neps\_chg\_neg_{i,t} + b_5\, log\_ana\_resid_{i,t}$

$+ b_6\, regulated_{i,t} + b_7\, retail\_ind_{i,t} + b_8\, tech\_ind_{i,t} + \varepsilon_{i,t}$

Model 4: $Logit(Pr\{dbadnews_{i,t} = 1\}) = b_0 + b_1\, log\_premium_{i,t} + b_2\, xlimit_{i,t} + b_3\, dfcast\_lag_{i,t} + b_4\, neps\_chg\_neg_{i,t} + b_5\, log\_ana\_resid_{i,t}$

$+ b_6\, regulated_{i,t} + b_7\, retail\_ind_{i,t} + b_8\, tech\_ind_{i,t} + b_9\, sresid_{i,t} + \varepsilon_{i,t}$

		Model 1			***Model 2***			***Model 3***			***Model 4***		
	Predicted Sign	***coeff***	***M.E.***	***z-stat***	***coeff***	***M.E.***	***z-stat***	***coeff***	***M.E.***	***z-stat***	***coeff***	***M.E.***	***z-stat***
Intercept		-0.296		-1.01	-0.250		-0.62	-0.457		-1.15	-0.596		-0.89
log_premium	+ (H1a)	0.452***	0.10	2.69	0.410**	0.10	2.46	0.347**	0.09	2.01	0.667***	0.14	2.95
xlimit		-0.577**	-0.14	-2.02	-0.615**	-0.15	-2.09	-0.485*	-0.12	-1.73	-1.152**	-0.28	-2.58
dfcast_lag		2.000***	0.33	7.19	1.823***	0.32	6.50	1.525***	0.33	5.39	2.481***	0.33	5.15
neps_chg_neg					0.03	0.01	0.28	-0.0002	0.00	0.00	-0.094	-0.02	-0.61
log_ana_resid					0.807***	0.18	2.67	0.500*	0.12	1.77	0.754*	0.16	1.70
regulated					0.548	0.13	0.75	1.259	0.28	1.55	1.379	0.25	1.57
retail_ind					0.115	0.03	0.11	0.705	0.17	0.67	-0.167	-0.04	-0.15
tech_ind					-0.212	-0.05	-0.70	-0.377	-0.09	-1.27	-0.711	-0.18	-1.49
sresid											29.793**	0.38	2.56
Likelihood ratio	*(p-value)*	77.296 (<0.0001)			88.524 (<0.0001)			74.483 (<0.0001)			68.958 (<0.0001)		
Pseudo Adj. R^2		0.307			0.346			0.296			0.479		
# of obs		297			297			297			157		

Table 4 (Continued) Logistic regressions of likelihood of issuing forecasts, good news forecasts and bad news forecasts on litigation risk (hypotheses 1)

Panel C: Logistic regressions of likelihood of issuing good news forecasts on litigation risk

Model 1: $Logit(Pr\{dgoodnews_{i,t} =1\}) = b_0 + b_1\ log\_premium_{i,t} + b_2\ xlimit_{i,t} + b_3\ dfcast\_lag_{i,t} + \varepsilon_{i,t}$

Model 2: $Logit(Pr\{dgoodnews_{i,t} =1\}) = b_0 + b_1\ log\_premium_{i,t} + b_2\ xlimit_{i,t} + b_3\ dfcast\_lag_{i,t} + b_4\ neps\_chg\_pos_{i,t} + b_5\ log\_ana\_resid_{i,t}$

$+ b_6\ regulated_{i,t} + b_7\ retail\_ind_{i,t} + b_8\ tech\_ind_{i,t} + \varepsilon_{i,t}$

Model 3: $Logit(Pr\{dgoodnews\_mkt_{i,t} =1\}) = b_0 + b_1\ log\_premium_{i,t} + b_2\ xlimit_{i,t} + b_3\ dfcast\_lag_{i,t} + b_4\ neps\_chg\_pos_{i,t} + b_5\ log\_ana\_resid_{i,t}$

$+ b_6\ regulated_{i,t} + b_7\ retail\_ind_{i,t} + b_8\ tech\_ind_{i,t} + \varepsilon_{i,t}$

Model 4: $Logit(Pr\{dgoodnews_{i,t} =1\}) = b_0 + b_1\ log\_premium_{i,t} + b_2\ xlimit_{i,t} + b_3\ dfcast\_lag_{i,t} + b_4\ neps\_chg\_pos_{i,t} + b_5\ log\_ana\_resid_{i,t}$

$+ b_6\ regulated_{i,t} + b_7\ tech\_ind_{i,t} + b_8\ sresid_{i,t} + \varepsilon_{i,t}$

	Predicted	***Model 1***			***Model 2***			***Model 3***			***Model 4***		
	Sign	***coeff***	***M. E.***	***z-stat***	***coeff***	***M.E.***	***z-stat***	***coeff***	***M.E.***	***z-stat***	***coeff***	***M.E.***	***z-stat***
Intercept		-2.692***		-4.92	-2.366***		-3.91	-1.052**		-2.42	-2.813***		-2.95
log_premium	- (H1b)	0.138	0.02	0.51	0.200	0.02	0.80	0.251	0.06	1.58	-0.189	-0.02	-0.57
xlimit		0.178	0.02	0.50	0.175	0.02	0.44	-0.400	-0.09	-1.43	0.083	0.01	0.16
dfcast_lag		1.872***	0.38	4.18	1.707***	0.32	3.81	1.695***	0.38	5.91	1.730**	0.32	2.34
neps_chg_pos					0.072	0.01	0.58	0.025	0.01	0.24	0.047	0.01	0.29
log_ana_resid					0.834**	0.12	2.30	0.523*	0.13	1.83	0.296	0.04	0.59
regulated					-0.118	-0.01	-0.18	1.071	0.26	1.59	0.467	0.06	0.64
retail_ind					-1.472	-0.09	-1.23	0.036	0.01	0.03			
tech_ind					-0.856**	-0.07	-2.15	-0.239	-0.06	-0.83	-1.387	-0.09	-1.63
sresid											-9.381	-0.12	-0.63
Likelihood ratio (p-value)		30.955 (<0.0001)			44.295 (<0.0001)			71.912 (<0.0001)			22.933 (0.004)		
Pseudo Adj. R^2		0.162			0.226			0.288			0.221		
# of obs		297			297			297			157		

Notes:

Panel A presents the logistic regression of likelihood of issuing forecast on litigation risk and control variables. It shows the results of two specifications (Models 1 and 2) with different sets of control variables.

Panel B presents the logistic regression of likelihood of issuing bad news forecast on litigation risk and control variables. In Models 1, 2 and 4, the dependent variable *dbadnews* is based on First Call's classification of the nature of forecasts. In Model 3, the dependent variable *dbadnews_mkt* is based on market responses to forecasts. Model 4 controls for the Dechow and Dichev 2002 earnings quality variable, *sresid*, and is based on a sub-sample of 157 firm-years with available data to compute *sresid*. In this model, the control variable *xlimit* is based on a first-stage regression of D&O insurance limit on its economic determinants that also include *sresid*.

Panel C presents the logistic regression of likelihood of issuing good news forecast on litigation risk and control variables. In Models 1, 2 and 4, the dependent variable *dgoodnews* is based on First Call's classification of the nature of forecasts. In Model 3, the dependent variable *dgoodnews_mkt* is based on market responses to forecasts. Model 4 controls for the Dechow and Dichev 2002 earnings quality variable, *sresid*, and is based on a sub-sample of 157 firm-years with available data to compute *sresid*. In this model, the control variable *xlimit* is based on a first-stage regression of D&O insurance limit on its economic determinants that also include *sresid*.

Variables are as defined in Appendices 1 and 2. In each model, coefficients (*coeff*), marginal effects (*M.E.*) at the mean levels of independent variables and z-statistics (*z-stat*) are reported. ***, **, and * denote significance at the 1%, 5%, and 10% levels of a two-tailed t-test, respectively, based on Huber-White standard errors adjusting for firm-level clustering.

Table 5 Litigation risk and forecast properties - forecast horizons (hypotheses 2)

$$log\_horizon_{j,\tau} = b_0 + b_1\,log\_premium_{j,\tau} + b_2\ goodnews_{j,\tau} * log\_premium_{j,\tau} + b_3\,goodnews_{j,\tau} + b_4\,d\_lag_{j,\tau}$$

$$+ b_5\ d\_lag_{j,\tau} * log\_horizon\_lag_{j,\tau} + b_6\ xlimit_{j,\tau} + b_7\,mills_{j,\tau} + b_8\,d\_annual_{j,\tau}$$

$$+ b_9\,log\_ana\_resid_{j,\tau} + b_{10}\,regulated_{j,\tau} + b_{11}\,retail\_ind_{\,j,\tau} + b_{12}\,tech\_ind_{\,j,\tau} + \varepsilon_{j,\tau}$$

Independent Variable	***Predicted Sign***	***Coefficient***	***t-stat***
Intercept		3.720***	[29.812]
log_premium	+ (Hypothesis 2a)	0.087*	[1.802]
*goodnews * log_premium*	- (Corollary 2c)	0.058	[0.334]
goodnews		0.154	[1.066]
d_lag		-0.843***	[-3.231]
*d_lag * log_horizon_lag*		0.282***	[5.338]
xlimit		-0.078	[-1.194]
mills		0.417**	[2.381]
d_annual		1.063***	[11.769]
log_ana_resid		0.159**	[2.380]
regulated		-0.161**	[-2.052]
retail_ind		0.135**	[1.973]
tech_ind		-0.040	[-0.492]
$b_1 + b_2$	- (Hypothesis 2b)	0.145	*F-test on ($b_1 + b_2 = 0$): 1.86 (p-value = 0.173)*
Adj. R-squared		0.464	
Number of observations		759	

Notes:
Table 5 presents the multivariate regression of one of the forecast properties, forecast horizons, on litigation risk and control variables. The sample includes 759 forecasts made by a subset of 124 firms that chose to issue at least one forecast during the sample period.

Variables are as defined in Appendix 2. ***, **, and * denote significance at the 1%, 5%, and 10% levels of a two-tailed t-test, respectively, based on Huber-White standard errors adjusting for firm-level clustering. The inverse Mills ratio (*mills*) is based on the model of forecast likelihood in Table 4 (Panel A, Model 2).

Table 6 Litigation risk and forecast properties - amount of news released in forecasts (hypotheses 3)

$$fcast\_diff_{j,\tau} = b_0 + b_1\, log\_premium_{j,\tau} + b_2\; goodnews_{j,\tau} * log\_premium_{j,\tau} + b_3\, goodnews_{j,\tau} + b_4\, act\_diff_{j,\tau}$$
$$+ b_5\, d\_lag_{\,j,\tau} + b_6\, d\_lag_{j,\tau} * fcast\_diff\_lag_{j,\tau} + b_7\; xlimit_{j,\tau} + b_8\, mills_{j,\tau} + b_9\, d\_annual_{j,\tau}$$
$$+ b_{10}\, log\_ana\_resid_{j,\tau} + b_{11}\, regulated_{j,\tau} + b_{12}\, retail\_ind_{j,\tau} + b_{13}\, tech\_ind_{j,\tau} + \varepsilon_{j,\tau}$$

Independent Variable	***Predicted Sign***	***Coefficient***	***t-stat***
Intercept		0.111*	[1.834]
log_premium	+ (Hypothesis 3a)	0.005	[0.15]
*goodnews * log_premium*	- (Corollary 3c)	-0.164*	[-1.659]
goodnews		0.118**	[2.551]
act_diff		0.237***	[3.549]
d_lag		-0.114**	[-2.198]
*d_lag * fcast_diff_lag*		0.809***	[7.39]
xlimit		0.013	[0.211]
mills		-0.039	[-0.548]
d_annual		0.084	[1.592]
log_ana_resid		-0.031	[-0.494]
regulated		-0.036	[-0.474]
retail_ind		-0.118	[-1.115]
tech_ind		-0.101***	[-2.653]
$b_1 + b_2$	- (Hypothesis 3b)	-0.159	*F-test on ($b_1 + b_2 = 0$): 10.77 (p-value = 0.001)*
Adj. R-squared		0.496	
Number of observations		624	

Notes:
Table 6 presents the multivariate regression of one of the forecast properties, amount of news revealed in forecasts, on litigation risk and control variables. The sample includes 624 forecasts made by a subset of 112 firms that chose to issue at least one point or range forecast during the sample period.

Variables are as defined in Appendix 2. ***, **, and * denote significance at the 1%, 5%, and 10% levels of a two-tailed t-test, respectively, based on Huber-White standard errors adjusting for firm-level clustering. The inverse Mills ratio (*mills*) is based on the model of forecast likelihood in Table 4 (Panel A, Model 2).

Table 7 Litigation risk and forecast properties - forecast precision (hypotheses 4)

Panel A: Logistic regression of forecast precision on litigation risk:

$$Logit(Pr\{Precision\ (0/1)_{j,\tau} = 1\}) = b_0 + b_1\ log\_premium_{j,\tau} + b_2\ goodnews_{j,\tau} * log\_premium_{j,\tau} + b_3\ goodnews_{j,\tau} + b_4\ d\_lag_{j,\tau} + b_5\ d\_lag_{j,\tau} * precision\_lag_{j,\tau} + b_6\ xlimit_{j,\tau} + b_7\ mills_{j,\tau} + b_8\ d\_annual_{j,\tau} + b_9\ log\_ana\_resid_{j,\tau} + b_{10}\ regulated_{j,\tau} + b_{11}\ retail\_ind_{j,\tau} + b_{12}\ tech\_ind_{j,\tau} + \varepsilon_{j,\tau}$$

Independent Variable	***Predicted Sign***	***coeff.***	***M. E.***	***z-stat***
Intercept		4.081***		7.28
log_premium	+ (Hypothesis 4a)	0.712**	0.010	2.58
*goodnews * log_premium*	- (Corollary 4c)	-1.923***	-0.102	-3.91
goodnews		-1.337*	-0.052	-1.74
d_lag		-2.315***	-0.150	-2.70
*d_lag * precision_lag*		3.665***	0.019	3.92
xlimit		0.181	0.003	0.43
mills		-1.218**	-0.044	-2.17
d_annual		0.268	0.005	0.60
log_ana_resid		0.787	0.010	1.54
regulated		0.719	0.010	0.87
tech_ind		-0.371	-0.009	-0.83
$b_1 + b_2$	- (Hypothesis 4b)	-1.211	*χ^2 test on ($b_1 + b_2 = 0$): 1.76 (p-value = 0.185)*	
Likelihood Ratio (p-value)		57.381	(<0.0001)	
Pseudo Adj. R-squared		0.229		
# of observations		759		

Notes:
Panel A of Table 7 presents the logistic regression of one of the forecast properties, forecast precision, on litigation risk and control variables. The sample includes 759 forecasts made by a subset of 124 firms that chose to issue at least one forecast during the sample period.

Variables are as defined in Appendix 2. ***, **, and * denote significance at the 1%, 5%, and 10% levels of a two-tailed t-test, respectively, based on Huber-White standard errors adjusting for firm-level clustering. The inverse Mills ratio (*mill*s) is based on the model of forecast likelihood in Table 4 (Panel A, Model 2).

Table 7 (Continued) Litigation risk and forecast properties - forecast precision (hypotheses 4)

Panel B: Multinomial regression of forecast precision on litigation risk:

$$Precision\ (1\text{-}to\text{-}4)_{j,\tau} = G(log\_premium_{j,\tau},\ goodnews_{j,\tau}{*}log\_premium_{j,\tau},\ goodnews_{j,\tau},\ d\_lag_{j,\tau},$$
$$d\_lag_{j,\tau}{*}precision\_lag_{j,\tau},\ xlimit_{j,\tau},\ mills_{j,\tau},\ d\_annual_{j,\tau},\ log\_ana\_resid_{j,\tau},$$
$$regulated_{j,\tau},\ retail\_ind_{j,\tau},\ tech\_ind_{j,\tau})$$

	Predicted	***Precision 4 vs. 1***		***Precision 3 vs. 1***		***Precision 2 vs. 1***	
Independent Variable	***Sign***	***coeff.***	***p-value***	***coeff.***	***p-value***	***coeff.***	***p-value***
Intercept		2.735	<0.0001	3.600	<0.0001	-0.253	0.773
log_premium	+ (Hypothesis 4a)	1.159	0.0003	0.553	0.047	0.397	0.332
*goodnews * log_premium*	- (Corollary 4c)	-1.634	0.110	-2.032	0.041	-2.009	0.081
goodnews		-0.603	0.524	-1.667	0.074	-1.127	0.343
d_lag		-6.070	<0.0001	-3.575	0.002	-2.773	0.078
*d_lag * precision_lag*		2.434	<0.0001	1.652	0.001	1.464	0.012
xlimit		-0.073	0.876	0.284	0.509	0.639	0.309
mills		-0.714	0.293	-1.352	0.025	0.497	0.635
d_annual		-0.012	0.980	0.325	0.448	-0.209	0.737
log_ana_resid		0.415	0.375	0.773	0.077	0.509	0.412
regulated		-0.563	0.231	0.883	0.425	2.562	0.034
tech_ind		-0.395	0.735	-0.241	0.575	-2.131	0.019
retail_ind		12.126	0.965	10.623	0.970	-0.944	0.998
Likelihood Ratio (p-value)		192.184	(<0.0001)				
# of observations		759					

Notes:
Panel B of Table 7 presents the multinomial regression of one of the forecast properties, forecast precision, on litigation risk and control variables. The sample includes 759 forecasts made by a subset of 124 firms that chose to issue at least one forecast during the sample period.

Variables are as defined in Appendix 2. P-values are two-tailed. The inverse Mills ratio (*mills*) is based on the model of forecast likelihood in Table 4 (Panel A, Model 2).