Determinants of Insurers' Reputational Risk*

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This draft: April 2013

*We thank Mark Browne, Elizabeth Odders-White and Jean-Paul Chavas for helpful comments. This study is partially sponsored by the Casualty Actuarial Society, Canadian Institute of Actuaries and the Society of Actuaries. All errors are our own.

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Abstract

Given that an insurance policy is a promise by an insurer to perform in the future, consumers cannot observe the insurer's risk-taking strategy until after having entered into the agreement. Furthermore, while a good reputation is a valuable asset, the lack of perfect monitoring and costliness of maintaining a positive reputation confront insurers with an economic choice about whether or not to act in accord with their reputation. The insurer can choose either to expend higher costs to maintain its positive reputation by fulfilling customer expectations or to expend lower costs that ultimately leads to performance below expectations (moral hazard) and a loss of reputation. The optimal strategy for an insurer depends on factors affecting the relative costs and benefits of each strategy. Here we consider relevant factors in selecting an optimal strategy and then test them using a rich data set on operational loss risk events. Results indicate that passage of the Sarbanes-Oxley Act had a significant effect on firm behavior. We also observe that leverage as measured by the capital-to-asset ratio, firm age, and executive shareholdings are significantly related to reputational risk. In some samples, Tobin's Q, the level of competition, and the discount rate also were related to instances of reputational loss. Further, we demonstrate that these factors tend to be associated with both insurers' choice of risk-taking (that is, whether or not to take risk) and the number of publicly revealed events that potentially cause reputational loss (a measure of degree of riskiness).

Keywords: reputational risk, moral hazard, operational risk, Sarbanes-Oxley Act

***JEL* Codes**: D81, D82, G22

1 Introduction

Over the past decade, a number of events have highlighted the fact that a good corporate reputation is fragile and that the potential financial impact of damage to a firm's reputation could be disastrous. Among those events include Toyota's recall of millions of vehicles because of defect concerns, the BP oil spill in the Gulf of Mexico, and various financial misdeeds by AIG, Lehman, and Bank of America. Organizations have long understood that sustained financial success is dependent on stakeholders' confidence in the integrity of the organization, that is, on a positive reputation. According to a 2005 survey conducted by the Economist Intelligence Unit (Economist Intelligence Unit, 2005),[1] protecting a firm's reputation is considered the most important and difficult task for senior executives responsible for managing risks. Furthermore, failure to comply with regulatory or legal obligations and a failure to deliver minimum standards of service and product quality to customers are considered by survey respondents as major threats to reputation. Thus, reputational risk does not stand alone but arises from an event that causes loss in stakeholders' confidence.[2]

The primary purpose of the research reported here is to identify factors that are likely to be associated with actions that lead to loss of reputation. The most notable contribution of this study is our focus on when a reputational risk event starts, rather than when it is revealed to the public. We are able, therefore, to identify factors associated with incentives to take actions that are hazardous from a reputational risk perspective. Although the approach is general and applicable to any type of business, this study focuses on insurance companies which rely heavily on their positive reputation to sell insurance policies to customers.

According to economic theory, reputation formation arises from repeated interactions between agents in the absence of perfect monitoring. Therefore, reputational risk exposure is believed to arise out of incentives that exist when actions are hidden.[3] Specifically, we investigate insurer's incentives to violate stakeholder expectation on implicit and explicit contractual promises where stakeholders cannot monitor insurer performance perfectly, a situation involving moral hazard.

[1] Reputational risk is listed as the top priority out of a choice of 13 risk categories such as regulatory risk, human capital risk, IT risk, market risk, and credit risk.

[2] Due to its nature, reputational risk is referred to as a "risk of risks."

[3] We do not deny the possibility that a firm's reputation can be lost even without incentive problems. For instance, false information in the media about the organization may cause loss of reputation, even though the organization acted appropriately. Our focus, however, is on firm incentive problems.

As is generally true in situations involving moral hazard, incentives to violate insurer contractual promises are not directly observable; therefore, we use observed actions as indicative of moral hazard. Specifically, we use insurer operational loss events as evidence of incentives to violate policyholder expectations. As discussed below, operational loss events have been shown to cause reputational damage. Further, of the generally-accepted categories of operational loss events, internal fraud has been associated most convincingly with loss of reputational value, while externally-caused events have been shown to have no effect on reputational value (Perry and de Fontnouvelle, 2005; Gillet, Hubner, and Plunus, 2007). Given these findings that specific types of operational loss events tend to cause reputation loss, our focus is on identifying factors that encourage behavior likely to increase the occurrence of those events.

The structure of this paper is as follows. Section 2 is a summary of the existing literature on causes of reputation damage, the relationship between reputation and moral hazard, and the influence of franchise value on willingness to risk a good reputation. In Section 3, we discuss our hypotheses, variables, and data. Operational loss events are explained in detail as a proxy for moral hazard. Empirical models are introduced in Section 4, followed by the test results in Section 5. The last section draws conclusions and discusses certain limitations of the empirical analysis.

2 Background: Studies on Reputation and Moral Hazard

2.1 Reputation-Damaging Events

A rich literature exists investigating the association between specific types of corporate misconduct and loss of firm value (reputation). The intent of these studies is to show the existence and level of market-based penalties for corporate misconduct. For instance, Karpoff and Lott (1993) identify significant losses in equity value when allegations of corporate fraud events are revealed to the public. They further find a greater reputational effect for events where customers, rather than others, are the injured parties. Alexander (1999) conducts a similar analysis with similar results using federal crime data. Karpoff, Lee, and Vendrzyk (1999) and Karpoff, Lott, and Wehrly (2005) observe negative abnormal returns following revelation of military procurement fraud and environmental violations, respectively. Karpoff, Lee, and Martin (2008) investigate the market reaction to the imposition of fines by the SEC due to financial misrepresentation and observe losses in firm value far in excess of the actual SEC fine. Murphy, Shrieves, and Tibbs (2009) add to our understanding by identifying lower profits and higher return volatility in the presence of various types of corporate misconduct.

In the financial services sector, Cummins, Lewis, and Wei (2006) consider the reputational effects of operational events. They conclude that the stock price reaction to operational loss events exceeds the underlying loss value, indicating reputational effects. They also find larger effects for insurers than for banks. Perry and de Fontnouvelle (2005) and Gillet, Hubner, and Plunus (2007) also investigate financial services firms and conclude that internal fraud significantly affects the firm's reputation, whereas externally caused losses show no significant effect on reputation. Each of these reputation studies demonstrates the reputational effects of specific types of operational loss events, but they do not investigate *how* reputational loss occurs. Our research is intended to help fill this gap.

The importance of moral hazard to reputation risk is clear even in the early theoretical studies on reputation formation. Klein and Leffler (1981) offer the seminal piece. They illustrate producers' self-regulatory constraint against moral hazard in that discounted future profits discourage producers from deceiving customers by selling low-quality products at a high-quality price. Their study describes a systematic association between firm integrity and future rents.[4] Despite some variation in the extant studies (e.g., Shapiro, 1983; Allen, 1984), a common finding is that once a firm acquires a good reputation, it can sell a high-quality product fulfilling customer expectations at a price higher than its marginal cost.

One of the major concerns from early reputation studies is the possibility that once a good reputation has been established, the firm will tend to rest on its laurels and fail to expend the effort to provide services/goods consistent with its reputation (Holmström, 1999). Studies such as Hörner (2002) and Tadelis (2002), however, present a solution to the incentive problem. Hörner (2002) argues that consumers' merciless behavior in abandoning firms that record a single bad outcome (i.e., perfect market discipline) strongly motivates firms always to exert high effort. Tadelis (2002) solves the problem by demonstrating that incentives to preserve reputation can be ageless if reputation can be separated from the entity (firm) and can be traded in the market. Neither of these solutions, however, is particularly realistic, nor easily obtained.

[4] Corporate governance literature is also related to this study in that firm attributes including future rents determines the quality of governance, which presumably influences firm's moral hazard (e.g., Durnev and Kim, 2005).

2.2 Franchise Value as a Measure of Reputation

The theoretical research just cited contends that reputation preservation is a moral hazard problem in a multiple period setting where the behavior cannot be observed directly. Reputation preservation, in this sense, is consistent with franchise (charter) value theory, which holds that sufficient future profits encourage firms to limit their risk-taking behaviors (Marcus, 1984). In particular, researchers have investigated the effect of market competition on risk-taking behavior through franchise value, and have identified an inverse association between franchise value and risk-taking in the banking industry (Keeley, 1990; Demsetz, Saidenberg, and Strahan, 1996; Fang, 2005). In the insurance literature, understanding that excessive underwriting risk is a major cause of insurer insolvency, Harrington and Danzon (1994) identify the inverse association between intangible assets and insurer price-cutting. Yu, Lin, Oppenheimer, and Chen (2008) also support an inverse relation when investigating insurer asset risk.

Yet the overall support for an association between franchise value and risk-taking incentives is mixed, and appears to depend on market conditions. For instance, Saunders and Wilson (2001) show that banks' risk-constraining incentives of franchise value depend on the overall market condition: market expansion/contraction periods. Boyd and Nicoló (2005) demonstrate that the association between bank risk taking and franchise value is not straightforward when competition in deposit as well as lending rates is taken into account. Ren and Schmit (2008) theoretically and empirically show that insurers with large franchise value take greater risk during periods of increased competition than do those with small franchise value. They posit that these firms are attempting to protect their market power.

Overall, although franchise value may restrain excessive risk-taking, the self-disciplinary effect may be diminished due to competition. We see, then, that a firm's decision to imperil its reputation (and therefore its franchise value) through excessive risk taking, appears to depend on market conditions.

3 Hypothesis Development, Variable Selection and Data Sources

Based on the literature regarding the underlying moral hazard incentives for firms to maintain a positive reputation as well as the relationship between operational loss events and reputation damage, we believe that moral hazard leads to specific types of operational loss events, which in turn lead to reputation damage. We therefore use a rich data set of operational loss events in the financial services industry to test the relationship between moral hazard factors and the occurrence of these events (our dependent variable). Below, we describe operational loss events, our hypotheses, as well as data sources. Variables and their descriptions are reported in Table 1. In what follows, we explain the detail of each variable.

[Insert Table 1 Here]

3.1 Operational Loss Event As a Proxy for Moral Hazard

Operational risk is defined as the risk of loss "resulting from inadequate or failed internal processes, people and systems, or from external events" (Basel Committee on Banking Supervision, 2006). The risk type was originally categorized within the banking regulatory framework as a third class of risk besides credit risk and market risk. Bank regulators use measures of these three risks to determine capital adequacy. Operational risk was added as a part of the regulatory framework after several notable bank failures due to conditions outside of market and credit risk, such as bank failures due to rogue trading losses at Societe Generale, Barings, AIB, and National Australia Bank. We employ the Algo OpVantage Financial Institutions Risk Scenarios Trends (FIRST) database of operational risk loss events provided by Algorithmics to measure our dependent variable of operational risk loss events, with specifics of the data set described below.

3.2 Types of Operational Risk Losses

According to the Bank for International Settlements (BIS), there are seven categories of operational risk events: Internal Fraud, External Fraud (ET2), Employment Practice & Workplace Safety (ET3), Clients, Products, and Business Practices (ET4), Damage to Physical Assets (ET5), Busi- ness Disruption and System Failure, and Execution (ET6), and Delivery& Process Management (ET7).

Operational risk losses, therefore, include both internally-caused events and externally-caused events. Specifically, Internal Fraud(ET1), Employment Practice & Workplace Safety (ET3), Clients, Products, and Business Practices (ET4), Business Disruption and System Failure(ET6),and Execution, Delivery & Process Management (ET7)are considered internally-caused operational losses. External Fraud (ET2) and Damage to Physical Assets (ET5) are categorized as externally-caused operational losses.

We posit that Internal Fraud (ET1) risk events strictly represent insurers' moral hazard because they arise out of intentional failure to meet stakeholders' expectation. Our position is supported by reputational loss studies such as Perry and de Fontnouvelle (2005) and Gillet, Hubner, and Plunus (2007) which demonstrate that internal fraud in the BIS event-category tends to cause loss of reputation in financial institutions. Thus, the reputational effect of internal fraud is strongly supported by existing studies.

Focusing only on internal fraud, however, may be too restrictive. Clients, Products, and Business Practices (ET4), for instance, is defined as "losses arising from an unintentional or negligent failure to meet a professional obligation to specific clients." This type of loss often results from a lack of sufficient corporate governance mechanisms, an indirect indication of insurer incentive problems.

Extending the argument, we may consider internally-caused operational loss events (all internal) as instances of moral hazard because they represent events directly or indirectly caused by incentives to take excessive risks. Even externally-caused events such as external fraud could be induced by incentive problems when the firm does not prevent these external behaviors. Thus, insurers take the "external risk" by their internal decisions.

Including externally-caused events, however, may be problematic because those events may not cause loss of reputation. Perry and de Fontnouvelle (2005) and Gillet, Hubner, and Plunus (2007) in particular document that externally-caused losses show no significant reputational effect, while they identify the reputational effects of internally-caused loss events. These studies, therefore, suggest that managerial control (measured by internally-caused events) is the major factor causing reputation damage from operational loss events.

To avoid arbitrarily identifying a unique set of events that represent insurer moral hazard and which eventually cause loss of reputation, we conduct several sets of tests with varied measures of the dependent variable. Each set represents a different level of managerial controls. Specifically, we use four combinations of event types based on the BIS event-type categories: (1) internal fraud (ET1); (2) internal fraud and negligence (ET1 and ET4); (3) all internally-caused events (ET1, ET3, ET4, ET6, and ET7); (4) all events (both internal and external).

Our first set, comprised of *internal fraud* (ET1) events, is most directly associated with managerial incentive problems and most strongly supported by empirical evidence of reputational effect. For our second set, we use a combination of ET1 and ET4 (*internal fraud and negligence*) because of prior evidence linking reputational effects to events adversely affecting customers (Karpoff and Lott, 1993). ET4 includes events where "customers and other related parties" are the injured parties. The third set includes all internally-caused event types (*all internal*), and the fourth set includes all operational loss events (*all events*). As noted above, this fourth set includes events not supported by empirical evidence of reputational effects, and we consider it the weakest measure of effects likely to cause reputational damage. We use these four sets both to avoid an arbitrary definition of relevant operational risk loss events, and to compare results across them for purposes of investigating the extent that these determinants explain reputational risk exposure.

3.3 Operational Loss Data Source

Algorithmics, a division of IBM, maintains, updates, and sells its FIRST dataset to "enable financial institutions and corporate treasuries to make risk-aware business decisions." The firm began collecting data on operational risk losses exceeding $1 million for events first reported in 1998, regardless of when the underlying activity occurred. It is important to note that many operational losses arise out of activity undertaken long before the activity is known publicly. Data are collected from public sources, such as news media, SEC press reports, and court decisions. The database provides a detailed description of each event, including organization name, the date when the event (activity) began, the date when the event (activity) ended, the date of public notice, settlement date, event trigger, and the type of event. Algorithmics updates the database on a quarterly basis. We use this resource to identify insurers' operational risk loss events. The FIRST database updated in August 2009 is used to identify 209 operational loss events for our insurance sample with activity start dates during 1997-2006 (and identified through August 2009). Table 2 shows the BIS event type distribution of these 209 events.

[Insert Table 2 Here]

Panel A in Table 2 shows the number of events for each BIS event type. The largest number of events is 123 for Clients, Products, and Business Practices (ET4), with 26 Internal Fraud (ET1) events during the sample period. Only three events are reported for each of ET6 and ET7. Panel B in Table 2 shows the time trend of each operational loss category. We note that 2001 included 11

"Damage to Physical Assets" (ET5) events resulting from the World Trade Center losses. Even without those loss events, 2001 would have been the year with the largest number of events at 25, including the highest number of "internal" loss events among our sample. The difference across years, however, would have been much smaller. In general, we observe that each year approximately 20 operational risk loss events occur, when excluding the World Trade Center events. We conducted the analyses both with and without these events, and observed no relevant differences in results.

An important attribute of operational loss events is that the risk activity leading to the event often begins many years prior to its public revelation. This attribute is one reason why organizations may have an incentive to undertake risky activity. They are able to earn profits on the risky activity for years before experiencing the negative effects of the activity. Figure 1 is an illustration of the time lag between the beginning of the activity for losses in our data set and public revelation of those events. The mean lag period is 5 years while the median is 3.5, given the long tail.

Because of the time lag between risky behavior and public revelation, inclusion of more recent years in our analysis is likely to underestimate relevant factors that lead to such activity. We therefore exclude the most recent three years (2007-2009) of events. We find no difference when we begin in 2006.

[Insert Figure1 Here]

3.4 Factors Affecting Costs and Benefits of Maintaining Positive Reputation

Our hypothesis is that firms have a choice of two strategies: (1) expend resources to generate and maintain a positive reputation in order to reap the economic rents of that reputation; or (2) violate the conditions of a positive reputation, with the expectation of greater profits in the short run, and a loss of profits in the long run. In the following subsections, we identify the factors that influence which strategy is most desirable to a particular firm.

3.4.1 Expected Future Rents

The effect of the expected future profit to be gained per policy from maintaining a positive reputation is straightforward: as the expected profit becomes smaller, incentives to commit moral hazard tend to become greater, *ceteris paribus*. Thus, we need to include a measure of the expected future profits from a positive reputation.

Tobin's Q: Tobin's Q (Tobin, 1969) is a common measure of a firm's economic rents, also thought of as the summation of its future expected profits (this same measure often is used to calculate a firm's franchise value). Tobin's Q is equal to the market value of assets (generally measured by its total stock value) divided by asset replacement value (often measured by its book value), and is used as a proxy for an all-in-one measure of the expected discounted value of a stream of future profits. We calculate market value of firm assets by the sum of its total stock value (the product of firm stock price and the number of outstanding shares), the book value of preferred shares at the end of each year, and the firm's liabilities. We expect a negative relationship between Tobin's Q and operational loss events. Data to construct the ratio are taken from the Center for Research in Security Prices (CRSP) and Compustat.

Herfindahl-Hirschman Index: As noted in the literature review section, the importance of economic rents on dampening firm risk taking appears to be affected by market competition. According to some theories, a competitive market reduces insurers' franchise value and induces excessive risk-taking (e.g., Keeley and Furlong, 1990). An alternative hypothesis with the same effect is presented by Harrington and Danzon (1994) who suggest that insurers with greater franchise value could become more aggressive in protecting their business when price-cutting competition is intense.

To account for the level of industry competition, we employ the Herfindahl-Hirschman market concentration indices, denoted as *Herfindahl* (*PC*) for property-casulaty insurers and *Herfindahl* (*Life*) for life insurers. As is the norm, we define each measure as the sum of the square of the top 10 insurers' market share at the group level.[5] The property-casualty insurers' market share is determined by their net premium written and the life insurer's market share is determined by their net premiums for new business issued. Premium data are taken from the National Association of Insurance Commissioners (NAIC) annual statements. We expect concentration to reduce competition and therefore be negatively related to the number of operational events.

3.4.2 Quality of An Insurer's Promise

Because premium payment and contract agreement occur prior to any loss payment, sometimes long before any loss payment, policyholders want assurance that the insurer will have assets avail-

[5]We also create the Herfindahl-Hirschman indices based on the top 20 insurers' market share rather than the top 10 insurers' market share. The empirical results obtained from these two measures are virtually identical. Therefore, we omit the results obtained with the indices measured by the top 20 insurers.

able when their claim is due. The extent to which the insurer holds capital to assure it can cover any future claims can be considered the "quality of an insurer's promise." Insurers are required to hold a certain level of capital according to regulatory rules. They may choose to hold even greater amounts than this minimum.

Capital-to-Asset Ratio: We use the capital-to-asset ratio to test for the quality of an insurer's promise. This ratio is defined as: 1-(Liability/Assets). Interestingly, both theoretical and empirical studies of the effectiveness of capital regulations are mixed (Furlong and Keeley, 1989; Hellmann, Murdock, and Stiglitz, 2000), although the evidence seems clear that policy-holders care about insurer strength, and are willing to pay higher prices for such security (Sommer, 1996). Cummins and Sommer (1996) draw on this result to show that property-casualty insurers use a combination of capitalization and portfolio risk to achieve target solvency levels. Furthermore, as the difference in profits between a high-quality and low-quality insurer rise, incentives for moral hazard also rise. Thus, capital and risk are expected to be positively associated.

3.4.3 Efficiency of Belief Updating

The expected amount of future profits that can be earned from moral hazard depends on the likelihood that the information is revealed to the public and on how long it takes for the information to be distributed once revealed. Not only must information but revealed for the misbehavior to be relevant, but customers also need to update their beliefs in order for the misbehavior to have a reputational effect; therefore we need measures of both information diffusion and consumer belief updating.

Sarbanes-Oxley Act: In response to lack of relevant information being reveled to the public, the U.S. Congress passed the Sarbanes-Oxley Act (SOX hereafter) in July 2002 (see Chhaochharia and Grinstein, 2007, for the detail of the legislation). SOX contains eleven provisions including a broad range of governance rules and penalties to protect investors. Several sections directly impact managerial decisions, which is our focus here. They are summarized in Appendix A.

The SOX rules discussed are intended to increase insurers' incentives to disclose adverse information to the public promptly. Thus, to the extent that events fall into the categories required to be reported, the SOX rules are relevant to the efficiency of adverse information distribution. To investigate the effect of the passage of the SOX Act, we introduce an indicator variable (*SOX*) which is one if the observation year is 2002 or later, and zero otherwise. We expect a negative relationship between SOX passage and insurers' reputational loss exposure.

Analyst Coverage: Financial analysts play a significant role in producing firm-specific and industry-wide information by processing financial information reported by firms and by collecting additional information from firms' stakeholders such as managers and customers. Information efficiency studies provide evidence that analysts promote efficient incorporation of private information into stock prices (Hong, Lim, and Stein, 2000; Kim, Lin, and Slovin, 1997; Frankel and Li, 2004; Griffin and Lemmon, 2002). Furthermore, the marginal effect of analyst coverage on information efficiency is greater for negative information than for positive information due to the firm's greater incentive to disclose good information than bad information. More analyst coverage, therefore, implies a more efficient flow of negative information, which could reduce potential profits earned from moral hazard. Therefore, we use analyst coverage as a proxy for the relative efficiency of negative information diffusion. We define analyst coverage as the number of analysts who reported fiscal year 1 estimates of earning per share available in the I/B/E/S Historical Summary File (Hong, Lim, and Stein, 2000). We anticipate a negative relationship between analyst coverage and number of reputational loss events.

Numerous studies (Bhushan, 1989; Hong, Lim, and Stein, 2000) show that the analyst coverage measure is strongly correlated with firm size, which we also observe in our sample. To separate the effect of analyst coverage from firm size and to avoid multicollinearity, we proxy information flow efficiency as the residual analyst coverage (*Residual of analysts*) (Hong, Lim, and Stein, 2000). The residual analyst coverage is a standardized residual after controlling for firm size measured as the logarithm of firm assets, *Ln*(*assets*).[6] Table 3 reports the OLS regression estimation result for this analysis. *Residual of analysts* is measured by the standardized residuals obtained from the regression.

[Insert Table 3 Here]

[6]Firm assets represent the total value of assets reported on the balance sheet available in COMPUSTAT.

Firm Age: The probability that adverse information is revealed and updated into customers' beliefs can be decomposed into two parts: (1) the probability that customers observe policy quality, and (2) the credibility of the information that customers use to update their beliefs. The perceived credibility of observed new information is expected to decline as customers form strong beliefs with repeated observations of policy quality. That is, once an insurer gains a strong positive reputation, customers anticipate that the insurer will perform consistently with their reputation, attributing observations that do not fulfill their beliefs to chance events. The marginal benefit of exerting high effort, therefore, may decrease as an insurer earns a positive reputation over time. In the absence of strong market discipline, a strong positive reputation could weaken incentives for insurers to keep exerting high effort (Holmström, 1999; Hörner, 2002).[7]

We expect that the duration over which an insurer continuously operates in the market affects its decision to take risks; therefore, we introduce a firm age measure, $Ln(age)$, defined as the logarithm of the number of years since establishment of the insured.[8] We expect firm age to be positively associated with the number of operational loss events.

3.4.4 Discount Factor

As the opportunity cost of capital (or discount rate) increases, the value of future rents generated by maintaining positive reputation decreases and so does the insurer's incentive to fulfill policyholder's expectation. Maximizing immediate profits through acts involving moral hazard could be relatively attractive under a large discount rate.

To assure that our results are not dependent upon which measure we use, we test for the effect with four different rates: (1) the insurance industry average stock holding annual return (*Insurance industry return*); (2) the S&P500 index annual return (*SP500*); and (3) the annual return of monthly Treasury bill rate (*Interest rate*). These measures are expected to be positively associated with insurer moral hazard because a stream of future rents is less attractive with high discount rates. Each measure, however, is intended to reflect a distinct type of discount rate: industry-wide, market-wide, and macroeconomic conditions, respectively (e.g., Saunders and Wilson, 2001 for the

[7] In contrast, Tadelis (2002) shows that incentives to maintain reputation can be "ageless" with a market for reputations. He incorporates the concept of a bankruptcy cost in the model by considering reputation as a tradable asset..

[8] The establishment year is retrieved primarily from the D&B Million Dollar Database licensed from Dun & Bradstreet, Inc.

effect of overall market condition on bank risk-taking).[9]

We add the market beta (*Market beta*), computed by the daily rates of return in the past one year period, to capture the effect of a systematic risk on incentive problems. The market beta is defined as the ratio of the covariance between the insurer's daily stock return and the equally-weighted market portfolio daily return to the variance of the market portfolio return.[10] All of these variables are constructed by data taken from the CRSP database.

3.4.5 Misalignment of the Incentives of Owners and Managers

All of the variables included in the analysis to this point have represented relevant factors to firm owners. Because owners and managers do not necessarily have the same incentives, implementation of owners' strategy may differ from their preferences. In particular, existing theory holds that owners will seek greater risk levels for higher returns than will managers who may be concerned with losing their employment if the firm experiences loss. To capture the effect of misalignment of owners' and managers' incentives, we measure the percentage of the firm's shares owned by executives. If executives hold a large proportion of issued shares, their objectives should be relatively closer to those of the shareholders. If executives hold only a small proportion of issued shares, they may behave according to their career concerns, for instance, which may deviate from shareholders' interests.

Incentive compensation for managers is intended to align managerial interests with shareholders' interests. A variety of compensation schemes such as bonuses, stock options and awards, non-equity incentive plans, and pensions may be used for this purpose. We use the proportion of shares owned by executives (*Executive Shareholding*), defined as the ratio of the number of shares owned (including the number of unexercised options held by executives at fiscal year end) by executives reported in Compustat Executive Compensation Anncomp File to the number of shares outstanding, to measure this effect.

[9] For both *Insurance industry return* and *SP500* we use the rate of return above the monthly Treasure bill rate (*Interestrate*).

[10] In our empirical tests, both the equally-weighted market portfolio return and the value-weighted market portfolio return are investigated. The estimation results obtained for those returns, however, are not substantially different in terms of both the coefficient and the statistical significance.

The executive compensation database, however, consists of the current S&P 1500 plus companies that were once part of the S&P 1500, covering only 2872 companies in total. Using this database significantly reduces the sample size in our analysis; therefore, we run tests both with and without this variable included.

3.4.6 Other Factors

We add two controlling factors. One is a size measure, which can account for a variety of variations across the data set, including simply the greater opportunity for operational risk loss events as the firm expands, and other similar issues. We measure size as $Ln(assets)$, defined by the logarithm of firm assets.

We also anticipate possible variations across industry markets. These variations may be due to one of a number of conditions. For instance, property-casualty insurers, life insurers, and health insurers operate under distinct regulations in terms of capital requirement, investment, and guaranty funds. Their products and distribution channels have different characteristics as well. Consumer attitudes also may differ across these types of products. To control for market heterogeneity, we use SIC codes to create two indicator variables: one to denote a property-casualty insurer (PC, code 633) and a second to denote a life insurer ($Life$, code 631). The hold-out group is health insurers. Reinsurers are not differentiated from primary insurers in this data set.

4 Empirical Analysis

To test our predictions, we collect data on U.S. based publicly-traded insurance companies (classified in the SIC major group 63). We begin with a total sample of 301 firms (and 1900 firm-year observations), which is reduced to 289 firms (and 1612 firm-year observations), after extracting available data from CRSP, Compustat, the NAIC annual statements, the D&B Million Dollar database, and the I/B/E/S database.

4.1 Model Specification

As discussed above, we use insurers' operational risk loss events as identified through the FIRST database as the foundation of (the four versions of) our dependent variable. Specifically, our dependent variable is measured as the number of operational risk events per year per insurer, with four distinct categories of events. In using this measure, however, we face two "limited dependent variable" problems. The first problem arises because of the potential for a significant lag between the date when an event started (event start date) and its public disclosure date. Therefore, the FIRST database is truncated from the right, which we address in two ways. First we exclude the final three years of the data set, ending the analysis with events begun in 2006. Second, we include year dummy variables in the regression models to account for the possibility that later years will differ from earlier years because of the inherent time lag in public revelation of events.

The other limited dependent variable problem arises because our sample universe is the full set of insurers listed in CRSP and Compustat while our dependent variable is generated only for insurers that have experienced an operational loss event included within the FIRST data set. As a result, our data set will include numerous zeroes, and further, some of those zeroes are true zeroes while other zeroes occur because operational risk events have occurred but have not been observed and reported publicly. These events are not in our data set.

To illustrate the implications of the limited dependent variable problems, let the observed dependent variable (or events reported in the FIRST database) for firm i at year t be z_{it}, while a latent variable to represent actual event counts be z^*_{it} .

As shown in the Figure 2, consequences from insurers behavior fall into three states. In the first, there is no insurer hidden action that could adversely affect its reputation.
No event is reported in the FIRST database, $z_{it} = z^*_{it} = null$ (Case 1), and the positive reputation remains intact. In the second, insurer's hidden actions occur but are not revealed to the public. Thus, $z_{it} = null | z^*_{it} > 0$ (Case 2) and insurer's positive reputation is not affected. In the third case, insurer's hidden actions occur and are revealed. We assume that any such revealed information adversely affects its reputation, i.e., $z_{it} > 0 | z^*_{it} > 0$ (Case 3). The dependent

variables constructed by the FIRST database represent only the first and third states. Non-events include both situations where there truly are no events (Case 1) and where events have occurred but have not been revealed publicly (Case 2). The omission of Case 2 is what concerns us.

[Insert Figure 2 Here]

Several possible approaches are available to overcome this limited dependent variable problem. One is to rely only on the recorded events in the FIRST database (Case 3) and assess the population of actual event occurrence (Case 2 and Case 3) as being represented by Case 3. A zero-truncated Poisson regression assumes a Poisson distribution for the event revelation counts and captures the population of unrevealed events. This approach is appealing because the distribution assumption allows us to estimate the unobservable population of event occurrence from what we do observe. The analysis based on the truncated distribution is, however, conditional on event occurrence, which does not include the entire universe of moral hazard behavior. This may be beneficial if our interest is in investigating the determinants of event revelation to the public, given the occurrence of an operational loss event. Our interest, however, is in identifying the factors that encourage moral hazard and eventually are likely to yield operational loss events; therefore, this is not a perfect measure.

Alternatively, we may assign zero to observations without reported events in the FIRST database:

$$Y_{it} = \begin{cases} 0, & \text{if } z_{it} = null \\ z_{it}, & \text{if } z_{it} > 0. \end{cases}$$

where Y_{it} stands for the new dependent variable for firm i at year t. Here, zeroes are assigned to both Case 1 and Case 2 regardless of the difference in actual event occurrence. Assigning zero to the dependent variables can be considered reasonable because reputation is affected only by new revealed information, and therefore the effect of Case 1 and Case 2 is the same. With this sample, we can estimate a basic Poisson regression model. While this approach may be sufficient to emphasize the heterogeneity between revealed events and unrevealed events, by combining specification of non-events with non-revealed events, it does not help us understand the factors that encourage moral hazard when the behavior is not revealed. Furthermore, excess zeroes in our new dependent variables may cause potential overdispersion.

We therefore look to hurdle models originally proposed by Mullahy (1986), which may fit our excess zero outcomes and our objectives better than the basic Poisson model. In the hurdle models, a binary probability model determines whether a zero or a nonzero outcome occurs, and a zero-truncated Poisson distribution captures the positive outcomes. Lambert (1992) proposes an extension called Zero-inflated Poisson (ZIP) regression, in which the zero outcome can arise from one of two regimes. In our insurers' reputational risk context, one regime represents the state where insurers perform as expected (Case 1). Thus, the outcome is always zero. In the other, insurers take opportunistic acts that could eventually cause loss of reputation (moral hazard), and the observed event counts are Poisson distributed. Because events may not be revealed to the public, the outcome can be either zero (Case 2) or positive (Case 3). Thus, we can draw a statistical inference regarding unobservable insurers' decision whether to take an opportunistic behavior (i.e., whether Case 1 or Case 2&3) from the estimates of a binary probability.

The hurdle models including the ZIP regression, however, incur costs in that a large proportion of zero outcomes imposes restrictions on the number of parameters that can be estimated in the regression models. Therefore, we conduct two analyses. First we estimate the basic Poisson regression models, and from this we select candidate variables to be tested in the ZIP model. We then run the ZIP regression with the pre-selected variables. We prefer the ZIP to the basic Poisson because it fits our goals of identifying underlying moral hazard better, yet we also understand the limitations of our data and therefore conduct both analyses and report results from each.

4.2 Model Specification

Basic Poisson Regression Model: Consider a vector of responses, $\mathbf{Y} = (\mathbf{Y}_1^T, ..., \mathbf{Y}_N^T)^T$, where : $\mathbf{Y}_i = (Y_{i1}, ..., Y_{iTi})^T$, is Poisson distributed with the mean $\lambda_i = (\lambda_{i1}, ..., \lambda_{iTi})^T$ for insurer ***i*** at year ***t***. Specifically, the Poisson regression model is specified as follows:

$$log(\lambda_i) = \mathbf{X}_i\beta, \quad i = 1, ..., N. \tag{1}$$

A generalized linear model is estimated by the maximum likelihood estimation. $\mathbf{X}_i$ where $\mathbf{X}_i = (X_{i1}, ..., X_{iTi})^T$ stands for the vector of independent variables for insurer i.

ZIP Regression Model: The ZIP model is extended to the panel data setting by Hall (2000). A vector of responses are distributed as:

$$Y_{it} = \begin{cases} 0, \text{ with probability } p_{it}; \\ Poisson(\lambda_{it}), \text{ with probability } (1 - p_{it}). \end{cases}$$

so that

$$Y_{it} = \begin{cases} 0, \text{ with probability } p_{it} + (1 - p_{it})e^{-\lambda_{it}}; \\ k, \text{ with probability } (1 - p_{it})e^{-\lambda_{it}}\lambda_{it}^k/k!, \ k = 1, 2, ... \end{cases}$$

where $\lambda_i = (\lambda_{i1}, ..., \lambda_{iTi})^T$ and $\mathbf{p}_i = (p_{i1}, ..., p_{iTi})^T$ with log-linear and logistic regression models:

$$log(\lambda_i) = \mathbf{X}_i\beta \quad \text{and} \tag{2}$$

$$logit(\mathbf{p}_i) = \mathbf{X}_{i\gamma}, \quad i = 1, ..., N. \tag{3}$$

where the same set of explanatory variables are used for both models. A one year lag between response variables and explanatory variables is applied to reduce a concern of potential endogeneity in that the number of events could affect some covariates. Note that all data are collected on the *event start date*, which is on average 3.5 median years before the event information is revealed to the public. Therefore, the empirical test can reasonably avoid the direct and indirect influence from insurer risk-taking to market related covariates. This may reduce the endogeneity concern. When explanatory variables are collected at the end of fiscal year t, the number of events is counted during the fiscal year $t+1$ as the corresponding response variables.

4.3 Descriptive Statistics

Panel A in Table 4 shows the distributions of dependent variables: the annual number of operational risk loss events, Y_{it}. We prepare four dependent variables associated with four types of events. Those are *Internal fraud*, *Internal fraud + negligence*, *All internal*, and *All events*. The majority of observations have zero operational loss events.

Panel B displays the descriptive statistics for firm-specific variables. The majority, 48% of our sample, represents property and casualty insurers and 21% represents life insurers. The remainder are health insurers. Note that we have only 650 observations for the Executive shareholding variable due to the limited sample size of Compustat Executive Compensation Anncomp File. Because of this significant sample size difference, we investigate the effect of executive shareholdings separately. Panel C in Table 8 shows the time series of market related variables.

[Insert Table 4-5 Here]

Pearson correlation coefficients across the primary variables are shown in Table 6. The columns of *Internal fraud* and *All internal* show the strongest positive correlation with firm size, $Ln(assets)$ as expected. $Ln(age)$ is also positively correlated with those response variables.

[Insert Table 6 Here]

Overall, the strongest correlation is -0.88 between *SOX* and *Interest rate*.[11] *SOX* variable is also strongly correlated with *Insurance industry return* and *SP500*, which all seems to be picking up a time dimension. To reduce multicollinearity concerns, we run two tests. One excludes SOX when discount rate variables are included in the estimation model, and the other includes SOX but not discount rate variables. Variance inflation factors (VIF) of independent variables are less than 2 under these scenarios

5 Estimation Results and Discussion

To test our hypotheses, we estimate the basic Poisson regression models first, both to test our hypotheses, and also to identify the key variables to be included in the ZIP analysis.[11] Potential heterogeneity between subjects is handled by the random effect. Reported p-values are based on empirical standard errors.

For the basic Poisson regressions, each table reporting parameter estimates contains four estimation results, one each for the different response variables. It may be helpful to note that the first response variable *Internal fraud* is the response most strongly supported by the literature as being related to reputational effect. The reputational effect becomes weaker for more broadly defined response variables.

5.1 Basic Poisson Models

Expected Future Rent: Table 7 reports parameter estimates of four models when the SOX variable and year dummy variables are included. Table 8 reports parameter estimates of the four models with SOX variable is excluded. For both analyses *Tobin's Q* is not significant in models with

[11] To avoid the influence of the perfect correlation between the SOX variable and some of year dummy variables, we also repeated the regression without year dummy variables. The standard errors for the SOX variables is reduced when year dummy variables are removed, and the coefficients remain significant at 1% level.

Internal fraud as the response variable, but unexpectedly captures a weak positive effect for the other dependent variable definitions and when the SOX variable is excluded (Table 8). This may imply that insurers' incentives to protect franchise value is greater for those activities under management's control than for other actions that also lead to operational losses.

[Insert Table 7-8 Here]

Market Competition/Concentration: In both models (with and without the SOX variable) and for all dependent measures other than *Internal fraud*, the change in the Herfindahl-Hirschman index for property-casualty insurers shows a significant positive sign, opposite of our expectations. Combined with the weak indications of counter-intuitive results for Tobin's Q, we are among the many researchers who find a complex relationship between risk and future expected profits/competition. A possible answer is found in our discussion of the ZIP analyses.

Quality of An Insurer's Promise: The capital-to-asset ratio is positively associated with the expected event counts regardless of model. This provides evidence that insurer capital does not restrain insurers from either reputational risk exposure specifically, or from operational risk exposure more generally. Furthermore, the coefficient is larger for internal fraud than for the other dependent variable measures, suggesting that a cross-sectional difference in insurers' capital holdings has a greater impact on reputational loss exposures than on overall operational risk exposures.

Belief Updating : We predict that insurers' incentive problems are more likely to arise when customers do not update adverse information efficiently. To investigate the hypothesis, we prepare three variables: SOX, analyst coverage, and firm age. The first two are intended to capture the efficiency of adverse information distribution, while the third is a proxy for customers' acceptance of new information to update their beliefs on an insurer.

Both Table 7 and Table 8 provide consistent results. While the analyst coverage variables are insignificant among models, the firm age variable is significant with the expected positive sign. Further, the coefficients for internal fraud models are greater than those for other models, indicating a greater cross-sectional impact of firm age on insurers' incentive to commit internal fraud than other operational risks. As Holmström (1999) predicts, the marginal benefit of exerting high effort to maintain firm reputation may decrease as customers gain strong beliefs. This result supports the hypothesis that incentives for insurers to keep exerting effort are weakened due to a lack of strong market discipline.

The effect of the SOX variable is significant and consistent regardless of tested models reported. The negative coefficients indicate that the expected event counts are significantly reduced after the SOX law was legislated. Further, the coefficient for internal fraud model has a greater negative value than that for other models, implying a greater impact on insurers' incentives to start commit internal fraud than other operational risks. This result is reasonable because the SOX law added new disclosure and penalty rules against corporate fraud. Because the SOX variable is defined completely by time (before and after passage of the law), it is perfectly correlated with some of the year dummy variables; therefore, the standard error is affected by collinearity. Even so, the SOX variable remains significant at the 1% level regardless the presence or absence of year dummy variables.

Thus, the SOX measure is a strong factor in explaining the expected event counts, and supports the information distribution hypothesis. Because our sample period of 1996-2005 covers the pre and post SOX legislation periods, it is be possible that the effect of our measures significantly changed in between the pre and post legislation periods. We test this possibility by splitting the sample period into the pre-SOX period (1996-2001) and the post-SOX period (2002-2005) and report the results in Table 9.

[Insert Table 9 Here]

The results for the pre-SOX period is generally consistent with results observed in Tables 7-8, and are not reported here. In contrast, the estimation results for the post-SOX period are notably different from our previous findings, and the results are reported in Table 9 . Both tables show the results representing publicly traded US insurers. In the post-SOX period, the change in market competition for PC insurers and capital holdings are no longer significant, while firm age continues to show significance. Thus, neither market competition/concentration nor insurers' capital holdings explain either reputation risk exposure or operational risk exposure in the post-SOX period. This result may imply that the SOX rules impose heavier costs on well-capitalized insurers' internal fraud. And better corporate governance practices employed in US insurers after the SOX Act legislation might reduce the impact of capital holdings and market condition on both intentional and unintentional failures to meet stakeholders' expectation.

Discount Rate: We predict that insurers' incentives are affected by the time value of money, which is measured by discount rates. The estimation results are reported in Table 8. While some discount rate variables show significance in the reported results, no variable is significant in internal fraud model. Thus, insurers' incentives to induce internal fraud are not explained by the level of and the change in discount rates investigated in the models. In terms of a broader range of events, the change in insurance industry return and S&P500 Index returns, however, are positively associated with the occurrence of events. The positive signs are consistent with our prediction that a greater discount discourages insurers from exerting effort to maintain their positive reputation. The positive signs on these measures may be interpreted that a higher required rate of return forces insurers to be more aggressive to maximize their current profit.

Conflict of Interest : We predict that insurers tend to increase reputational risk exposure when ownership and management are more closely aligned. To investigate the hypothesis we employ the executive shareholding ratio. We report these analyses separately due to the much smaller samples available. They are shown in in Table 10 and Table 11. The sample universe of these estimations is limited to US-based insurers listed in S&P1500. Table 10 reports parameter estimates of the models with the SOX variable and year dummy variables, and Table 11 reports test results for the models with discount rate variables.

[Insert Tables 10-11 Here]

With a few exceptions, the estimation results are generally consistent with those reported in Tables 7 and Table 8. Notably, change in market concentration for PC insurers, capital holdings, firm age, and firm size all remain significant. Of particular interest in these analyses is the executive shareholdings variable. As predicted, it is significant with positive sign only in internal fraud models. The lack of significance in the models with other measures of the dependent variable strongly supports our hypothesis that when managers' interests are closely aligned with owners' interests, insurers' positive reputation tends to be exposed to potential loss through internal fraud.

In addition, it is not surprising that firm size is consistently positively associated with the event counts regardless of the dependent variables and choice of explanatory variables. Larger insurers tend to have more revealed events that could cause loss of positive reputation.

5.2 ZIP Regression Models

As discussed in the model specification section, a basic Poisson analysis does not necessarily address the zero outcomes in our data. We therefore also conduct analyses using a zero-inflated Poisson (ZIP) regression as proposed by Lambert (1992). Zero-inflated Poisson regressions are appropriate when modeling count data that have an excess of zero counts. Theory further suggests that the excess zeroes are generated by a process distinct from the process that generates count values and therefore the excess zeroes can be modeled independently of the count values. Thus, the ZIP model has two parts, a Poisson count model and a logit excess zero model. Essentially, we take the ZIP Poisson to indicate public revelation of operational loss events while the ZIP logit represents the underlying insurer strategy regarding the extent of risky behavior it is willing to undertake. The ZIP is appealing because the zero outcomes can be explained by both no event and events incurred but not revealed in our context. The regression model, however, imposes a restriction on the number of parameters that can be estimated. Since our sample outcomes do not allow estimating all parameters at once, we run the analysis with the variables that demonstrated statistical significance in the basic Poisson models.

Parameter estimates of the basic Poisson models (now with a refined set of independent variables) are reported in Table 12, along with the ZIP Poisson and logit models for each response variable (although *Internal fraud* failed to obtain estimates due to relatively too few observed events, and hence, too many observed zero outcomes; therefore, we do not have results for these tests).[12] Variables that showed significance in the original basic Poisson generally continue to be significant, which suggests that we have a reasonable model in reduced form. We do not, however, observe significant improvement in the model fit for the ZIP, with both AIC and predicted zero outcomes similar to that in the original basic Poisson. The parameter estimates of the ZIP Poisson

[12] Regression results for all events response variable are available upon request.

models, however, differ in two respects. First, our measure of competition, the change in the Herfindahl-Hirschman index for PC insurers, is insignificant in the ZIP models. Our measure of information dispersion, change in analyst coverage, however, is significant with the expected negative sign. Further, we note that years following passage of SOX are significant and negative, supporting our hypothesis that SOX has had a dampening effect on operational loss events.

[Insert Table 12 Here]

The logit regressions in the ZIP model yield additional interesting results. Recall that the logit predicts excess losses, and therefore, can be considered as a representation of the insurer's underlying risky behavior, whether that behavior is revealed or not. In these analyses, we find that the capital-to-asset ratio is consistently significant with negative sign. Tobin's Q shows week significance only for "all internal," and that also is negative. These results are in line with our original hypotheses of a self-regulating effect. Unexpectedly, however, firm age and firm size also show negative signs, which, on first blush, seems contrary to our predictions. One possible interpretation is as follows. Large insurers, those that are highly evaluated by the market, and those with long histories are less likely to expose their positive reputation to potential loss. Once they take such action, however, they have "gone over the cliff," so to speak, and as a result greater numbers of reputational loss events are incurred and caught by the public.

The estimation results, therefore, are consistent with our prediction. As indicated above, zero events that can be explained by the Poisson model is estimated solely by revealed loss events (Case 3: conditional on both loss and revelation). Therefore, it is reasonable that those zeroes are more likely to represent unrevealed loss events (Case 2: conditional on loss). Thus, in the ZIP model, we argue that the Poisson models are more likely to explain public revelation given loss events (Case2 and 3) and then the logit models would capture whether insurers take reputation strategy (Case 1) or not (Case2 and 3). This means that those variables with statistically significant negative sign in the logit models and positive sign in the Poisson models capture the self-regulatory effect of insurers' reputational risk taking and are positively associated with stringent market discipline which makes it hard for insurers to hide events.

This explanation may also apply to our findings regarding industry competition/concentration.

We know already from prior research that the influence of Tobin's Q on firm risk-taking incentives is complex. The inclusion of the competition measure has been considered an explanation for the complex results with Tobin's Q to date. We find, however, that measures of concentration (the inverse of competition) yield results opposite of our expectations for the Poisson but not the Logit. What we may be observing is this "cliff" nature of an insurer's strategy. That is, an insurer's incentives to risk its reputation may not be on a continuum but rather take a jump process, either in or out fully.

6 Conclusion

In the research reported here, we provide one approach to identifying the primary determinants of reputational risk exposure. Our focus is on those conditions adversely affecting the insurer's reputation. When the expected benefit of an opportunistic performance (here, we denote it as moral hazard) exceeds the expected benefit obtained from maintaining a positive reputation, insurers may be willing to take the opportunistic strategy, which causes a conflict of interest between insurer and policyholder. Thus, identifying factors that induce insurer moral hazard should help determine situations associated with reputational loss potential.

In our empirical analysis, we find that capital holdings (leverage ratio), firm age, executives' shareholdings, and firm size all induce insurer's reputational loss exposure through internal fraud. Although capital and agency problems are widely studied in the risk-taking literature, reputational risk studies differ in that they need to consider the efficiency of belief updating. Firm age and analyst coverage both proxy this factor and demonstrate support for our hypothesis in some of the models.

We also observe that several other factors are associated with insurers' exposure to potential reputational loss. Franchise value, market competition/concentration for the property-casulaty insurance industry, and discount rates such as insurance industry average return, market index return, and interest rate all explain the occurrence of a broader range of operational risk loss events, which may cause loss of reputation.

We also investigate the consistency of outcomes before and after the passage of SOX. Firm age and executives' shareholdings show robust results in that they are statistically significant with positive sign regardless of the sample periods. In contrast, capital holdings and market competition/concentration for property-casualty insurers are no longer significant during the post-SOX period. We may be observing the effect of strengthened corporate governance practices, reducing the occurrence of intentional and unintentional operational loss events.

Our study is limited particularly in that the number of operational risk loss events reported in the database is small compared with the number of firms included in the analysis. To overcome the problem of the excess zero observations in dependent variables, we conduct two analyses. One is the Basic Poisson regression, which assumes all zeroes to be truly non-events. This analysis has the advantage of allowing us to consider our full spectrum of potentially influential factors, yet it is limited in that the approach may be measuring the likelihood of public revelation rather than actually identifying prominent determinants of reputational risk.

The ZIP regression estimations, in contrast, differentiates the zeroes to account for the fact that some likely involve non-reported events while others are true zeroes. The ZIP regression is limited, however, in the number of factors that can be considered as potential influencers of moral hazard. We use the results from the Poisson analysis to select which factors to include in the ZIP. This analysis more directly offers implication for insurers' underlying decisions regarding whether they take an opportunistic act. We demonstrate that the effect of determinants on insurers' risk-taking decision and on revealed event counts are dramatically different.

Our approach to identify factors that could affect a firm's incentives to maintain its positive reputation are generally applicable to other industries. Extending our study to the banking industry, for instance, is one way to have sufficiently large operational risk loss events, which allow additional analysis.

Appendix A

Sarbanes-Oxley Act

Section 3: Corporate responsibility

This provision describes that executives' responsibility for the accuracy of financial reports and forfeitures of benefits and civil penalties for non-compliance.

Section 4: Enhanced financial disclosure and internal controls

This section describes enhanced reporting requirements for financial transactions including insider trading of stock and requires disclosure of managerial assessment of internal controls.

Section 8: Corporate and Criminal Fraud Accountability

This provision describes specific criminal penalties for manipulation, destruction or alteration of financial records or other interference with investigations.

Section 9: White Collar Crime Penalty Enhancement

This section increases the criminal penalties associated with white-collar crimes and conspiracies. Stronger sentencing guidelines and failure to certify corporate financial reports are discussed.

Section 11: Corporate Fraud Accountability

This section identifies corporate fraud and records tampering as criminal offenses, and revises sentencing guidelines and strengthens their penalties.

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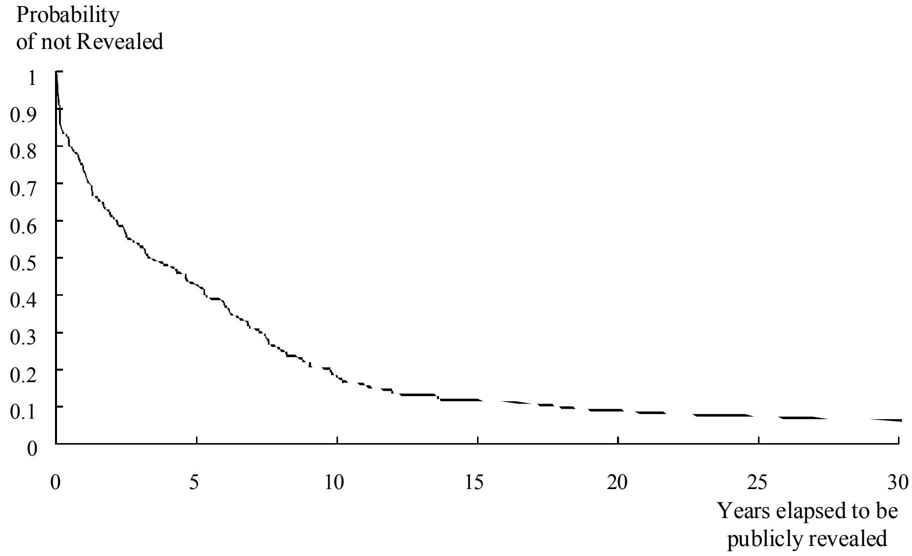

Figure 1: Duration until Public Revelation

This figure shows years of time lag between the date when an event started to occur (*event start date*) and its public disclosure date. It takes about five years on average (3.5 years in median) for event information to be revealed to the public. And the distribution has a long right tail, indicating that some events are not revealed for many years.

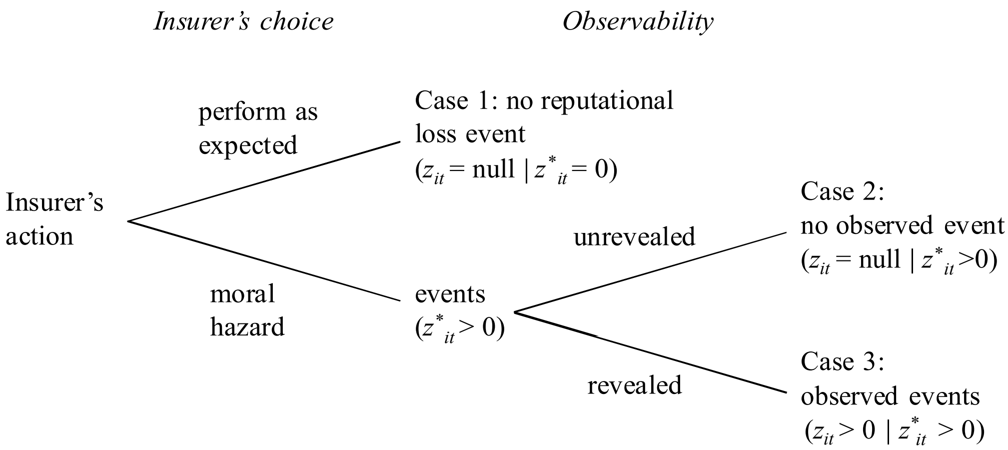

Figure 2: Observable and Unobservable Events

Table 1: Definitions of Variables

Variables	Description
Response Variables	
Internal fraud	The number of *ET1* operational risk loss events
Internal fraud + negligence	The number of *ET1* and *ET4* operational risk loss events
All internal	The number of *internally-caused* operational risk loss events
All events	The number of *all types* of operational risk loss events
Explanatory Variables	
Tobin's Q	Tobin's Q is defined by the ratio of the market value of assets minus the book value to the book value of capital..; *Change in Tobin's Q* is a percent change in *Tobin's Q* from previous year
Herfindahl (*PC*) (*Life*)	The Herfindahl-Hirschman Index defined as the sum of squared market share of top 10 property-casualty (life) insurers in net premium written
Capital-to-asset ratio	1-(Liability/Assets); *Change in capital-to-asset ratio* is a percent change in *Capital-to-asset ratio* from previous year
SOX	1 if observation year is 2002 or later
Residual of analysts	OLS estimation residual obtained by regressing the number of analysts who reported EPS (I/B/E/S Historical Summary File) on the log-transformed assets; *Change in residual of analysts* is a percent change in *residual of analysts* from previous year
Log(*age*)	The log-transformed number of years since firm establishment
Insurance industry return	Sample insurers' average holding annual return minus interest rate; *Change in insurance industry return* is a difference in *Insurance industry return* from previous year
SP500	S&P 500 index annual return minus interest rate; *Change in SP500* is a difference in SP500 from previous year
Interest rate	Annualized monthly treasury bill rate; *Change in interest rate* is a difference in *Interest rate* from previous year
Market beta	The ratio of covariance between the firm-year stock holding return and weighted-average market return to the variance of weighted-average market return; *Change in market beta* is a percent change in *Market beta* from previous year
Executive shareholdings	The ratio of the number of shares owned by executives reported in Compustat Executive Compensation Anncomp File to the number of shares outstanding.
Log(*assets*)	Log-transformed total value of assets (US Million $)
PC	1 if SIC industry group is 633 (property and casualty insurance), 0 otherwise
Life	1 if SIC industry group is 631 (life insurance), 0 otherwise
Year [*year*]	1 if observation year is [*year*], 0 otherwise

Table 2: BIS Event Type Distribution of 209 Identified Events

209 operational loss events which started to occur during 1997-2006 are identified in the FIRST database updated in August 2009. The 209 events are used to construct response variables.

Panel A: Event Distribution by BIS Event Type

BIS Event Type	Event Counts
Internal Fraud (ET1)	26
Employment Practices and Workplace Safety (ET3)	23
Clients Products and Business Practices (ET4)	123
Business Disruption and System Failures (ET6)	3
Execution Delivery and Process Management (ET7)	3
All Internal (ET1+ET3+ET4+ET6+ET7)	178
External Fraud (ET2)	15
Damage to Physical Assets (ET5)	16
All Events	209

Panel B: Event Distribution by Year

Year	ET1	ET3	ET4	ET6	ET7	Internal	ET2	ET5	All Events
1997	2	3	12	0	0	17	0	0	17
1998	2	2	14	0	0	18	1	0	19
1999	4	3	14	0	1	22	2	0	24
2000	4	0	14	0	0	18	3	0	21
2001	5	5	12	1	0	23	1	12	36
2002	2	2	15	0	0	19	0	1	20
2003	1	1	19	0	0	21	0	0	21
2004	2	3	12	1	2	20	2	0	22
2005	3	2	7	0	0	12	1	3	16
2006	1	2	4	1	0	8	5	0	13
Year Total	26	23	123	3	3	178	15	16	209

Table 3: Analyst Coverage: OLS Estimation

This table reports the coefficients of analyst coverage OLS regression. The dependent variable is the number of analysts who reported EPS annual estimate in I/B/E/S database. $Ln(assets)$ is used as explanatory variables. Estimated standardized residuals, denoted by *Residual of analysts*, are used as a proxy for the efficiency of information sharing. *** represent 1% significance level.

Variable	Estimate	t-statistic
Intercept	-36.626 ***	-17.26
Log(assets)	7.603 ***	28.28
Number of Observation	1710	
Adjusted R^2	0.32	

Table 4: Summary Statistics (1)

All variables are on an annual basis. 289 firms are observed in maximum 10 year periods. CRSP daily stock file data is used for market related data, and Compustat Fundamentals Annual file is used to collect financial statement data. Panel A shows the distribution of response variables used in our estimations. Each response variable represent different set of event types. Panel B displays the descriptive statistics for firm-specific variables and Panel C shows the time series of market related variables.

Panel A: Distribution of Response Variables

Counts	0	1	2	3	4	5	6+
Internal fraud	1590	20	2	0	0	0	0
Internal fraud + negligence	1525	67	17	2	1	0	0
All internal	1498	79	26	6	3	0	0
All events	1480	93	26	8	2	3	0

Panel B: Firm-specific Variables

Variables	Obs.	Mean	Standard Deviation	Median	Minimum	Maximum
Internal fraud	1612	0.015	0.131	0	0	2
Internal fraud + negligence	1612	0.069	0.316	0	0	4
All internal	1612	0.100	0.409	0	0	4
All events	1612	0.119	0.468	0	0	5
Tobin's Q	1567	0.723	1.853	0.359	-18.155	21.869
Capital-to-asset ratio	1568	0.277	0.196	0.243	-1.520	0.996
Residual of analysts	1568	0.000	0.992	-0.097	-2.834	6.824
Log(age)	1612	2.778	1.507	3.091	0.000	5.361
Market beta	1568	0.754	0.540	0.713	-1.493	5.189
Executive shareholdings	650	0.064	0.087	0.034	0.000	0.744
Log(assets)	1568	7.516	2.201	7.420	0.643	13.66
PC	1568	0.476	0.500	0	0	1
Life	1568	0.214	0.410	0	0	1
Change in Tobin's Q	1450	-0.284	0.101	-0.146	-2.769	0.805
Change in capital-to-assets ratio	1452	0.045	0.013	0.000	-0.293	0.252
Change in residual of analysts	1300	-1.175	0.316	-0.043	-9.685	3.423
Change in market beta	1320	-0.050	0.053	0.050	-1.182	0.538

Table 5: Summary Statistics (2)

Panel C: Other Variables

year	*Herfindahl (PC)*	*Change in Herfindahl (PC)*	*Herfindahl (Life)*	*Change in Herfindahl (Life)*	*Insurance industry return*	*Change in insurance industry return*	*SP500*	*Change in SP500*	*Interest rate*	*Change in interest rate*
1996	0.031	-	0.015	-	0.106	-	0.151	-	0.052	-
1997	0.030	-0.033	0.017	0.140	0.256	0.150	0.258	0.107	0.053	0.001
1998	0.030	-0.018	0.016	-0.063	-0.042	-0.298	0.218	-0.039	0.049	-0.004
1999	0.029	-0.020	0.019	0.210	-0.175	-0.133	0.148	-0.070	0.047	-0.002
2000	0.027	-0.070	0.016	-0.189	0.159	0.335	-0.160	-0.309	0.059	0.012
2001	0.028	0.022	0.017	0.086	0.048	-0.112	-0.169	-0.009	0.039	-0.020
2002	0.032	0.154	0.018	0.053	-0.026	-0.074	-0.250	-0.081	0.016	-0.022
2003	0.032	-0.011	0.020	0.107	0.415	0.441	0.254	0.504	0.010	-0.006
2004	0.031	-0.005	0.022	0.095	0.219	-0.196	0.078	-0.175	0.012	0.002
2005	0.032	0.007	0.023	0.075	0.106	-0.113	0.000	-0.078	0.030	0.018
Mean	0.030	0.003	0.018	0.057	0.106	0.000	0.053	-0.017	0.037	-0.002

Table 6: Pearson Correlation Coefficients

Upper row: Pearson correlation coefficients, Lower row: p-value under $H_0 : \rho = 0$

	Internal fraud	*All internal*	*Tobin's Q*	*Capital-to-asset ratio*	*SOX*	*Residual of analysts*	*Ln (age)*	*Insurance industry return*	*SP500*	*Interest rate*	*Market beta*	*Executive share-holdings*	*Ln (assets)*
Tobin's Q	0.048	0.069	1										
	[0.056]	[0.006]											
Capital-to-asset ratio	-0.027	-0.104	0.115	1									
	[0.291]	[<.0001]	[<.0001]										
SOX	-0.015	0.027	-0.069	-0.039	1								
	[0.537]	[0.281]	[0.006]	[0.125]									
Residual of analysts	-0.018	0.004	0.136	0.073	0.000	1							
	[0.466]	[0.867]	[<.0001]	[0.004]	[0.999]								
Log(age)	0.088	0.106	-0.015	-0.143	0.158	0.055	1						
	[0.001]	[<.0001]	[0.544]	[<.0001]	[<.0001]	[0.03]							
Insurance ind. return	-0.007	0.007	0.011	0.010	0.278	0.001	0.041	1					
	[0.768]	[0.774]	[0.653]	[0.681]	[<.0001]	[0.001]	[0.102]						
SP500	-0.012	-0.037	0.062	0.032	-0.411	0.005	-0.066	0.266	1				
	[0.631]	[0.14]	[0.014]	[0.199]	[<.0001]	[0.83]	[0.009]	[<.0001]					
Interest rate	0.007	-0.048	0.054	0.032	-0.883	0.000	-0.128	-0.310	0.131	1			
	[0.79]	[0.055]	[0.033]	[0.198]	[<.0001]	[0.999]	[<.0001]	[<.0001]	[<.0001]				
Market bete	0.032	0.099	0.169	-0.051	0.155	0.072	0.069	0.072	0.137	-0.215	1		
	[0.208]	[<.0001]	[<.0001]	[0.044]	[<.0001]	[0.004]	[0.006]	[0.005]	[<.0001]	[<.0001]			
Executive shareholdings	-0.017	-0.116	0.041	0.057	-0.033	-0.147	-0.319	-0.024	0.006	0.037	-0.038	1	
	[0.659]	[0.003]	[0.299]	[0.145]	[0.4]	[0.001]	[<.0001]	[0.537]	[0.884]	[0.344]	[0.329]		
Ln(assets)	0.139	0.336	-0.028	-0.422	0.191	-0.013	0.354	0.067	-0.069	-0.184	0.261	-0.214	1
	[<.0001]	[<.0001]	[0.27]	[<.0001]	[<.0001]	[0.611]	[<.0001]	[0.008]	[0.006]	[<.0001]	[<.0001]	[<.0001	
PC	-0.005	-0.025	-0.202	0.100	0.132	-0.001	0.095	0.017	-0.078	-0.106	-0.069	0.183	-0.027
	[0.854]	[0.326]	[<.0001]	[<.0001]	[<.0001]	[0.967]	[0.001]	[0.49]	[0.002]	[<.0001]	[0.007]	[<.0001]	[0.283]
Life	-0.033	-0.056	-0.039	-0.252	-0.102	-0.099	0.056	-0.001	0.054	0.087	0.005	-0.109	0.137
	[0.194]	[0.027]	[0.121]	[<.0001]	[<.0001]	[<.0001]	[0.025]	[0.974]	[0.031]	[0.001]	[0.833]	[0.006]	[<.0001]

Table 7: Parameter Estimates With SOX and Year Dummy Variables

This table reports the estimated coefficients of operational loss event models. Models are estimated by generalized linear models with random-effects to accommodate heterogeneity between subjects. The response variable is the number of operational loss events that fall in the BIS operational risk category. *Internal fraud* represents internal fraud, and *internal fraud + negligence* includes unintentional failure to meet a professional obligation in addition to internal fraud. *All Internal* includes all internally-caused operational loss events (ET1, ET3, ET4, ET6 and ET7). Year dummy variables are included in these models but the estimation results are not reported here. Discount rate variables are not included due to the strong correlation with SOX variable. *Executive shareholdings* is also not included in these models to avoid significant loss of observations.

Random-Effects Models with Year Dummy Variables									
	Pred. (sign)	*Internal fraud*		*Internal fraud + negligence*		*All internal*		*All events*	
Variable		Estimate	*p* -value	Estimate	*p* -value	Estimate	*p* -value	Estimate	*p* -value
Intercept		-14.49	<.0001	-12.33	<.0001	-12.68	<.0001	-12.23	<.0001
Tobin's Q	(-)	0.088	0.662	0.148	0.140	0.131	0.199	0.128	0.169
Change in Tobin's Q	(-)	-0.012	0.497	-0.007	0.588	-0.008	0.544	-0.006	0.589
*Herfindahl(PC)*PC*	(-)	3.940	0.267	0.909	0.563	0.833	0.563	-0.551	0.669
*Change in Herfindahl(PC)*PC*	(-)	1.644	0.385	0.868	0.028	0.820	0.028	0.704	0.047
*Herfindahl(Life)*Life*	(-)	-6.269	0.541	-1.624	0.484	-1.619	0.413	-1.085	0.523
*Change in Herfindahl(Life)*Life*	(-)	1.792	0.230	0.355	0.308	0.296	0.344	0.323	0.255
Capital-to-asset ratio	(+)	4.528	0.055	3.110	0.024	3.360	0.014	3.039	0.016
Change in capital-to-asset ratio	(+)	0.265	0.545	0.085	0.822	0.061	0.883	0.128	0.656
SOX	(-)	-4.075	<.0001	-2.989	<.0001	-2.963	<.0001	-2.889	<.0001
Residual of analysts	(-)	0.028	0.875	0.069	0.508	0.043	0.667	0.030	0.743
Change in residual of analysts	(-)	0.017	0.373	0.009	0.532	0.011	0.354	0.010	0.361
Ln (age)	(+)	0.914	0.010	0.409	0.010	0.434	0.007	0.411	0.005
Ln (assets)	(+)	0.653	0.002	0.773	<.0001	0.810	<.0001	0.792	<.0001
PC		-11.45	0.283	-2.707	0.565	-2.511	0.560	1.764	0.647
Life		9.040	0.598	2.368	0.557	2.427	0.482	1.381	0.646
Year dummy variables		Yes		Yes		Yes		Yes	
AIC		205		522		561		632	
Number of Obs.		1289		1289		1289		1289	

Table 8: Parameter Estimates With Discount Rate Variables

This table reports the estimated coefficients of operational loss event models. Models are estimated by generalized linear models with random-effects to accommodate heterogeneity between subjects. The response variable is the number of operational loss events that fall in the BIS operational risk category. *Internal fraud* represents internal fraud, and *internal fraud + negligence* includes unintentional failure to meet a professional obligation in addition to internal fraud. *All Internal* includes all internally-caused operational loss events (ET1, ET3, ET4, ET6 and ET7). Discount rate variables are included but SOX variable and year dummy variables are excluded due to the strong correlation with discount rate variables. *Executive shareholdings* is also not included in these models to avoid significant loss of observations.

Random-Effects Models with Discount Rate Variables									
	Pred. (sign)	*Internal fraud*		*Internal fraud + negligence*		*All internal*		*All events*	
Variable		Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept		-16.84	<.0001	-13.41	<.0001	-13.74	<.0001	-12.72	<.0001
Tobin's Q	(-)	0.179	0.311	0.172	0.066	0.164	0.084	0.158	0.067
Change in Tobin's Q	(-)	-0.010	0.544	-0.008	0.581	-0.008	0.532	-0.006	0.598
*Herfindahl(PC)*PC*	(-)	3.124	0.369	0.700	0.648	0.803	0.566	-0.795	0.518
*Change in Herfindahl(PC)*PC*	(-)	0.083	0.931	0.759	0.040	0.657	0.056	0.582	0.082
*Herfindahl(Life)*Life*	(-)	-2.612	0.688	-1.288	0.554	-0.731	0.685	-1.010	0.537
*Change in Herfindahl(Life)*Life*	(-)	1.224	0.310	0.180	0.571	0.022	0.937	0.132	0.613
Capital-to-asset ratio	(+)	4.712	0.047	2.996	0.029	3.174	0.020	2.847	0.022
Change in capital-to-asset ratio	(+)	0.291	0.525	0.072	0.860	0.056	0.895	0.130	0.667
Residual of analysts	(-)	0.052	0.774	0.079	0.433	0.054	0.575	0.026	0.772
Change in residual of analysts	(-)	0.012	0.500	0.006	0.669	0.009	0.502	0.007	0.596
Ln (age)	(+)	0.919	0.011	0.406	0.010	0.431	0.007	0.404	0.006
Insurance industry return	(+/-)	-0.317	0.903	-1.248	0.285	-0.854	0.439	-1.201	0.228
Change in insurance ind. return	(+/-)	1.684	0.416	2.058	0.027	1.954	0.023	2.447	0.001
SP500	(+/-)	3.306	0.244	3.123	0.022	3.023	0.016	2.892	0.010
Change in SP500	(+/-)	-3.900	0.149	-2.167	0.104	-1.905	0.115	-2.464	0.019
Interest rate	(+/-)	26.61	0.276	14.95	0.184	13.88	0.179	4.531	0.639
Change in interest rate	(+/-)	-37.00	0.288	-39.58	0.026	-38.37	0.018	-23.27	0.090
Market beta	(+/-)	-0.108	0.879	0.077	0.809	-0.003	0.993	0.159	0.555
Change in market beta	(+/-)	-0.001	0.980	0.007	0.790	0.009	0.712	0.011	0.644
Ln (assets)	(+)	0.680	0.001	0.775	<.0001	0.816	<.0001	0.780	<.0001
PC		-9.203	0.377	-2.048	0.655	-2.385	0.568	2.495	0.496
Life		2.778	0.802	1.831	0.628	0.905	0.774	1.272	0.660
Year dummy variables		No		No		No		No	
AIC		207		521		563		635	
Number of Obs.		1298		1298		1298		1298	

Table 9: Parameter Estimates With Year Dummy Variables: Post SOX Legislation Period

This table reports the estimated coefficients of operational loss event models. Models are estimated by generalized linear models with random-effects to accommodate heterogeneity between subjects. The response variable is the number of operational loss events that fall in the BIS operational risk category. *Internal fraud* represents internal fraud, and *internal fraud + negligence* includes unintentional failure to meet a professional obligation in addition to internal fraud. *All Internal* includes all internally-caused operational loss events (ET1, ET3, ET4, ET6 and ET7). Year dummy variables are included in these models, though the estimation results are not reported here. Discount rate variables are not included due to the strong correlation with SOX variable and year dummy variables. *Executive shareholdings* is also not included in these models to avoid significant loss of observations.

Post SOX Period (2002-2005): Random-Effects Models with Year Dummy Variables									
	Pred. (sign)	*Internal fraud*		*Internal fraud + negligence*		*All internal*		*All events*	
Variable		Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept		-18.93	0.002	-11.39	<.0001	-10.98	<.0001	-10.78	<.0001
Tobin's Q	(-)	-0.385	0.277	0.115	0.531	0.052	0.778	0.115	0.455
Change in Tobin's Q	(-)	-0.022	0.829	-0.039	0.194	-0.036	0.212	-0.036	0.195
*Herfindahl(PC)*PC*	(-)	4.043	0.945	3.509	0.911	3.380	0.905	3.402	0.894
*Change in Herfindahl(PC)*PC*	(-)	-0.080	0.961	0.711	0.373	0.600	0.410	0.475	0.472
*Herfindahl(Life)*Life*	(-)	-8.078	0.989	2.267	0.717	1.281	0.826	1.500	0.762
*Change in Herfindahl(Life)*Life*	(-)	1.002	0.997	3.442	0.600	5.257	0.395	5.091	0.331
Capital-to-asset ratio	(+)	5.784	0.164	1.382	0.470	1.903	0.284	1.520	0.372
Change in capital-to-asset ratio	(+)	-0.242	0.935	0.682	0.534	0.663	0.518	0.654	0.494
Residual of analysts	(-)	0.063	0.793	-0.017	0.897	-0.018	0.883	0.032	0.779
Change in residual of analysts	(-)	-0.008	0.930	-0.039	0.165	-0.024	0.387	-0.023	0.383
Ln (age)	(+)	0.887	0.141	0.495	0.050	0.455	0.048	0.398	0.062
Ln (assets)	(+)	0.902	0.014	0.643	<.0001	0.661	<.0001	0.676	<.0001
PC		-11.49	0.950	-11.113	0.910	-11.102	0.901	-11.076	0.890
Life		7.985	0.993	-9.268	0.608	-8.971	0.597	-9.080	0.529
Year dummy variables		Yes		Yes		Yes		Yes	
AIC		87		222		285		307	
Number of Obs.		530		530		530		530	

Table 10: Parameter Estimates With Executive Shareholdings Variable and Year Dummy Variables

This table reports the estimated coefficients of operational loss event models. Models are estimated by generalized linear models with random-effects to accommodate heterogeneity between subjects. The response variable is the number of operational loss events that fall in the BIS operational risk category. *Internal fraud* represents internal fraud, and *internal fraud + negligence* includes unintentional failure to meet a professional obligation in addition to internal fraud. *All Internal* includes all internally-caused operational loss events (ET1, ET3, ET4, ET6 and ET7). *Executive shareholdings* is included in these models to investigate the effect of aligning managerial and shareholders' interests. Note significant loss of observations due to limited samples in Compustat Executive Compensation Anncomp File. SOX variable and year dummy variables are included but discount rate variables are excluded due to the strong correlation with them.

Random-Effects Models with Year Dummy Variables

Variable	Pred. (sign)	*Internal fraud*		*Internal fraud + negligence*		*All internal*		*All events*	
		Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept		-19.11	<.0001	-10.91	<.0001	-10.95	<.0001	-10.76	<.0001
Tobin's Q	(-)	-0.076	0.782	0.058	0.614	0.035	0.754	0.090	0.372
Change in Tobin's Q	(-)	-0.015	0.376	-0.007	0.549	-0.007	0.515	-0.006	0.591
*Herfindahl(PC)*PC*	(-)	3.776	0.323	1.229	0.451	0.786	0.595	0.156	0.909
*Change in Herfindahl(PC)*PC*	(-)	1.551	0.408	0.924	0.022	0.907	0.018	0.784	0.032
*Herfindahl(Life)*Life*	(-)	-6.013	0.517	-1.542	0.482	-1.991	0.312	-1.405	0.412
*Change in Herfindahl(Life)*Life*	(-)	1.840	0.224	0.347	0.337	0.315	0.341	0.289	0.345
Capital-to-asset ratio	(+)	8.562	0.013	3.297	0.041	3.425	0.028	2.879	0.066
Change in capital-to-asset ratio	(+)	0.975	0.508	0.140	0.856	0.110	0.883	0.160	0.811
SOX	(-)	-4.982	<.0001	-2.735	<.0001	-2.633	<.0001	-2.603	<.0001
Residual of analysts	(-)	-0.019	0.924	0.024	0.819	0.002	0.983	0.010	0.918
Change in residual of analysts	(-)	0.043	0.378	0.017	0.401	0.019	0.300	0.018	0.317
Ln (age)	(+)	1.495	0.002	0.461	0.013	0.467	0.011	0.470	0.010
Executive shareholdings	(+)	9.123	0.013	0.527	0.851	-0.138	0.961	-0.101	0.971
Ln (assets)	(+)	0.874	0.005	0.612	<.0001	0.629	<.0001	0.611	<.0001
PC		-11.36	0.323	-3.84	0.432	-2.540	0.566	-0.441	0.914
Life		9.244	0.552	2.571	0.502	3.364	0.328	2.342	0.439
Year dummy variables		Yes		Yes		Yes		Yes	
AIC		180		473		511		554	
Number of Obs.		562		562		562		562	

Table 11: Parameter Estimates With Executive Shareholdings Variable and Discount Rate Variables

This table reports the estimated coefficients of operational loss event models. Models are estimated by generalized linear models with random-effects to accommodate heterogeneity between subjects. The response variable is the number of operational loss events that fall in the BIS operational risk category. *Internal fraud* represents internal fraud, and *internal fraud + negligence* includes unintentional failure to meet a professional obligation in addition to internal fraud. *All Internal* includes all internally-caused operational loss events (ET1, ET3, ET4, ET6 and ET7). *Executive shareholding* is included in these models to investigate the effect of aligning managerial and shareholders' interests. Note significant loss of observations due to limited samples in Compustat Executive Compensation Anncomp File. Discount rate variables are included but SOX variable and year dummy variables are not included due to the strong correlation with discount rate variables.

Random-Effects Models with Discount Rate Variables

Variable	Pred. (sign)	*Internal fraud*		*Internal fraud + negligence*		*All internal*		*All events*	
		Estimate	*p* -value	Estimate	*p* -value	Estimate	*p* -value	Estimate	*p* -value
Intercept		-22.12	<.0001	-11.68	<.0001	-11.49	<.0001	-11.17	<.0001
Tobin's Q	(-)	0.071	0.769	0.107	0.312	0.086	0.414	0.134	0.156
Change in Tobin's Q	(-)	-0.013	0.430	-0.007	0.559	-0.008	0.510	-0.006	0.588
*Herfindahl(PC)*PC*	(-)	3.453	0.363	0.839	0.603	0.527	0.716	-0.130	0.921
*Change in Herfindahl(PC)*PC*	(-)	0.045	0.964	0.741	0.046	0.738	0.035	0.641	0.059
*Herfindahl(Life)*Life*	(-)	-1.999	0.740	-1.079	0.603	-1.375	0.446	-1.026	0.524
*Change in Herfindahl(Life)*Life*	(-)	1.343	0.328	0.148	0.658	0.051	0.863	0.065	0.817
Capital-to-asset ratio	(+)	8.450	0.012	3.178	0.047	3.222	0.037	2.722	0.075
Change in capital-to-asset ratio	(+)	0.952	0.510	0.095	0.901	0.079	0.915	0.158	0.808
Residual of analysts	(-)	0.027	0.894	0.045	0.660	0.024	0.807	0.021	0.821
Change in residual of analysts	(-)	0.050	0.306	0.016	0.470	0.017	0.383	0.014	0.443
Ln (age)	(+)	1.535	0.002	0.458	0.014	0.467	0.011	0.470	0.009
Insurance industry return	(+/-)	-1.775	0.531	-1.489	0.226	-1.127	0.337	-1.237	0.249
Change in insurance ind. return	(+/-)	3.292	0.150	2.516	0.012	1.974	0.025	2.182	0.007
SP500	(+/-)	4.748	0.129	3.436	0.017	2.515	0.047	2.734	0.019
Change in SP500	(+/-)	-5.054	0.089	-2.824	0.045	-1.632	0.177	-2.111	0.051
Interest rate	(+/-)	22.25	0.394	10.47	0.362	10.45	0.327	5.280	0.596
Change in interest rate	(+/-)	-54.93	0.168	-44.31	0.021	-26.95	0.085	-20.42	0.144
Market beta	(+/-)	-0.310	0.712	0.003	0.993	-0.044	0.892	0.055	0.857
Change in market beta	(+/-)	0.005	0.945	0.007	0.787	0.010	0.706	0.012	0.659
Executive shareholdings	(+)	8.873	0.011	0.590	0.834	-0.008	0.998	0.106	0.969
Ln (assets)	(+)	0.878	0.003	0.626	<.0001	0.640	<.0001	0.623	<.0001
PC		-10.43	0.358	-2.599	0.590	-1.704	0.694	0.449	0.909
Life		2.213	0.832	1.825	0.615	2.339	0.460	1.709	0.548
Year dummy variables		No		No		No		No	
Log Likelihood		184		474		515		558	
Number of Obs.		562		562		562		562	

Table 12: ZIP Regression Models and Basic Poisson Models

This table reports the estimated coefficients of the ZIP regression models and the basic Poisson models. A random-effect is employed to accommodate heterogeneity between subjects. The response variable is the number of operational loss events that fall in the BIS operational risk category. *Internal fraud + negligence* includes unintentional failure to meet a professional obligation in addition to internal fraud. *All Internal* includes all internally-caused operational loss events (ET1, ET3, ET4, ET6 and ET7). Models with *Internal fraud* response variable fail to obtain estimates due to excess zero outcomes. Year dummy variables after 2002 are included in these models. *Executive shareholdings* is also not included in these models to avoid significant loss of observations.

		Internal fraud + negligence						*All internal*					
		Basic Poisson		ZIP: Poisson		ZIP: Logit		Basic Poisson		ZIP: Poisson		ZIP: Logit	
Variable	Pred. (sign)	Estimate	*p* -value	Estimate	*p* -value	Estimate	*p* -value	Estimate	*p* -value	Estimate	*p* -value	Estimate	*p* -value
Intercept		-12.04	<.0001	-11.06	<.0001	9.09	<.0001	-12.38	<.0001	-11.17	<.0001	10.33	<.0001
Tobin's Q	(-)	0.169	0.052	0.122	0.082	-0.130	0.125	0.167	0.052	0.125	0.093	-0.154	0.081
*Change in Herfindahl(PC)*PC*	(-)	0.786	0.013	0.097	0.361	-0.544	0.083	0.709	0.020	0.089	0.581	-0.572	0.103
Capital-to-asset ratio	(+)	3.068	0.017	2.439	0.016	-2.490	0.035	3.313	0.008	2.335	0.004	-2.963	0.014
Change in residual of analysts	(-)	0.004	0.813	-0.011	0.002	-0.003	0.868	0.006	0.666	-0.010	<.0001	-0.004	0.781
Ln (*age*)	(+)	0.400	0.009	0.371	0.009	-0.290	0.037	0.424	0.005	0.388	0.003	-0.344	0.016
Ln (*assets*)	(+)	0.745	<.0001	0.663	<.0001	-0.617	<.0001	0.775	<.0001	0.681	<.0001	-0.716	<.0001
Year 2002	(-)	-0.556	0.213	-0.073	0.687	0.488	0.279	-0.578	0.176	-0.064	0.784	0.611	0.223
Year 2003	(-)	-0.284	0.365	-0.159	0.214	0.024	0.936	-0.048	0.861	-0.130	0.186	-0.152	0.628
Year 2004	(-)	-0.703	0.052	-0.271	0.017	0.539	0.110	-0.629	0.060	-0.249	0.015	0.576	0.118
Year 2005	(-)	-1.568	0.001	-1.142	0.005	1.146	0.009	-1.337	0.001	-0.944	0.012	1.238	0.006
Log Likelihood		509		501				550		537			
Number of Obs.		1298		1298				1298		1298			
Predicted Zero Outcomes		1229		1233				1219		1223			