Determinants of Insurers' Reputational Risk

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Abstract

When purchasing coverage, insurance consumers are unable to observe an insurer's ultimate performance on the explicit and implicit promises incorporated into their policy. As a result, these consumers must rely on an insurer's reputation to evaluate the offered coverage when deciding which insurer's product to purchase. In fact, others (e.g., Klein and Leffler, 1981) have demonstrated that consumers will pay a premium to purchase coverage from a highly-reputable insurer. Maintaining that good reputation, however, is costly. Whether or not it is profit maximizing to meet a consumer's expectation associated with an insurer's reputation, therefore, depends on a variety of factors, such as the size of expected profits from maintaining a good reputation, the discount rate into the future, and the efficiency of information sharing that would affect the speed of change in an insurer's reputation. We believe these factors can help us identify determinants of reputational risk. Our empirical results indicate that the level of capital holding and the efficiency of belief updating are strongly associated with insurers' reputational risk takings, which the literature suggests eventually cause loss of reputation. The results also indicate that reputational risks are more likely to be taken when market rate of return is high.

1 Introduction

The purpose of the research reported here is to identify key factors associated with insurer reputational risk. As defined by the Comité Européen des Assurances (CEA) and the Groupe Consultatif Actuariel Européen (Groupe Consultatif) in their work on Solvency II, reputational risk is "The risk that adverse publicity regarding insurer's business practices and associations, whether accurate or not, will cause a loss of confidence in the integrity of the institution" (Comité Européen des Assurances, 2005). As such, an organization's reputation depends not only on how it acts, but also on how the action is perceived by various stakeholders with different interests and distinct preferences. Thus, insurers must behave as expected by stakeholders to maintain their reputation. Our focus, therefore, is on identification of factors that induce behaviors that deviate from stakeholders' beliefs regarding the organization's actions.

For insurance companies a positive reputation is not just a factor for their financial success but a necessary factor to survive in the market. Building and maintaining a positive reputation is necessary for insurers to sell policies because consumers cannot observe how an insurer will actually perform before purchasing the policy. For instance, an insurer's protocols on executing implicit and explicit contractual promises, such as good customer service, appropriate and prompt claim payments, sufficient amount of capital, adequate reserves, and safe investments are not easily observed by customers. In reality, therefore, both insurers and customers must heavily rely on insurers' reputation in insurance transactions, even though regulators restrict insurers' performance such as excessive risk-taking in investment and inappropriate underwriting practices.

In general, customers are willing to pay a higher price for a stronger sense of confidence in the firm's ability to perform (e.g., Klein and Leffler, 1981); hence, we know that a positive reputation has value in the marketplace. Furthermore, according to a 2005 survey conducted by the Economist Intelligence Unit, protecting a firm's reputation is the most important and difficult task that senior executives responsible for managing risks face (Economist Intelligence Unit, 2005).[1] We investigate the conditions that generate incentives for insurers to behave in a way that causes loss of their positive reputation.

The structure of this paper is as follows. In Section 2, we discuss our two-step research design. Key factors of reputational risk and a measure of reputational loss are discussed in Section 3 and 4, respectively. We then present our data and empirical models in Section 5, followed by the test results in Section 6. The last section draws conclusions and discusses certain limitations of our arguments.

2 Research Design

To identify factors that might affect insurers' reputational risk, we take two steps. First, we argue that an insurer's established positive reputation could be damaged by its moral hazard. Here moral hazard is defined as insurer incentives against fulfilling stakeholder expectation on implicit and explicit contractual promises when stakeholders cannot perfectly observe insurer performance.

[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. The survey collects responses from various industries, of which 36% are from companies in the financial service sectors.

Second, we identify those factors that likely induce moral hazard. Taken together, factors identified in the second step are determinants of reputational risk.

Although moral hazard connects the two steps, what we observe are insurers' actions that would not fulfill stakeholder expectation on contractual promises, rather than the incentive themselves. In order to test the association between identified factors and reputational risk, we rely on a proxy for insurer moral hazard. Specifically, we utilize insurers' operational losses defined as loss events that fall in the *operational risk* category as a proxy for their moral hazard because these losses tend to be induced by imperfect monitoring of insurer performance.[2]

To illustrate the first step, we provide a description of operational loss event, which conveys adverse information regarding an insurer's performance on implicit contractual promises. This event description is taken from the Algo OpVantage Financial Institutions Risk Scenarios Trends (FIRST) database provided by Algorithmics (Event ID: 61; Insurer name is replaced by *Insurer A*).

> "*Insurer A* agreed to pay $42.7 million in order to resolve allegations that it overcharged 750,000 Texas drivers. ... The overcharges occurred primarily because *Insurer A* tried to subsidize premiums for its high-cost drivers by charging other less risky policyholders more. The refunds affect *Insurer A* customers who purchased an auto insurance policy between June 30, 1995, and Sept. 8, 1997. The complaints... were raised after a state review of *Insurer A* rates filed in 1995 and 1996."

The premium overcharge started in 1995 but the information was not publicly revealed until news media reported the settlement in August 30, 1997; hence, the insurer's behavior was hidden from stakeholders for more than one year. We claim that a lack of stakeholders' ability to have real time monitoring enabled the insurer to undertake the premium overcharge practice. If the insurer's operation were perfectly transparent, the insurer's practice would not be an optimal strategy simply because low-cost policyholders would be unwilling to purchase coverage from the insurer.

Further, the literature on reputational loss supports that such internally-caused operational losses in fact reduce a firm's reputation value. In the financial services sector, Cummins, Lewis, and Wei (2006) are the first to consider reputational effects of operational loss events. They

[2] See Section 5 for the details of operational loss events.

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.

Considering that *Insurer A* has been operating for more than seventy years and has been one of the largest insurers in the US property-liability insurance market, we would reasonably believe that the insurer had a positive reputation before the event information was revealed. Given the positive reputation, the revelation of *Insurer A*'s premium overcharge practice might lead to a loss of confidence by low-cost policyholders because the insurer acted differently from their beliefs. Thus, we can argue that a loss of reputation is caused by moral hazard from existing empirical findings.[3] Therefore, our primary discussion in this paper focuses on the second step of the two-step approach.

Our second step is to identify factors that would lead an insurer to expose its positive reputation to possible damage. Our effort is similar to the identification of factors that encourage policyholders' moral hazard under their insurance coverage. Consider an automobile driver, for instance, who has relatively low insurance rates because of an excellent driving record. A lack of insurer's perfect monitoring allows this policyholder to choose to drive safely or recklessly. The decision regarding whether to maintain the driver's good reputation corresponding to a good claim history is dependent on how the expected benefit of doing so (the discounted premiums) stacks up against the potential benefit from giving it up (arriving sooner at one's destination by speeding, for example). Just as the policyholder's decision on whether to keep or abandon a good reputation was based on a weighing of the costs and benefits of each alternative, so too will the insurer's decision be heavily dependent on a cost-benefit calculation.

For *Insurer A* the analysis of why the firm started to overcharge premiums in Texas in 1995 needs a consideration of the expected benefits and costs. To chance losing a positive reputation, the expected benefit of overcharging premiums (moral hazard) must have exceeded the expected cost accrued from loss of reputation and other associated costs. If factors that lead to insurer's

[3]This argument is also supported by the economic theory of reputation. For instance, see Klein and Leffler (1981)

Table 1: Definitions of Variables

Variables	Description
Response Variables	
Events(*internal*)	The number of *internally-caused* operational risk loss events
Explanatory Variables	
Franchise value per capital	The ratio of the franchise value to the book value of capital. The franchise value is the market value of assets minus the book value.
Capital-to-asset ratio	1-(Liability/Assets)
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
Log(*age*)	The log-transformed number of years since firm establishment
Insurance industry return	Sample insurers' average holding annual return minus interest rate.
SP500	S&P 500 index annual return minus interest rate
Interest rate	Annualized monthly treasury bill rate
Log(*assets*)	Log-transformed total value of assets (US Million $)
PC	1 if SIC industry group is 633 (health and accident 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

moral hazard are successfully identified, we conclude that the identified factors are determinants of reputational risk.

3 Factor Identification

We investigate factors that could be associated with insurer incentives to commit moral hazard and discuss the proxies in the following section (see Table 1 for a brief description of variables used in our empirical analysis). Specifically, we anticipate that the following are factors inducing reputational risks: 1) franchise value, 2) capital holdings, 3) discount rates, and 4) information sharing efficiency.

Franchise value: Classic reputation studies (e.g., Klein and Leffler, 1981; Shapiro, 1983; Allen, 1984) suggest that an insurer's incentives against moral hazard are determined by discounted expected future rents earned by its operation. Similarly, the risk-taking literature (e.g., Keeley, 1990;

Demsetz, Saidenberg, and Strahan, 1996; Fang, 2005) documents that franchise (charter) value is expected to be a primary factor that affects incentives for financial institutions' moral hazard.

Our measure of future expected profits is the market-to-book ratio, which is the ratio of the market value of the firm's assets to their book value (e.g., Barclay and Smith, 1995). The market value of equity is calculated by the closing stock price multiplied by the number of common shares outstanding plus the book value of preferred stock at the end of each quarter. Financial data to construct the ratio and other variables discussed below are taken from the Center for Research in Security Prices (CRSP) database and Compustat.

The market-to-book ratio (*Market-to-book*) is used as a proxy for an all-in-one measure of the expected discounted value of a stream of future profits. Using the market-to-book ratio makes it possible to capture all factors beyond tangible assets, which is considered as a self-regulatory factor against insurer's excessive risk-taking. Negative prospects for future profits reduce the ratio and also cause incentive problems.

Despite the self-regulatory aspect of franchise value, a number of conditions may alter the impact on insurer incentives. One scenario that could induce a positive association between future profits and moral hazard is an extended time since insurer establishment, because the marginal benefit of performing as expected decreases as an insurer earns a positive reputation (e.g., Holmström, 1999).[4] Once an insurer obtains a strong positive reputation, customers may fully anticipate that the insurer will perform as customers expect, attributing observations that do not fulfill their beliefs to just random events. Thus, the cost of risk-taking could be smaller when an insurer has a long duration of strong positive reputation. This is further discussed later.

Similarly, customers might not switch their insurer even after observing adverse information due to the associated costs, such as search costs. If insurers recognize such customer behavior, the lack of strong market discipline could weaken incentives for insurers to keep exerting best efforts (e.g., Hörner, 2002).

Capital holdings: The standard regulatory response to concern about excessive risk taking is to

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

tighten capital requirements. Although a straightforward argument can be made that increased shareholder assets at stake discourage an insurer from taking excessive risks, the theoretical implications of these regulatory requirements for effectiveness are mixed. For instance, several studies (e.g., Furlong and Keeley, 1989; Keeley and Furlong, 1990) show that asset risk-taking incentives do indeed decline for well-capitalized banks. In contrast, studies such as Shrieves and Dahl (1992) and Cummins and Sommer (1996) provide evidence of the positive relationship between capital and risk-taking.[5] We do not, therefore, have a clear a priori expectation regarding the sign of the effect of capital on risk-taking, but we do believe it is relevant.

We define the capital-to-asset ratio (*Capital-to-asset*) as 1-(Liability/Assets). In addition, we introduce an interaction term between the market-to-book ratio and the capital-to-asset ratio to investigate the effectiveness of franchise value per capital as a risk-constraining incentive.

Discount rate: Given that the benefit from maintaining a positive reputation is the sum of discounted future profits, the discount rate is important. When discount rates are high, an insurer may become opportunistic and choose to increase current profits rather than waiting for an expected stream of future profits available through maintaining a positive reputation.

We use three rates to represent the discount factor: the insurance industry average stock holding return (*Insurance industry return*), the S&P500 index return (*SP500*), and 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 profits is less attractive with high discount rates. However, each measure is intended to reflect different types of discount rates: industry-wide, market-wide, macroeconomic condition, respectively.

Information sharing efficiency: The extent to which an insurer can gain from engaging in 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 if it is revealed. If such adverse information is disseminated quickly, the profit insurers can earn from moral hazard is reduced, providing less incentive to damage their reputation.

[5] See Staking and Babbel (1995), for a comprehensive view of these factors for property-liability insurers.

Table 2: 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. *Log*(*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	

We utilize analyst coverage as a proxy for the efficiency of information diffusion. Analyst coverage is defined as the number of analysts who reported fiscal year 1 estimates of earnings per share available in the I/B/E/S Historical Summary File (e.g., Hong, Lim, and Stein, 2000). Financial analysts play a significant role in producing firm-specific and industry-wide information, and help firm fundamentals to be fairly valued. Furthermore, Hong, Lim, and Stein (2000) and others document that the marginal effect of analyst coverage on information efficiency is greater for adverse information than for favorable information due to a firm's greater incentives to disclose good information than adverse information. Thus, more analyst coverage implies more efficient flow of adverse information, which could reduce potential profits earned from moral hazard. Hence, it is expected that an increase of analyst coverage reduces operational loss events, if other things are equal.

To control for the effects of firm size as observed by Bhushan (1989) and Hong, Lim, and Stein (2000), we use residual analyst coverage (*Analyst*) as our information flow efficiency variable. The residual analyst coverage is a standardized residual after controlling for firm size, measured as the logarithm of firm assets, *Log(assets)*, as well as calender year effects. Table 2 reports the estimation result; the firm asset variable shows a positive and significant coefficient as expected, while a time trend of increasing analyst coverage is not obvious in our sample.

As mentioned earlier, whether the information is updated into customers' beliefs (market discipline) depends on credibility on the observed quality information customers use to update their beliefs. The credibility is expected to decline as customers form strong beliefs with repeated observations of policy quality. Specifically, once an insurer gains strong positive reputation, customers may fully anticipate that the insurer will perform as they expect, attributing observations that do not fulfill their beliefs to just chance events. Thus, Bayesian updating implies that the marginal benefit of exerting high effort may decrease as an insurer earns a positive reputation over time. If insurers recognize a lack of strong market discipline, it could weaken incentives for insurers to keep exerting high efforts (e.g., Holmström, 1999; Hörner, 2002).[6]

Therefore, we expect that the duration over which an insurer continuously operates in the market affects its decision to take risks. To investigate the relationship between a firm's record of past performance and its incentives, we introduce firm age measure, $Log(age)$, defined as a logarithm of the number of years since established.[7] We expect firm age to be positively associated with moral hazard.

Other Factors: Our sample insurers represent several insurance markets such as property-liability insurance, life insurance, and health insurance. These markets have substantially different characteristics with respect to the factors discussed above. To capture the market disparity, we employ two variables: a property-liability insurer indicator variable (PC) and a life insurer indicator variable (*Life*). These variables are defined using the SIC property-liability insurance industry code and life insurance industry code, respectively.

For instance, life insurance policies are more likely to have a longer policy period and there is little opportunity for policyholders to receive personally the service guaranteed by the policy. These conditions may make it difficult for potential customers to update their beliefs based on policyholder experience. With a higher claim frequency for health insurance than life insurance, receiving high-performance professional service is generally very important to health insurance customers. Hence, claim experience information may travel more efficiently to potential customers.

We also introduce a firm size variable, the logarithm of firm assets, *Log(assets)*, to control for the impact of firm size on operational loss counts.

[6] 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.

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

4 Operational Loss Events: Proxy for Moral Hazard

We use operational loss events as a proxy for insurer moral hazard. The Basel Committee on Banking Supervision has defined operational risk (from which operational losses derive) 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). Operational risk is categorized within the banking regulatory framework as a third class of risk category in addition to credit risk and market risk. Bank regulators rely on measures of these three risks to determine capital adequacy. Operational risk was added as a part of the regulatory framework after numerous bank failures accrued from conditions other than market risk and credit risk. Bank failures due to rogue trading losses at Societe Generale, Barings, AIB and National Australia Bank are examples of losses due to operational risks. To offer additional insight into operational losses, we provide the BIS (Bank for International Settlements) operational risk classification in Table 3.

Operational losses include both internally-caused events and externally-caused events (see Table 3 for the detail of the event classification). We define instances of moral hazard to be associated with internally-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 as internally-caused operational losses to represent insurers' actions that do not fulfill stakeholder expectation.[8] Both External Fraud (ET2) and Damage to Physical Assets (ET5) are excluded from a proxy for moral hazard because those events may not represent insurers' incentive problems.[9]

As a proxy for the intensity of insurer's moral hazard, we utilize the annual number of internally-caused operational loss events as the response variable (*Events*).

Events are allocated to time periods according to their *event start occurrence date*, the date when the operational risk loss event started to occur as identified in the FIRST database. This event date identification distinguishes this study from existing reputational loss studies, which focus on the date when event information is revealed to the public.

To illustrate how the database identifies *event start occurrence date*, the following case de-

[8] Several case descriptions are provided in Appendix A to illustrate the BIS classification.

[9] Our estimation results reported in the next section are insensitive to the removal of the two event types from the instances of moral hazard.

Table 3: BIS Operational Risk Event Type Classification (1)

Event-Type Category (Level 1)	Definition	Categories (Level 2)	Activity Examples (Level 3)
Internal fraud (ET1)	Internal fraud Losses due to acts of a type intended to defraud, misappropriate property or circumvent regulations,the law or company policy, excluding diversity/discrimination events, which involves at least one internal party	Unauthorised Activity	Transactions not reported (intentional)
			Transaction type unauthorised (w/monetary loss)
			Mismarking of position (intentional)
		Theft and Fraud	Fraud / credit fraud / worthless deposits
			Theft / extortion / embezzlement / robbery
			Misappropriation of assets
			Malicious destruction of assets
			Forgery
			Check kiting
			Smuggling
			Account take-over / impersonation / etc.
			Tax non-compliance / evasion (wilful)
			Bribes / kickbacks
			Insider trading (not on firm's account)
External fraud (ET2)	Losses due to acts of a type intended to defraud, misappropriate property or circumvent the law, by a third party	Theft and Fraud	Theft/Robbery
			Forgery
			Check kiting
		Systems Security	Hacking damage
			Theft of information (w/monetary loss)
Employment Practices and Workplace Safety (ET3)	Losses arising from acts inconsistent with employment, health or safety laws or agreements, from payment of personal injury claims, or from diversity / discrimination events	Employee Relations	Compensation, benefit, termination issues
			Organised labour activity
		Safe Environment	General liability (slip and fall, etc.)
			Employee health & safety rules events
			Workers compensation
		Diversity & Discrimination	All discrimination types

Source: Basel Committee on Banking Supervision (2006), p.305.

Table 3: BIS Operational Risk Event Type Classification (2)

Event-Type Category (Level 1)	Definition	Categories (Level 2)	Activity Examples (Level 3)
Clients, Products & Business Practices (ET4)	Losses arising from an unintentional or negligent failure to meet a professional obligation to specific clients (including fiduciary and suitability requirements), or from the nature or design of a product.	Suitability, Disclosure & Fiduciary	Fiduciary breaches / guideline violations
			Suitability / disclosure issues (KYC, etc.)
			Retail customer disclosure violations
			Breach of privacy
			Aggressive sales
			Account churning
			Misuse of confidential information
			Lender liability
		Improper Business or Market Practices	Antitrust
			Improper trade / market practices
			Market manipulation
			Insider trading (on firm's account)
			Unlicensed activity
			Money laundering
		Product Flaws	Product defects (unauthorised, etc.)
			Model errors
		Selection, Sponsorship & Exposure	Failure to investigate client per guidelines
			Exceeding client exposure limits
		Advisory Activities	Disputes over performance of advisory activities
Damage to Physical Assets (ET5)	Losses arising from loss or damage to physical assets from natural disaster or other events.	Disasters and other events	Natural disaster losses
			Human losses from external sources (terrorism, vandalism)
Business disruption and system failures (ET6)	Losses arising from disruption of business or system failures	Systems	Hardware
			Software
			Telecommunications
			Utility outage / disruptions

Source: Basel Committee on Banking Supervision (2006), p.306.

Table 3: BIS Operational Risk Event Type Classification (3)

Event-Type Category (Level 1)	Definition	Categories (Level 2)	Activity Examples (Level 3)
Execution, Delivery & Process Management (ET7)	Losses from failed transaction processing or process management, from relations with trade counterparties and vendors	Transaction Capture, Execution & Maintenance	Miscommunication
			Data entry, maintenance or loading error
			Missed deadline or responsibility
			Model / system misoperation
			Accounting error / entity attribution error
			Other task misperformance
			Delivery failure
			Collateral management failure
			Reference Data Maintenance
		Monitoring and Reporting	Failed mandatory reporting obligation
			Inaccurate external report (loss incurred)
		Customer Intake and Documentation	Client permissions / disclaimers missing
			Legal documents missing / incomplete
		Customer / Client Account Management	Unapproved access given to accounts
			Incorrect client records (loss incurred)
			Negligent loss or damage of client assets
		Trade Counterparties	Non-client counterparty misperformance
			Misc. non-client counterparty disputes
		Vendors & Suppliers	Outsourcing
			Vendor disputes

Source: Basel Committee on Banking Supervision (2006), p.307.

scription (The FIRST database, Event ID: 5170; Insurer name is replaced by *Insurer B*) may be helpful.

> "*Insurer B* announced on November 23, 2004 that it had agreed to pay $126,366,000 in order to settle allegations that it aided two companies with committing alleged accounting fraud. Under the terms of the agreement with the Securities and Exchange Commission, *Insurer B* agreed to pay a $46 million fine to the regulator for structuring finite insurance transactions for PNC Financial Services that allegedly resembled loans rather than insurance contracts. The insurance contracts were issued to PNC Financial Services between June 28, 2001 and November 30, 2001. *Insurer B* agreed to pay an additional $80 million to the U.S. Department of Justice in order to settle its ongoing investigation."

For this event, June 28, 2001 is identified as the *event start occurrence date* because the contract between *Insurer B* and PNC Financial Services was validated on that day, whereas this event was not publicly disclosed until September 2004, from which news media started reporting this event.

5 Empirical Methods

5.1 Sample Selection and Data Source

U.S. based publicly-traded insurance companies (classified in the SIC major group 63) are chosen as our sample. After collecting data on the *event start occurrence date* from several databases: CRSP, Compustat, the NAIC annual statements, the D&B Million Dollar database, and the I/B/E/S database, we have 289 firms and 1,612 firm-year observations for the period.

As mentioned earlier, insurers' operational risk loss events are identified through the FIRST database, which updates the database on a monthly basis.[10] The FIRST database as of August

[10]The vender started building the database in 1998 and collects operational risk losses from public sources such as news media, SEC press reports and court decisions. The oldest event reported in the database starts in 1914, but the number of events significantly increases in the 90s. The database lists loss events in both financial and non-financial industries across the world and consists of 8610 loss events as of August 26, 2009. Furthermore, the FIRST database provides a very detailed description of each event including organization name, the date when the event started, the date when the event ended, settlement date, event trigger, and the type of the event.

2009 is used to identify 209 operational loss events which started to occur during 1997-2006. Table 4 shows the BIS event type distribution of 209 events.

Panel A in Table 4 shows the number of events for each BIS event type. The largest number of events is 123 for Clients, Products, and Business Practices (ET4), and Internal Fraud (ET1) is 26 during the sample period. Only three events are reported for each of ET6 and ET7. Panel B shows a time trend of the number of events. Overall, the number of events started to increase until 2001, where 36 events are reported, and has a decreasing trend after 2001. The change in the trend may be explained by SOX Act legislated in July 2002. Eleven out of twelve events reported in Damage to Physical Assets (ET5) in 2001 are September 11 related losses.

5.2 Limited Dependent Variable

Our dependent variables are limited in two respects. The first limitation arises because of years of time lag between the date when an event started to occur (*event start occurrence date*) and its public disclosure date (see Figure 1). It is possible that events occurred before 2006 but not revealed yet. Including events that started in recent years may cause to underestimate the effects of factors on the occurrence of events because many of those events may not yet have been revealed. Therefore, the FIRST database is truncated from the right. To reduce the concern, we remove 2007-2009 from our sample to allow more than two years for operational risk loss events to be publicly revealed.[11] Further, year effect is controlled by introducing year dummy variables to estimation models.

Another problem is potential overdispersion that arises because our dependent variables and explanatory variables are prepared from different data sources. Our sample frame is insurers listed in CRSP and Compustat, while the dependent variables are constructed according to the FIRST database, a collection of publicly observed events, only when there are reported events during a financial year.

Let the observed dependent variable (or event counts reported in the FIRST database) for firm i at year t be z_{it} and a latent variable to represent actual event counts be z_{it}^*. Figure 2 illustrates possible states regarding whether events occur and are observed. Consequences from insurer's incentive problems fall in primarily three states. First, there is no insurer's hidden action

[11] When we remove events starting in 2006 from our analysis to allow the three years, the test results are unaffected.

Table 4: 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
Internal (ET1+ET3+ET4+ET6+ET7)	178
External Fraud (ET2)	15
Damage to Physical Assets (ET5)	16
Total	209

Panel B: Event Distribution by Year

Year	ET1	ET3	ET4	ET6	ET7	Internal	ET2	ET5	All Types
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

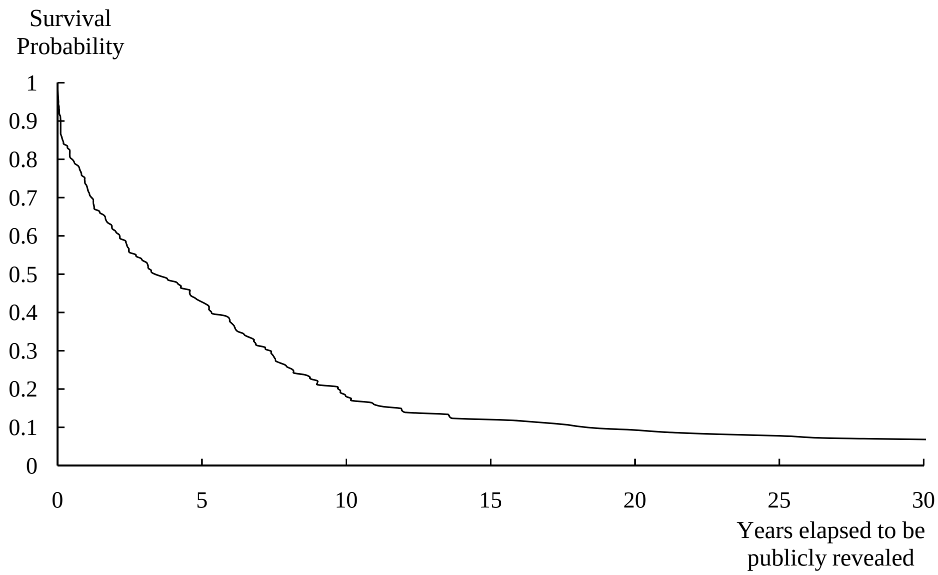

Figure 1: Survival Probability That Event is Not Revealed to the Public

This figure shows years of time lag between the date when an event started to occur (*event start occurrence 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.

that could adversely affect its reputation. Therefore, no event is reported in the FIRST database, $z_{it} = z^*_{it} = null$ (Case 1), and the positive reputation remains intact. 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. And the third case is that insurer's hidden actions occur and are revealed. The revealed information adversely affects its reputation, i.e., $z_{it} > 0|z^*_{it} > 0$ (Case 3). The dependent variables constructed by the FIRST database represents only this state.

We first assign zero to observations without reported events in the FIRST database:

$$Y_{it} = \begin{cases} 0 \quad if \;\; z_{it} = null \quad and \\ z_{it} \quad if \; z_{it} > 0 \quad , \end{cases}$$

where Y_{it} stands for the new dependent variable for firm i at year t in that zeros are assigned to both Case 1 and Case 2 regardless of the difference in actual event occurrence. This operation induces excess zeros in our new dependent variables, which may cause potential overdispersion.

The hurdle models originally proposed by Mullahy (1986) fit better to relax the overdispersion concern and our objectives as well. In the hurdle models, a binary probability model illustrates

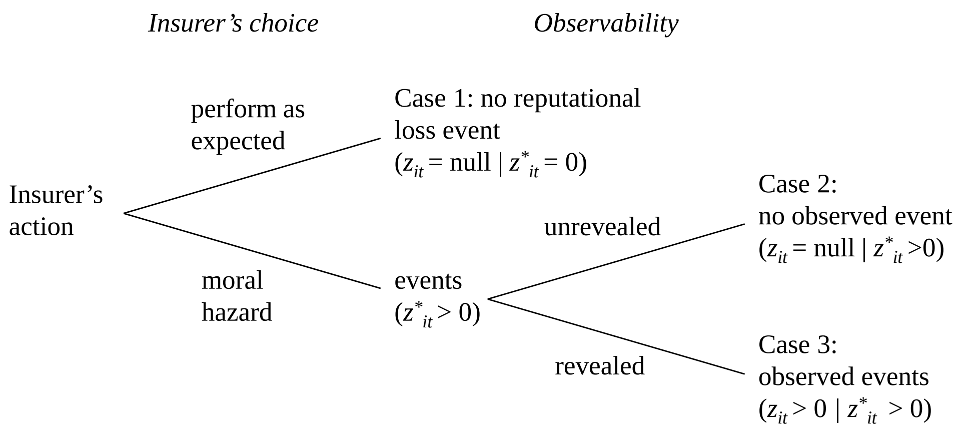

Figure 2: Observable and Unobservable Events

insurers' risk-taking decisions, and a zero-truncated Poisson distribution captures the revealed event counts. 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 insurer's reputational risk context, one regime represents the state where an insurer performs as expected by stakeholders (Case 1), where the reputational loss event is zero (see Figure 3). Otherwise, insurers take opportunistic acts that could eventually cause loss of reputation (*moral hazard*), and the observed event counts are Poisson distributed. Since events may not be revealed to the public, the outcome can be either zero (Case 2) or positive (Case 3). Thus, we can draw an implication regarding unobservable insurers' decision whether to take an opportunistic behavior (or whether Case 1 or Case 2 and 3) from the estimates of a binary probability.

5.3 ZIP Regression Model

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

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

so that

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

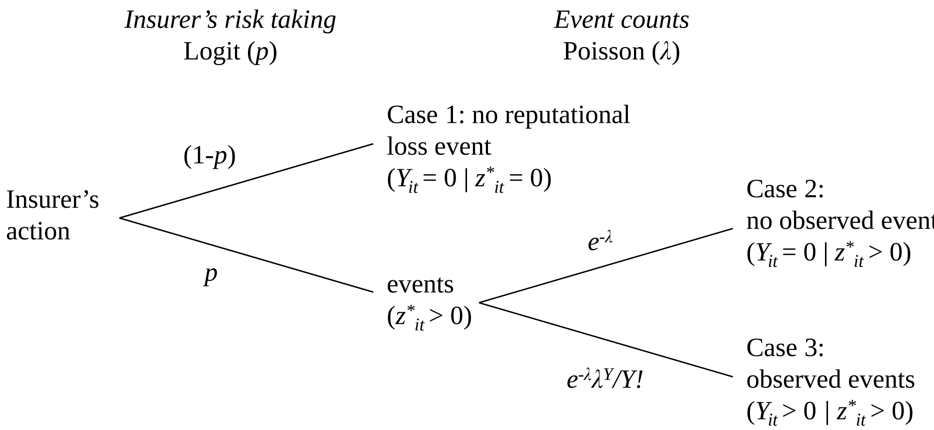

Figure 3: Logit Regression To Capture Insurers' Risk-taking Decision

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

$$\log(\lambda_i) = \mathbf{X}_i\beta \quad and \tag{1}$$

$$logit(\mathbf{p}_i) = \mathbf{X}_i\gamma, \quad i = 1, \ldots, N. \tag{2}$$

where the same set of explanatory variables are used for both models. A one year lag between response variables and explanatory variables is used to reduce a concern on potential endogeneity in that the number of events could affect some covariates. Note that all data are collected on the *event start occurrence 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.

5.4 Descriptive Statistics

Panel A in Table 5 shows the distributions of dependent variables: the annual number of operational risk loss events, Y_{it}. Our dependent variable is the number of internally-caused operational loss events, $Events(internal)$. The majority of observations have zero operational loss events as a consequence of assigning zeros to observations without reported events in the FIRST database. The maximum number of events in firm-year observation is four.

Panel B displays the descriptive statistics for firm-specific variables. 48% of our sample represents property-liability insurers and 21% of that represents life insurers. Panel C shows the time series of discount rate variables.

Pearson correlation coefficients across the primary variables are also computed but not reported here. Overall, the strongest correlation is -0.52 between *Log(assets)* and *Capital-to-asset*, as could be expected. All the variance inflation factors (VIF) of independent variables are less than 2, indicating that our concern for multicollinearity may be relaxed.

6 Estimation Results and Discussion

Table 6 reports parameter estimates of three models with a different discount rate variable. In each model, regression estimates for both Logit model and Poisson model are reported. Our primary interest is the estimation result for the Logit model because, as illustrated in Figure 3, the parameter p should closely represent the likelihood of insurers' reputational risk-taking. Each discount rate variable is separately estimated to avoid the computational difficulty faced when all those variables are included in one model. In addition, industry indicator variables, *PC* and *Life*, are omitted for the same reason. The potential heterogeneity between insurers is handled with random effects. Reported p-values are based on empirical standard errors.

Franchise value per capital is weakly significant with unexpected positive signs. Thus, the measure does not confirm the risk-constraining role. Rather, the measure weakly captures the positive association between franchise value and insurers' risk-taking.

The capital-to-asset ratio is consistently positively associated with the expected event counts regardless of models. This provides evidence that insurer capital does not restrain insurers from reputational risk-taking and that insurers may adjust their risk-takings to achieve their target solvency risk. Thus, greater capital holdings seem to be associated with both more risk-taking and a greater number of revealed reputational loss events.

We predict that insurers' incentive problems are more likely to arise when customers cannot update adverse information efficiently. To investigate the hypothesis, we prepare two variables: analyst coverage and firm age. The former is intended to capture the efficiency of adverse information distribution and the latter is a proxy for customers' credibility on new information to update their beliefs of an insurer. All models provide consistent results. While the analyst coverage variables

Table 5: Summary Statistics

All variables are annual basis. 289 firms are observed in maximum 10 year periods. 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 represents a 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+
Events(internal)	1498	79	26	6	3	0	0

Panel B: Firm-specific Variables

Variables	Obs.	Mean	Standard Deviation	Median	Minimum	Maximum
Events (internal)	1612	0.100	0.409	0	0	4
Franchise value per capital	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
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

Panel C: Other Variables

year	*Insurance industry return*	*SP500*	*Interest rate*
1996	0.106	0.151	0.052
1997	0.256	0.258	0.053
1998	-0.042	0.218	0.049
1999	-0.175	0.148	0.047
2000	0.159	-0.160	0.059
2001	0.048	-0.169	0.039
2002	-0.026	-0.250	0.016
2003	0.415	0.254	0.010
2004	0.219	0.078	0.012
2005	0.106	0.000	0.030
Mean	0.106	0.053	0.037

Table 6: ZIP Regression 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 dependent variable, *Events*(*internal*), is the number of all internally-caused operational loss events (ET1, ET3, ET4, ET6 and ET7). Year dummy variables after 2002 are included in these models.

Variable	Hypothesis (sign)	ZIP Model 1				ZIP Model 2				ZIP Model 3			
		Logit		Poisson		Logit		Poisson		Logit		Poisson	
		Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept		-11.06	<.0001	-9.09	<.0001	-11.17	<.0001	-10.33	<.0001	-8.968	<.0001	-11.36	<.0001
Franchise value per capital	-	0.122	0.082	0.130	0.125	0.125	0.093	0.154	0.081	0.089	0.143	0.188	0.031
Capital-to-asset ratio	+	2.439	0.016	2.490	0.035	2.335	0.004	2.963	0.014	1.900	0.030	3.322	0.006
Residual of analysts	-	-0.011	0.020	0.003	0.868	-0.010	0.024	0.004	0.781	-0.007	0.028	0.003	0.851
Log(*age*)	+	0.371	0.009	0.290	0.037	0.388	0.003	0.344	0.016	0.219	0.048	0.388	0.007
Insurance industry return	+	-0.663	0.509	-0.617	0.330								
SP500	+					3.036	0.015	2.910	0.009				
Interest rate	+									14.576	0.189	14.328	0.162
Log(*assets*)	+	0.617	<.0001	0.663	<.0001	0.716	<.0001	0.681	<.0001	0.824	<.0001	0.779	<.0001
Log Likelihood		501				537				587			
Number of Obs.		1298				1298				1298			

are insignificant for all models, the firm age variable is significant with positive signs for both Logit and Poisson models. The positive sign on firm age variable implies that, as Holmström (1999) predicts, the marginal benefit of exerting high efforts may decrease as customers gain strong beliefs. This result supports the hypothesis that incentives for insurers to keep performing as expected are weakened due to a lack of strong market discipline.

Our model predicts that insurers' incentives are affected by the discount rates. Only S&P500 Index return is significant with the expected positive signs. The positive signs are consistent with our prediction that a greater discount discourages insurers to maintain their positive reputation. Especially, the positive sign on the market index measure may be interpreted that a higher required rate of return forces insurers to be more aggressive to maximize their current profit.

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.

7 Conclusion

In the research reported here, we provide one approach to identify the primary determinants of reputational risk. Our focus is on factors adversely affecting insurer's incentives to preserve its positive reputation. When the expected benefit of an opportunistic performance (here, we denote 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 customers. 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, market rate of return, and firm size are positively associated with both insurer's reputational risk-taking decision and the number of revealed reputational loss events. In addition, we investigate the efficiency of information distribution and belief updating, which may distinguish reputational risk study from other risks. Analyst coverage measure is intended to capture the efficiency of adverse information distribution, and firm age is used to capture the impact of market discipline on insurers' decision making. In our analysis, the latter measure demonstrates the importance of information sharing efficiency.

Our study is limited particularly in that the number of operational risk loss events reported in the database is small. To overcome the problem of the excess zero observations in dependent variables, we employ the ZIP regression estimations, which also offer the implication to insurers' underlying decisions regarding whether they take an opportunistic act. We demonstrate the effect of determinants on insurers' risk-taking decisions and on revealed event counts is primarily consistent.

Our approach to identify factors that could affect a firm's incentives to maintain its positive reputation is 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.

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