Rating standards for catastrophic risks and the insurers' capital structure*

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Abstract

In the aftermath of hurricane Katrina in 2005, the major rating agencies have increased the amount of capital that an insurer has to hold in order to maintain the current rating standard. The changes of the rating methodology and the catastrophic models had a significant impact on the amount and composition of capital and reinsurance needed to achieve a particular rating. In this paper, we analyze the impact of the new standards on the capital structure of insurance companies. We show that new standards have a heterogeneous effect. While some insurers increase the amount of capital and improve the credit quality, others find the new standard too costly. In the later case the insurers either reduce the exposure to catastrophic risk by selling fewer policies, or admit the rating downgrade, reduce the capital and become more risky. We derive the implications of new standards for the ability of the insurance industry to sustain natural catastrophe losses.

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1 Introduction

In the aftermath of hurricane Katrina in 2005, the major rating agencies have increased the amount of capital that an insurer need to hold in order to maintain the current rating standard. The changes of the rating methodology and the catastrophic models had a significant impact on the amount and composition of capital and reinsurance needed to achieve a particular rating. In this paper, we analyze the impact of the new standards on the capital structure of insurance companies. We show that new standards have a heterogeneous effect. While some insurers increase the amount of capital and improve the credit quality, others find the new standard too costly. In the later case the insurers either reduce the exposure to catastrophic risk by selling fewer policies, or admit the rating downgrade, reduce the capital and become more risky. We derive the implications of new standards for the ability of the insurance industry to sustain natural catastrophe losses.

In order to understand the impact of new standards on the capital structure choices of companies, we build a model that derives the optimal targeted rating for the insurance firm. The unique feature of an insurance policy is that insurance buyers care about the credit risk of the insurer and are willing to pay a higher price for the policy that has lower risk. The buyer uses the credit rating of the insurer to assess its financial strength. Holding more capital increases the credit rating and allows charging higher prices. The amount of capital needed to satisfy a particular rating standard depends on the volatility of insurer's liabilities. Since capital is costly, more volatile companies are more likely to admit lower rating. Ultimately, the capital structure decision depends on the cost of capital and the elasticity of aggregate demand for insurance with respect to financial quality.

Since the rating agency pools heterogeneous companies in one rating grade, the new standard will have asymmetric effect on companies with the same credit rating. For companies close to the lower boundary of the rating bin the new standard is binding and they need to raise more capital to maintain it. At the same time, companies on the top of the rating bin do not need to adjust their capital structure to maintain the rating. If the cost of raising new capital is too high relative to the benefits of maintaining the same rating under more stringent standards, the firm is better off admitting the rating downgrade and reducing the amount of capital.

We use the theory to empirically investigate the reaction of insurers to the change of the rating criteria after 2004-2005 hurricane seasons. The results support they main hypothesis. Insurers that are close to the lower boundary of a given rating standard have increased their capital more compared to insurers close to the higher boundary of the standard.

The rest of the paper is organized as follows. In the next section we discuss the institutional setup and review the main changes that have been introduced by major credit rating agencies regarding the capital requirements for catastrophic exposures in 2006. In Section 3 we analyze the model of pricing, capital and rating decisions of the insurance firm. We use the model to derive the reaction of the industry to new standards. In Section 4 we provide the econometric analysis of the adjustments in the US property-casualty industry.

2 Ratings in insurance and reinsurance market

2.1 Major rating agencies

The U.S. property-casualty insurance market is followed by several credit rating agencies (CRAs). Four CRAs, A.M. Best, Fitch, Moody's and Standard and Poor's (S&P), have NRSRO status[1] and together provide coverage of 97.48% of the insurance market measured by asset size[2].

Among the NRSRO CRAs, the insurance industry views A.M. Best as a benchmark CRA rating insurance companies. A.M. Best ratings are widely incorporated in various local and state regulations. During the period of this study, A.M. Best provided ratings of 75.65% of insurance companies. Though on average insurers have ratings from 1.31 CRAs, A.M. Best rating is the first choice for the majority of companies. Indeed, the number of companies that do *not* have A.M. Best rating but have at least one rating from the other three NRSRO CRAs is only 1.95%.

The prominent role of A.M. Best is due to its monopoly position in the U.S. insurance market for most of the 20th century till late 1980s. Beginning 1990s, the monopoly of A.M. Best was challenged by Standard and Poor's (S&P). S&P established a solid position on the market of insurers ratings during the 1990s. The entry of S&P was followed by the entry of the other two agencies, Moody's and Fitch. In 2009, the market shares of A.M. Best, Fitch, S&P and Moody's were 95.36%, 47.93%, 51.13% and 24.88%, respectively. These CRAs have ovelapping market coverage. The most widespread ratings portfolio was composed of two ratings from A.M. Best and Fitch, accounting for 10.95% of insurance companies. Table 1 provides further details on the ratings portfolios in the insurance industry.

Demotech is another CRA that rates insurers. It does not have NRSRO status. However, insurers rated by this CRA qualify for several regulatory benefits. Demotech is a CRA that has been rating insurers since late 1980s. Its market coverage has been increasing during the period of 1990-2010, especially in the hurricane prone zones on the south-east of the U.S. About 37.11% of Demotech rated companies are not rated by the major NRSRO CRAs. Table 1 provides the comparison of the basic company characteristics of companies rated only by Demotech and the

[1] Explain NRSRO status

[2] History of CRAs. Year founded, etc.

major NRSRO CRAs. The focus of Demotech is smaller younger regional companies that are not rated by A.M. Best either due to their size or the short performance history. Since the market share of this type of companies has increased during the 2000s, the importance of Demotech ratings has grown as well.

2.2 The role of ratings

Both the practitioners and the academics agree that ratings are important for insurers and reinsurers. The main reason is that the value of an insurance policy to the buyer depends on the financial ability of the insurer to fulfill the terms of the contract. Often financial strength ratings are the main source of buyers' information about the credit quality of insurers. As a result, buyers are willing to pay higher prices for an insurance policy sold by an insurer with higher ratings.

Several studies has found empirical support for the demand sensitivity to insurer's credit risk. Epermanis and Harrington (2006) analyze the relationship between premium growth and changes in A.M. Best financial strength ratings for a large sample of property/casualty insurers during 1992-1999. They provide evidence of premium declines for downgraded insurers following the downgrades. The size of the effect depends on demand sensitivity to credit risk. Indeed, declines were concentrated in commercial lines that exhibit high sensitivity due to the lack of the state guarantee funds support and substantial customization of individual policies. Also the premium declines were especially pronounces for companies that initially had A- rating that the insurance industry views as a threshold between high and average quality companies. Cummins and Danzon (1997) develop a model of price determination in insurance markets. They show that imperfect price elasticity of demand and sensitivity of demand to credit risk imply that insurer will optimally choose the level of credit risk. The analysis of liability insurance industry during 1976-1987 reveals that the price of insurance is positively related to financial quality, measured by the ratio of equity to liabilities. Also price is inversely related to loss shocks to prior liabilities. Sommer (1996) uses the measures of insolvency risk implied by the option-based model of insurance (Doherty and Garven 1986, Cummins 1988) and finds a negative relationship between insolvency risk and insurance prices in the property-liability insurance market for the period between 1979 and 1988.

2.3 Rating standards for catastrophic risk exposures

Catastrophic losses have the significant, rapid and unexpected impact that can impair the financial strength of P&C insurers. The exposure to this losses has been increasing due to high demographic concentration and increasing property values in catastrophe prone areas. Higher frequency and severity of losses are the main two reasons that CRAs use to justify the higher capitalization needed to support catastrophic risks.

Ratings standards can also affect the capital allocation and cost of capital in the reinsurance market. In order to diversify the large catastrophic exposures associated with hurricane and earthquake in the US, rating agencies encourage reinsurers to spread their capital across Japanese, European and Australian wind and earthquake exposures. Diversification results in inadequate capital left for the US market where the need is the highest. Froot (2008) provides the evidence on capacity shortage in the U.S. exposures and suggests that the S&P "forced diversity" is one of the factors that would explain the large increase in the costs of reinsurance from 2005 to 2006.

3 Optimal pricing, capital and rating

3.1 The model

In this section we build a model of insurance pricing that is used to analyze how the rating standard determines the capital structure decisions of the insurance firm. The model is grounded on two basic assumptions. First, the higher is the financial quality of the insurance firm, the higher is the price consumers are willing to pay per dollar of insurance. Second, consumers use the insurer's rating as a measure of financial quality.

The insurer's financial quality (insolvency risk) is usually measured by the insurer's insolvency put option per dollar of liabilities.[3] However, insurers buyers do not directly observe the financial quality of the firm. Though the value of insolvency put can be computed using public information that insurance firms file to the National Association of Insurance Commissioners (NAIC), this evaluation requires time and effort, and can be too costly to some consumers. In contrast, financial strength rating of a rating agency is a simple quantification of the insurer's insolvency risk. Thus it is plausible that many consumers will rely on a rating.

The insurance firm faces the demand function $Q(p, R)$, where p is the price charged per one dollar of insurance, $p \geq 1$, and R is the rating. The demand function is assumed to be continuous, decreasing and concave in price, $Q_p < 0$, $Q_{pp} < 0$.

The rating agency evaluates the firm's probability of default d (explained below) and assigns

[3] See Cummins (1988), Cummins and Danzon (1997) and Cummins and Sommer (1996).

a firm one of the three ratings[4], $R \in \{A, B, C\}$,

$$R = \begin{cases} A \text{ if } d < \alpha, \\ B \text{ if } \alpha \leq d < \beta, \\ C \text{ if } d \geq \beta, \end{cases} \tag{1}$$

where $0 < \alpha < \beta < 1$ are the boundaries of ratings. The demand function is assumed to be increasing in rating, $Q(p, A) > Q(p, B) > Q(p, C)$ for any $p \geq 1$. The cost of the rating to the insurance firm is normalized to zero.

The insurance firm maximizes the value of its equity. The equity of a solvent insurer is the difference between its assets and liabilities. If the insurer defaults, the value of equity is zero.

The assets are composed of the revenue, $pQ(p, R)$ and the capital, K. Capital is costly. Raising one unit of capital yields $(1-r)$, $0 < r < 1$ units of capital at company's disposal. Thus the total assets of a company that raises K units of capital are

$$A = pQ(p, R) + (1 - r)K.$$

The liabilities L are random, with the expected value equal to the amount of sold insurance, $Q(p, R)$. The industry is composed of heterogeneous insurance firms that differ with respect to the variance of liabilities. Formally, the firms are indexed by type $\theta \in [0, 1]$. The liability distribution function of firm type θ is $F(L; \theta)$, with a continuous density $f(L; \theta)$. The family of distribution functions $\{F(L; \theta)\}_{\theta \in [0,1]}$ is ordered according to the second order stochastic dominance. That is, for any $\theta_1, \theta_2 \in [0, 1]$ with $\theta_1 < \theta_2$ and any non-decreasing concave function $v(L)$, the following condition is satisfied.

$$\int v(L) dF(L; \theta_1) \geq \int v(L) dF(L; \theta_2).$$

In words, the insurance firm θ_1 is less risky than the insurance firm θ_2.

The expected value of equity of firm type θ is $\max\{A - Q(p, R), 0\}$. The realized value of equity depends on the distribution of liabilities of type θ,

$$E(L; \theta) = \max\{A - L_\theta, 0\} = \max\{pQ(p, R) + (1 - r)K - L_\theta, 0\}.$$

The CRA observes the type θ and evaluates insurer's insolvency risk. The probability of default of type θ can be written as

$$d(\theta) = \Pr(pQ(p, R) + (1 - r)K - L_\theta < 0). \tag{2}$$

[4]In practice, the major rating agencies use rating scales with 15-18 rating categories. Using three ratings is a simplification that does not affect the qualitative prediction of the model.

Thus the insurer increases its financial strength by holding more capital K. It is immediate to derive a rating $R(p, K; \theta)$ that is assigned to the insurance firm type θ charging price p and holding capital K.

The insurer chooses the price p and the capital K to maximize the expected firm value net of the investment costs. Assuming that the interest rate in the economy is zero, the investment cost is K. The objective of the insurer is

$$\max_{p, K_R(\theta)} [\max\{A - Q(p, R(p, K; \theta)), 0\} - K] = [(p-1)Q(p, R(p, K; \theta)) - rK].$$

This expression explains the role of the cost of capital. If the capital were costless, $r = 0$, the insurer's objective to maximize the profits $(p-1)Q(p, R(p, K; \theta))$ implies that the insurer would have obtain enough capital to guarantee the highest possible rating. Interestingly, in this case the insurer would hold enough capital so that default never occurs. However, the fact that capital is costly results in the trade-off between the benefits of better rating and costs of holding capital.

3.2 Analysis

The optimal capital structure and pricing decisions of the insurance firm can be characterized in the following three steps. First, for each type θ the rating standards define a set of prices and capital levels that result in the same rating R. Next, for each rating R, one can define the optimal choice of price and capital, $(p^*(R), K^*(R))$, that maximizes the insurer's profit. The optimal targeted rating will be the one that obtains the highest profit to the insurance firm.

The rating standard (1) and the insurer's probability of default (2) imply that a combination of price and capital (p, K) of type θ result in a rating

$$R(p, K; \theta) = \begin{cases} A, \text{ if } 1 - F(pQ(p, A) + (1-r)K) \leq \alpha, \\ B, \text{ if } \alpha \leq 1 - F(pQ(p, B) + (1-r)K) \leq \beta, \\ C, \text{ if } 1 - F(pQ(p, C) + (1-r)K) > \beta. \end{cases}$$

Therefore, for a given type θ the following conditions define the combination of prices and capital (p_R, K_R) that result in rating R,

$$\begin{aligned} K_A &\geq \frac{1}{1-r}(F^{-1}(1-\alpha) - p_A Q(p_A, A)), \\ K_B &\geq \frac{1}{1-r}(F^{-1}(1-\beta) - p_B Q(p_B, B)), \\ K_C &\geq 0. \end{aligned}$$

Figure 1 illustrates these constraints. The figure indicates that higher rating requires charging higher price and/or holding more capital.

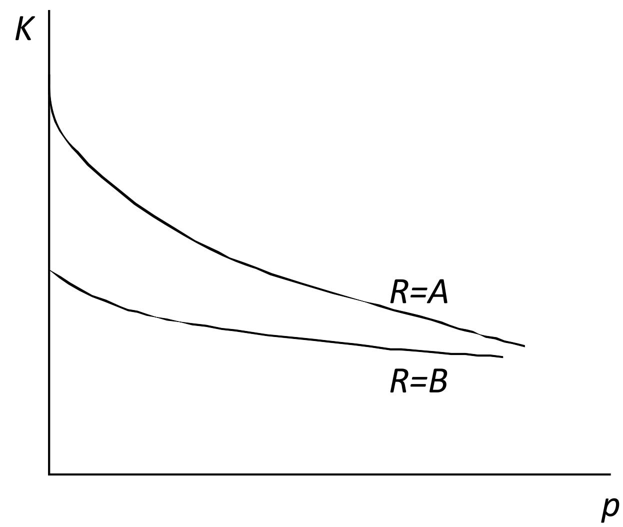

Figure 1: The curves $R = A$ and $R = B$ define the combinations of (p, K) that lead to the same rating R.

An insurer targeting a rating R maximizes his expected profit,

$$\pi(R) = (p-1)Q(p,R) - rK,$$

subject to the constraint

$$R(p,K;\theta) = R.$$

The first order conditions of the problem are

$$Q + (p-1)Q_p + \frac{r}{1-r}(Q + pQ_p) = 0, \tag{3}$$

$$K = \frac{1}{1-r}(\rho(\theta) - pQ), \tag{4}$$

where $\rho(\theta)$ denotes $F_\theta^{-1}(1-\alpha)$ and $F_\theta^{-1}(1-\beta)$ for ratings A and B, respectively. We omit the arguments of the demand function $Q(p,R;\theta)$ to save on notations.

Condition (3) can be written as

$$\frac{p-1}{p} = \frac{1}{\varepsilon} - \frac{r}{1-r}(1 - \frac{1}{\varepsilon}) < \frac{1}{\varepsilon},$$

where $\varepsilon = -\frac{dQ}{dp}\frac{p}{Q}$ is the price elasticity of demand. This condition is a modification of the optimal pricing rule for the firm facing imperfectly elastic demand. If the cost of capital is zero, $r = 0$, the price mark-up is proportional to the inverse of the elasticity of demand[5]. Cost of

[5] See Tirole (1988) for the optimal pricing formulas.

capital forces the insurance firm to charge lower price than the one implied by this rule. The reason is that selling more insurance is a substitute for raising external capital. As the cost of capital increases, raising capital by selling more insurance at a lower price becomes more attractive than paying the cost of external capital r.

Condition (4) explains how the optimal amount of capital depends on the type of the firm. The second order stochastic dominance implies that $\rho(\theta)$ is increasing in θ. Therefore, an insurer with higher volatility of liabilities has to hold more capital than a less risky insurer to obtain a given rating R. At the same time, the optimal capital is decreasing in the revenue from selling the policies, pQ. Since higher rating implies higher revenues, it reduces the capital needed per dollar of liabilities. However, higher rating also requires more assets, $\rho(\theta)$ increases. The net of the two effects, $\rho(\theta) - pQ$, depends on the distribution of liabilities, F_θ, and the elasticity of demand with respect to insurers financial strength.

We summarize these results in the next proposition.

Proposition 1 *For any targeted rating R, the insurance firm (i) charges the price that is decreasing in the cost of capital r; (ii) holds more capital the higher is the volatility of liabilities; (iii) may decrease or increase capital per dollar of liabilities depending on the elasticity of demand with respect to insurer's financial strength and the distribution of liabilities.*

The optimal targeted rating can be obtained by comparing the expected profits of the insurance firm for different ratings. Denote (p_R, K_R) the optimal pricing and capital under rating R defined by (3) and (4). The expected value of the insurance firm is

$$\pi(R) = (p_R - 1)Q(p_R, R) - \frac{r}{1-r}(\rho(\theta) - p_R Q(p_R, R)).$$

The firm thus will set the price and capital to target rating A rather than rating B if $\pi(A) > \pi(B)$. The benefits and cost of higher rating can be seen from the following expression

$$\begin{aligned} & \pi(A) - \pi(B) \\ = \; & (p_A - 1)Q(p_A, A) - (p_B - 1)Q(p_B, B) \\ & -\frac{r}{1-r}(F_\theta^{-1}(1-\alpha) - F_\theta^{-1}(1-\beta)) \\ & +\frac{r}{1-r}(p_A Q(p_A, A) - p_B Q(p_B, B)). \end{aligned}$$

It shows that the choice between ratings A and B depends on three factors. First, it has an effect on the net profit. A higher rating allows the insurance firm to gain higher net profits. Second, it increases the amount of capital that an insurance firm needs to hold. The size of this effect depends on the cost of capital and the volatility of firm's liabilities. Higher volatility types will need more capital to satisfy a given rating standard. Third, higher rating increases the revenue of the insurance firm and thus reduces the need for external capital. This effect will be more pronounces when the cost of capital is higher and the demand for insurance is more elastic with respect to financial quality of the firm. The main properties of the optimal rating choice are summarized below.

Proposition 2 *There are threshold volatility types θ_A and θ_B such that types $\theta \leq \theta_A$ target rating A, types $\theta_A < \theta \leq \theta_B$ target rating B, and types $\theta > \theta_B$ target rating C. The number of companies that obtain the highest rating is (i) increasing in the elasticity of demand with respect to financial quality, (ii) decreasing in the cost of capital, (iii) decreasing in the stringency of the rating standard that corresponds to higher α and β.*

In the next section we analyze how the optimal pricing and capital choices are adjusted when a rating agency changes the rating standards.

3.3 Adjustment of the rating standard

The increase of the standard stringency applied by the major rating agencies to insurers exposed to natural catastrophes has been justified by the increased frequency and severity of losses. Indeed, the concentration of high value properties in the coastal areas has been increasing over the last several decades. The climate change lead to more frequent and pronounced events. At the same time, major hurricanes are rare events that leads to abrupt reassessment of the probability distribution of losses. Hurricane Katrina indicated that the insurance industry has to be prepared to sustain substantial losses.

In terms of the model, the new information about the probability of losses can be viewed as the shift of the original distribution to the right by some constant. Denote the new adjusted distribution by $\widehat{F}_\theta$. We assume that it satisfies all the properties of the original distribution F_θ. Higher risk will increase the assets needed to attain the same solvency levels α and β. Thus it will be the case that $\widehat{F}_\theta^{-1}(1-\alpha) > F_\theta^{-1}(1-\alpha)$ and $\widehat{F}_\theta^{-1}(1-\beta) > F_\theta^{-1}(1-\beta)$. The new distribution will lead to the following adjustment of the targeted ratings by insurance firms.

Proposition 3 *Under the new standard derived from distribution $\widehat{F}_\theta$, there are threshold volatility types $\widehat{\theta}_A$ and $\widehat{\theta}_B$ such that types $\theta \leq \widehat{\theta}_A$ target rating A, types $\widehat{\theta}_A < \theta \leq \widehat{\theta}_B$ target rating B, and types $\theta > \widehat{\theta}_B$ target rating C. The number of firms that target higher rating deceases, $\widehat{\theta}_A \leq \theta_A$ and $\widehat{\theta}_B \leq \theta_B$.*

The change of the rating standard thus has a heterogeneous effect on firms decisions regarding the targeted rating. For low risk types $\theta < \widehat{\theta}_A$ the new standard is not binding and they maintain the original high rating A. However, for the intermediate firms $\theta \in (\widehat{\theta}_A, \theta_A)$, the cost of the new rating is too high and the optimal targeted rating reduces to B. Similarly, firms $\theta \in (\theta_A, \widehat{\theta}_B)$ maintain the original rating B but lower quality firms $\theta \geq \widehat{\theta}_B$ reduce the targeted rating.

How the new standards of the industry will affect the insurance firm behavior in the presence of price regulation? Our analysis suggests that one of the major benefits of higher rating is that the insurer can charge higher price per dollar of insurance. Since selling more insurance at higher price is a substitute for raising external capital, withdrawing the opportunity to charge higher prices increases the need for external capital. If external capital is scares, the price regulation will increase the likelihood of targeting lower ratings.

4 How did insurance companies react to new rating standards?

In this section we empirically investigate the reaction of insurers to the change of the rating criteria after 2004-2005 hurricane seasons. For the purpose of this study, we focus on the ratings of A.M. Best.

4.1 Data

We collect two sets of data for the period of 2000-2009. The first set of data is insurance companies characteristics extracted from SNL, which is based on the annual regulatory statements of insurance companies. The second set is A.M. Best rating information collected from Best's annual Key Rating Guide.

4.2 Econometric analysis and results

Our theoretical analysis suggests two main hypotheses. First, we hypothesize that if an insurance firm in hurricane exposed states take credit rating into account for their optimal surplus level, the companies close to the lower boundary of each rating category will increase their surplus in order to stay safely in the same rating and companies close to upper boundary may also want to increase their capital in order to move up to the next level. Second, this effect should be stronger from year 2005 to 2006 around the rating standard change.

Since the adjustment of standard must have a heterogeneous effect depending on the company's location to the rating boundary, we first group insurance companies in each rating category into three groups: companies close to upper boundary, in the middle, and close to lower boundary. To do so we need a statistic that is comparable to the information that rating agencies use to assess insurance companies' financial strength. Consistent with the previous literature and the A.M. Best definition of the financial strength rating, we rank companies according to the estimated one year default probability. We employ the discrete-time hazard model methodology of Shumway (2001). Similarly to Doherty, Kartasheva and Phillips (2010), we use the logit model where the dependent variable equals one when a firm become insolvent the following year, and equals zero otherwise. Consistent with insurance insolvency studies we define an insurance company is insolvent from the year of regulatory action is taken against the insurance firm (e.g., Cummins et al., 1995; Doherty et al., 2010). We collect the insolvent firm-year data from Best's annual Key Rating Guide and the SNL data on corporate change.

The explanatory variables of the hazard model are the standard list of regulatory ratios and organizational characteristics used for insurers' insolvency prediction. We include 20 NAIC's Financial Analysis and Surveillance Tracking (FAST) ratios[6]. In addition to the FAST ratios, we add one year lagged A.M. Best rating. Rating agencies collect more information than publicly available information through the interviews and internal channels with the management group of insurance companies. Rating agencies reflect their private information and judgment to the company's rating. Therefore, we expect that rating provides extra information for insolvency. The reason why we use one year lagged rating is that it is possible that the rating information comes after the insolvent information due to the usage of annual data. We also include Herfindahl Index for line of business concentration, Risk Based Capital (RBC) ratio, the percentage of long-tail premium, and a five year net earnings volatility measure.

Due to the high correlation between these variables (e.g. the percentage of net premium written to surplus and the percentage of direct premium written), many variables are insignificant. Since our main objective is to estimate the insurer's default probability, we reduce the list of variables to those with Pr>Chisq less than 0.5 in order to limit the estimation noise. The final data set contains 11,716 solvent firm-year observations and 56 insolvent firm-year observations during 2001-2009. The summary statistics and descriptions of the explanatory variables are shown in table 2 and table 3.

The regression result is presented in table 4. The result in table 4 displays a parsimonious model with limited number of explanatory variables. The model has the Pseudo R-squared of 41.66%. Some variables such as investment yield has the opposite sign of our intuition, which may be due to the fact all coefficients here presets the marginal effect after controlling for the Best Rating. If all 20 FAST ratios are included in the regression, the Pseudo R2 increases only to 43.80% from 41.66%. Panel A of Table 5 presents the estimated default probability for insolvent companies and solvent companies. Panel B of Table 4 shows the estimated default probability for each A.M. Best rating. The average default probability of insolvent group 23%, whereas it is 0.37% for solvent group. The mean and median default probability of each rating is almost

[6] List of FAST ratios can be found in Klein (2009).

monotonically increasing as the rating becomes weak. These results show the estimated default probability from discrete hazard model works reasonably.

With the estimated default probability from discrete hazard model, we assign two dummy variables for companies close to upper boundary of each rating and lower boundary or each rating, Upper (Lower) Dummy equals 1 if the default probability is within lower (upper) 25 percentile of each rating category, and 0 otherwise. We compute the upper and lower quartile probability every year, and assign the two dummies for each firm-year observation.

The next step is testing the asymmetric reaction of the companies in different groups to the rating standard change. Insurance companies' capital ratio will react to the rating change if rating is one of their decision factors for optimal surplus level. However, the propensity of an insurer to defend a rating must depend on the price and demand elasticity to financial quality. If the sensitivity to quality is low, the gain of raising new capital to defend a rating must not be high. In order to incorporate the different sensitivity to ratings, we run the first stage regression to estimate how the price, measured by the loss ratio, depends on company's characteristics and the rating. Then, in second stage, we use the calculated sensitivity of the price for each firm interacted with the position of the firm relative to the boundary. The two stage regression model is the following.

$$Y = \alpha + \beta_1 UD + \beta_2 LD + \beta_3 UD05 + \beta_4 LD05 + \beta_5 UD06 + \beta_6 LD06 + \sum y_i X_i + \varepsilon$$

$$Sensitivity = \alpha + \beta_1 Cap + \beta_2 Iyield + \beta_3 Exratio + \beta_4 PS + \beta_5 (Rating = A-) + \beta_6 Stock + \varepsilon$$

where

- Y is the change in surplus to asset, or premiums surplus ratio,
- UD(LD) = Upper (Lower) Dummy*Sensitivity,
- UD05(LD05) = Upper (Lower) Dummy * Sensitivity * CAT * Year05,
- UD05(LD06) = Upper (Lower) Dummy * Sensitivity * CAT * Year06,
- X_i are other control variables,
- Cap is surplus to asset ratio,
- Iyield is the investment yield,
- Exratio is expense ratio,
- PS is premium surplus

- Rating = A- is a dummy equal to 1 if A.M. Best rating is A-.

To estimate the sensitivity to rating change, we run a regression model where the dependent variable equals the loss ratio sensitivity to prior year's rating change, (loss ratio increase from year t to t+1)/(A.M. Best rating change from t-1 to t). Epermanis and Harrington find that consumers react to the rating the most for the companies with more commercial lines of business because personal lines have more protection from the state guarantee fund than commercial lines in case of insolvency. They also find consumers are most sensitive to the insurers with rating near the boundary of secure rating and vulnerable rating, which are A- and B++. Following their logic, we include proportion of premium written in commercial lines of business to total premium written, and rating dummies for A++ and A+, A, A-, B++, B+, and B and below. In addition, we include other control variables for financial characteristics of insurance companies such as size, capital to asset ratio, premium surplus ration, and etc.

We limit our sample to the Property-Casualty insurance companies with catastrophic risk prone lines of business because our interest is on the reaction to the rating standard change related with the hurricane risks. We define the hurricane risk prone line of business as direct premium written in homeowners, farm owners, auto physical damage, commercial multiperil, or inland marine in AL, FL, MI, SC, or TX.

Table 6 shows the regression result. Because we need to compute estimated sensitivity, we only keep those variables with Pr>Chisq less than 0.1 in order to reduce noise from not significant coefficient estimates. By definition, negative coefficient means loss ratio increase (price reduction) followed by downgrade. Consistent with Eperimanis and Harrington, the result implies that insurers with rating A- are the most sensitive to the rating change. The coefficient sign of proportion of commercial lines of business was consistent with the prediction from Epermanis and Harrington, but it was statistically insignificant. All other variables, including rating category dummies, were included but they were all insignificant. Therefore, we removed them from the final model.

We now conduct the second stage regression models. To evaluate the reaction in capital structure decision to the rating standard change, we use two dependant variables: surplus to asset ratio and premium to surplus ratio. Dummy variables from hazard model are interacted with the sensitivity estimate from the previous regression model to capture the rating effect year by year. Then, we interact these variables with 2005 year dummy and proportion of premium written in hurricane related lines of business to total premium in order to measure the extra effect occurred due to the rating standard change between 2005 and 2006. Alternatively, we construct a variable for each firm-year to the difference between the median estimated default probability of insurers within it's A.M. Best rating category of that year and insurer's own estimated default probability. And use this variable instead of the two dummy variables.

Table 7 and table 8 report the regression results with two dependent variables. First and second column shows the regression results with firm-year observation where A.M. Best rating is B++ and above, and the third and fourth column displays the regression results with firm-year observations where A.M. Best rating is B+ or below. The coefficients of dummy variables and the distance variables are not statistically significant in all models of companies in six out of eight models, implying that these insurers do not adjust their surplus to asset or premium surplus ratio. However, the coefficients for lower dummies and distance variables for 2005-2006 and 2006-2007 are statistically significant in most models and the signs are consistent with our prediction in the regression models with rating of B++ and above companies. That is, secure companies close to lower boundary, therefore exposed to the risk of downgrade, did increase their surplus capital ratio and reduce premium surplus ratio. On the other hand, vulnerable insurers respond to the standard change in the exactly opposite way compare to the secure insurers; they decrease surplus to asset ratio and increase the premium surplus ratio.

5 Conclusion

In this paper we build a model of insurer pricing, capital and target rating decision. The analysis of the model suggests that adjustment of rating standard must have a heterogeneous effect on insurers' target rating. The econometric analysis of the reaction to new standards for catastrophic risks mainly supports this hypothesis.

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Table I. Major Rating Agencies in Insurance

	All PC companies			Hurricane risk exposed PC companies		
	Number	%DPW	%Asset	Number	%DPW	%Asset
A.M. Best	14,613	95.36%	93.29%	5,853	87.43%	86.37%
S&P	3,430	47.93%	48.13%	1,923	48.43%	46.48%
Fitch	4,237	51.13%	59.37%	2,049	48.03%	54.16%
Moodys	1,346	24.88%	33.49%	811	25.77%	32.61%
A.M.Best and at least one more rating from major agency	5,956	73.36%	69.87%	3,061	69.14%	71.25%
At least one from major four agency	14,990	97.48%	97.37%	5,975	87.51%	86.42%
Demotech only	639	0.45%	0.19%	241	0.36%	0.12%
Total	19,316	100.00%	100.00%	7,157	100.00%	100.00%

	All PC companies	Demotech rated	Demotech only
N	19,316	1,083	639
Asset	538,481.04	276,681.65	31,368.85
Surplus	198,550.41	104,822.75	12,150.25
Surplus/Asset	0.488	0.43	0.47
Premium/Surplus	0.98	1.22	1.27
Premium Written	188,315.02	114,922.93	25,791.36

Table 2. Variable names and definitions

Table 1 displays variable names used in the analysis and their definitions.

Variable Name	Definition
Asset	Net Admitted Asset (in regression: log(asset))
Investment Yield	Annualized investment return based on average invested assets
1 year change in combined ratio	1 year change in Combined Ratio, combined ratio is loss and loss adjustment expense ratio plus expense ratio plus policyholder dividend ratio. This is the primary indicator of underwriting profitability.
Expense ratio	Commissions and brokerage expenses plus taxes, licenses and fees as a percent of direct premiums written
Reinsurance recoverables to Surplus	Reinsurance recoverable as a percent of surplus
Reserves to Surplus	Loss and loss adjustment expense reserves as a percent of surplus
2 Year Negative Reserve Development	Dummy=1 if this firm has 2 year negative reserve development
Affiliated Receivables to Surplus	Net admitted receivables from parent, subsidiaries and affiliates includes unsecured current accounts receivable from parent, subsidiaries and affiliates. Excludes amounts owed due to intercompany tax sharing agreements, amounts related intercompany reinsurance transactions, and any valuation allowance. Net admitted assets exclude assets for which the state does not allow the company to take credit.
Other invested asset to Surplus	Other investment as a percent of surplus
Change in Surplus	1 year surplus growth
Stock Company	Dummy=1 if this firm is stock company
Publicly traded company (Ultimate Parent)	Dummy=1 if the ultimate parent of this company is publicly traded company
AMBEST	AM Best rating
Capital/Asset	Surplus/Asset
DPW_PHS	Direct Premium Written to Surplus

Table 3. Summary Statistics of Variables Used in the Regression Analysis

Table 2 shows the summary statistics of the variables used in the regression analysis. Sample includes property-liability companies with A.M. Best rating in United States during 2001-2009. Due to some missing variable 26% of companies are removed from the sample and the final sample includes 11,772 firm-year data.

Variable Name	Mean	Median	STD	MIN	MAX
Asset	823,694	105,692	3,814,582	3,135	15,145,491
Investment Yield (%)	4.10	3.83	1.66	0.70	8.25
1 year change in combined ratio (%)	-0.96	0.00	71.90	-141.00	141.00
Expense ratio(%)	33.18	30.00	43.60	0.00	134.00
Reinsurance recoverables to Surplus (%)	46.61	12.00	91.41	-2.00	466.00
Reserves to Surplus (%)	90.54	73.00	85.57	0.00	339.00
2 Year Negative Reserve Development	0.52	1.00	0.50	0.00	1.00
Affiliated Receivables to Surplus	0.03	0.00	0.02	0.00	0.43
Other invested asset to Surplus	0.03	0.00	0.09	0.00	0.43
Change in Surplus	16,446.80	1,778.50	287,177.67	-208,298	508,477
Stock Company	0.75	1.00	0.43	0.00	1.00
Publicly traded company (Ultimate Parent)	0.32	0.00	0.46	0.00	1.00
AMBEST	10.29	11.00	1.73	0.00	13.00
Capital/Asset	19,932.57	3,537.74	97,529.95	222.45	302,538.63
DPW_PHS	1.81	1.17	2.55	0.00	11.30

Table 4. Discrete-Time Hazard Insolvency Model Regression Results

Table 3 shows the results of the discrete-time hazard regression model. The dependent variable yit = 1 for each insurer that has a formal regulatory action taken against the insurer in year t+1 or become insolvent in t+1. Otherwise, yit = 0. Sample includes property-liability companies with A.M. Best rating in United States during 2001-2009. Due to some missing variable 26% of companies are removed from the sample and the final sample includes 11,772 firm-year data. Among 11,772, 56 observations are insolvent firm-year. We include all 20 FAST ratios and other factors that may have prediction power for insolvency.

Independent Variable	Coefficient Estimate		Chi-square statistic	Pr>Chisq
Asset	-0.1113		0.8753	0.3495
Investment Yield	0.048		0.5	0.4795
1 year change in combined ratio	-0.00181	*	3.5899	0.0581
Expense ratio	0.00237		1.0829	0.2981
Reinsurance recoverables to Surplus	0.00439	***	35.0864	<.0001
Reserves to Surplus	0.00425	***	20.686	<.0001
2 Year Negative Reserve Development	-0.6942	*	3.5027	0.0613
Affiliated Receivables to Surplus	1.8513	**	5.3133	0.0212
Other invested asset to Surplus	1.1231		1.5617	0.2114
Change in Surplus	-5.00E-07		2.0788	0.1494
Stock Company	0.4449		1.0106	0.3148
Publicly traded company (Ultimate Parent)	-1.6086	**	5.7019	0.0169
AMBEST(t-1)	-0.393	***	38.8128	<.0001
Likelihood Ratio	274.5286			
Wald Chi-square	1,131.9851			
Pseudo R2	0.4166			
Number of Observations	11,772			
Number of Insolvent companies	56			

*** - significant at the 1 percent level; ** - significant at the 5 percent level; * - significant at the 10 percent level.

Table 5. Discrete-Time Hazard Insolvency Model Regression Estimates

Table displays summary statistics of the estimated one-year probability of insolvency. Panel A shows the estimated default probability for solvent firm-year and insolvent firm-year, and Panel B shows the default probability for each A.M. Best rating category.

Panel A **Hazard Model default risk by solvency/insolvency**

Firm Type	Num	Mean	Median	STD	1st Percentile	99th Percentile
Solvent	11,716	0.37%	0.10%	2.33%	0.01%	4.71%
Insolvent	56	23.14%	5.66%	33.48%	0.03%	100.00%

Panel B **Hazard Model default risk by AM Best rating**

Firm Type	Num	Mean	Median	STD	1st Percentile	99th Percentile
A++	592	0.06%	0.02%	0.69%	0.00%	0.31%
A+	1,940	0.06%	0.03%	0.24%	0.01%	0.37%
A	3,580	0.11%	0.07%	0.20%	0.01%	0.79%
A-	3,019	0.20%	0.13%	0.35%	0.02%	1.22%
B++	1,142	0.35%	0.21%	0.92%	0.03%	2.76%
B+	711	0.57%	0.35%	0.99%	0.04%	3.62%
B	412	1.21%	0.60%	4.61%	0.07%	8.97%
B-	176	2.82%	1.17%	8.28%	0.10%	64.51%
C++	93	5.76%	2.93%	10.64%	0.12%	82.50%
C+	33	9.47%	4.89%	11.79%	0.61%	53.39%
C	19	12.80%	6.19%	15.47%	0.41%	52.86%
C-	10	15.11%	8.88%	14.59%	1.59%	44.79%
D	19	19.61%	7.47%	22.76%	0.08%	75.21%
E,F,Ex	26	38.50%	15.51%	41.55%	0.51%	100.00%

Table 6. Loss Ratio Sensitivity Regression Result: 2001-2009

Table 5 displays robust OLS regression results where the dependent variable equals the loss ratio sensitivity to prior year's rating change, (loss ratio increase from year t to t+1)/(A.M. Best rating change from t-1 to t). Negative coefficient means loss ratio increase (price reduction) followed by downgrade. Sample includes Property-Casualty insurance companies with catastrophic risk prone lines of business, which are defined as direct premium written in homeowners, farmowners, auto physical damage, commercial multiperil, or inland marine in AL, FL, MI, SC, or TX. Only those firm-year observations with A.M. Best rating change from year t-1 to t are included in the sample. Rating A- is a dummy variable equals to 1 if rating in year t is A-. The description of other variables can be found in table 2.

Independent Variable	Coefficient Estimate		Chi-square statistic	Pr>Chisq
Capital/Asset	-0.0002	**	4.99	0.0254
Investment Yield	4.9054	***	13.18	0.0003
Expense Ratio	0.0904	**	6.17	0.0130
DPW_PHS	-2.0603	**	4.38	0.0364
Rating A-	-16.1558	***	13.66	0.0002
Stock Company	-13.1703	*	2.88	0.9000
Pseudo R2	0.2212			
Number of Observations	96			

*** - significant at the 1 percent level; ** - significant at the 5 percent level; * - significant at the 10 percent level.

Table 7. Surplus Change Regression Results: 2001-2009

Table 6 displays robust OLS regression results where the dependent variable equals change of surplus as a proportion of net admitted asset from year t to t+1. Sample includes Property-Casualty insurance companies with catastrophic risk prone lines of business, which are defined as direct premium written in homeowners, farmowners, auto physical damage, commercial multiperil, or inland marine in AL, FL, MI, SC, or TX. First and second column shows the regression results with firm-year observation where AM Best rating is B++ and above, and the third and fourth column displays the regression results with firm-year observations where AM Best rating is B+ or below. Upper (Lower) Dummy equals 1 if the default probability is within lower (upper) 25 percentile of each rating category, otherwise 0. Upper (Lower) Dummy05 equals 1 if the default probability is within lower (upper) 25 percentile of each rating category in year 2005, otherwise 0. Sensitivity is loss ratio sensitivity estimates from the regression model in table 5. CAT is the percentage direct premium written in the hurricane risk related lines of business to total direct premium written. The model also contains year indicator variables but the results are suppressed to save space. The full results with the estimated coefficients for the year indicator variables are available upon request. The description of other variables can be found in table 2.

	Rating=B++ and above		Rating=B+ and below	
Independent Variable	Model (1)	Model (2)	Model (3)	Model (4)
UD	0.00		0.0007	
	(0.81)		(0.98)	
LD	0.00		0.0007 **	
	(0.32)		(5.90)	
UD05	0.0030		0.0064	
	(0.03)		(1.22)	
LD05	0.0044 *		-0.0119 ***	
	(2.85)		(9.28)	
UD06	-0.0018		0.0004	
	(0.01)		(0.03)	
LD06	0.0048 **		-0.0030	
	(6.01)		(0.08)	
[Insurer Pr(Def.) -Median Pr(Def.|		-0.0100 **		-0.0007
A.M. Best)]*Sensitivity		(4.11)		(0.11)
[Insurer Pr(Def.) -Median Pr(Def.|		1.2003 ***		-0.5102 ***
A.M. Best)]*2005*Sensitivity		(12.52)		(17.17)
[Insurer Pr(Def.) -Median Pr(Def.|		0.3293 ***		-0.0691 ***
A.M. Best)]*2006*Sensitivity		(5.85)		(0.02)
Asset	0.0006	0.0011 ***	0.0009	0.0038
	(1.57)	(6.55)	(0.13)	(2.29)
AM Best Rating	-0.0004	-0.0008	-0.0037	-0.0035
	(0.26)	(1.43)	(1.77)	(1.60)
Change in reinsurance	-0.0003 ***	-0.0003 ***	-0.0002 ***	-0.0003 ***
recoverable to surplus	(569.69)	(556.65)	(21.04)	(35.16)
Change in rating (t-1, t)	-0.0040 ***	-0.0039 **	0.0028	0.0008
	(5.80)	(5.45)	(0.75)	(0.06)
Pseudo R2	0.1096	0.1108	0.1092	0.0963
Number of Observations	3,361	3,361	283	283

*** - significant at the 1 percent level; ** - significant at the 5 percent level; * - significant at the 10 percent level.

Table 8. Premium/Surplus Change Regression Results: 2001-2009

Table 7 displays robust OLS regression results where the dependent variable equals change in direct premium written as a proportion of surplus from year t to t+1. Sample includes Property-Casualty insurance companies with catastrophic risk prone lines of business, which are defined as direct premium written in homeowners, farmowners, auto physical damage, commercial multiperil, or inland marine in AL, FL, MI, SC, or TX. First and second column shows the regression results with firm-year observation where AM Best rating is B++ and above, and the third and fourth column displays the regression results with firm-year observations where AM Best rating is B+ or below. Upper (Lower) Dummy equals 1 if the default probability is within lower (upper) 25 percentile of each rating category, otherwise 0. Upper (Lower) Dummy05 equals 1 if the default probability is within lower (upper) 25 percentile of each rating category in year 2005, otherwise 0. Sensitivity is loss ratio sensitivity estimates from the regression model in table 5. CAT is the percentage direct premium written in the hurricane risk related lines of business to total direct premium written. The model also contains year indicator variables but the results are suppressed to save space. The full results with the estimated coefficients for the year indicator variables are available upon request. The description of other variables can be found in table 2.

	Rating=B++ and above				Rating=B+ and below			
Independent Variable	Model (1)		model (2)		model (3)		model (4)	
UD	0.0001				-0.0031			
	(0.39)				(0.22)			
LD	0.0001				-0.0003			
	(0.07)				(0.01)			
UD05	0.0130	*			0.0050			
	(3.36)				(0.01)			
LD05	0.0247				0.2081	***		
	(1.81)				(34.77)			
UD06	0.0054				0.0027			
	(0.51)				(0.01)			
LD06	-0.1405	***			-0.0422			
	(131.82)				(0.18)			
[Insurer Pr(Def.) -Median Pr(Def.|			0.0328				-0.1021	***
A.M. Best)]*Sensitivity			(0.96)				(29.30)	
[Insurer Pr(Def.) -Median Pr(Def.|			-13.9912	***			0.3176	
A.M. Best)]*2005*Sensitivity			(34.84)				(0.08)	
[Insurer Pr(Def.) -Median Pr(Def.|			-9.2981	***			-2.4531	
A.M. Best)]*2006*Sensitivity			(95.58)				(0.34)	
Asset	-0.0006		-0.0011		-0.0230		-0.0377	
	(0.04)		(0.13)		(0.91)		(2.66)	
AM Best Rating	0.0057		0.0075		0.0672	**	0.0834	***
	(1.29)		(2.37)		(6.94)		(10.67)	
Change in reinsurance	0.0026	***	0.0026	***	0.0046	***	0.0046	***
recoverable to surplus	(754.15)		(736.35)		(121.65)		(128.44)	
Change in rating (t-1, t)	0.0145		0.0026		0.0455	*	0.0219	
	(1.51)		(2.21)		(2.47)		(0.52)	
Pseudo R2	0.0577		0.0610		0.1453		0.1383	
Number of Observations	3,361		3,361		283		283	

*** - significant at the 1 percent level; ** - significant at the 5 percent level; * - significant at the 10 percent level.

Appendix I. Rating conversion table

AM Best rating	Numeric Conversion
A++	13
A+	12
A	11
A-	10
B++	9
B+	8
B	7
B-	6
C++	5
C+	4
C	3
C-	2
D	1
E,F,Ex	0