Real Effects of Changing Rating Standards for Catastrophic Risks*

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December 30, 2011

Abstract

The paper analyzes how rating standards affect firms credit quality. In the aftermath of hurricane Katrina in 2005, the major rating agencies have changed the rating standards for exposures to catastrophic risks. As a result, insurers with catastrophic risks exposures had to hold more capital to maintain the same rating grade. In this paper we argue that firms' adjustment to new standards is obtained as a trade off between the benefits and the cost of maintaining the rating. We demonstrate that new standards produced a heterogeneous effect on the credit quality of insurers and identify two distinct groups of firms. While high credit quality firms focused in commercial lines of insurance have increased the capital, low rated personal lines insurers have accepted the downgrade and reduced the credit quality. The results suggest that the rating standards are significant for the distribution of credit risks in the insurance industry and its ability to sustain catastrophic losses.

*We are grateful to Neil Doherty, Itay Goldstein, Howard Kunreuther, Erwann Michel-Kerjan, Greg Nini, Bilge Yilmaz and the participants at NBER, Risk Theory Society, and Wharton Risk Center meetings for very useful discussions. The usual disclaimer applies.

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1 Introduction

Credit ratings classify issuers in broad rating categories. From investors' perspective, a rating reduces the information asymmetry about issuer's credit risk. The ability of an issuer to signal better credit quality translates into the ability to improve a rating. This practice implies that the scale used to assign ratings can have real effects on firm's corporate decisions. In spite of the feedback effect of rating standards on corporate decisions, rating agencies have autonomy in the design of their rating criteria. In practice, rating criteria differ both across different rating agencies and among different security/issuer classes within the same rating agency. For example, while 80-95% of MBS deals were assigned AAA ratings in 2007, only 5% of corporate bonds and 8.5% of insurance companies in the U.S. have the highest rating.[1] This is about to change. One of the provisions of the recent Dodd-Frank Act aims to expand the authority of the regulators to control the standards used by the NRSROs[2] to assign ratings. How do more stringent rating standards affect the issuers' credit quality?

Relying on an exogenous change of the rating scale used by a rating agency, the paper analyzes the effect of more stringent rating standards on the credit quality of firms. We use the natural experiment of hurricane Katrina in 2005. Following the hurricane season, the major credit rating agencies have changed the criteria applied to rate the financial strength of insurance companies with exposure to catastrophic losses. Firms were required to hold more capital or reduce exposure to catastrophic losses in order to maintain the same letter rating. We analyze how the companies adjusted to new standards. Our main finding is that more stringent standards produced a heterogenous reaction. In particular, a large group of firms became more risky as a result of the change.

Our explanation of the interaction between the rating standards and corporate decisions is built on the trade-off between the benefits and the cost of a better rating. The benefits come from two sources. First, a higher credit rating can reduce the cost of capital and facilitate firm's access to external capital markets.[3] Second, a higher rating can improve firm's position

[1] Ashcraft, Goldsmith-Pinkham and Vickery (2010), Standard and Poor's and A.M. Best.

[2] NRSRO stands for Nationally Recongnized Statistical Rating Organizations. Credit rating agencies that obtain a NRSRO status from the U.S. Securities and Exchange Commission issue ratings that can be used as reference in various regulations.

[3] For example, the rating of A or higher is required to issue high quality commercial paper that offers low-cost short-term funds. Also higher ratings increase the investors pool due to regulatory requirements on banks, insurance companies, mutual funds and other financial institutions. Finally, lower ratings can trigger costly covenants of bond contracts. See Kisgen (2007) for details.

vis-à-vis its competitors, customers and suppliers. But higher ratings come at cost. A bank or a financial intermediary need to hold more reserve capital, and thus forego profitable investment opportunities. An industrial firm may need to limit the investment in high return high risk projects or reduce the volatility of cash flow by the means of a restrictive risk management program. The optimal targeted rating is the result of the trade-off.

In the context of the insurance industry, insurance buyers are willing to pay a higher price for a contract that has lower credit risk. Indeed, the contract has no value in the event the insurer defaults. This constitutes the benefit of a higher credit rating. The cost of higher rating is due to the need to hold more equity capital to satisfy the higher rating standard. Thus the optimal credit rating is obtained from the trade-off between the ability to charge a higher price for the contract with higher credit quality and the cost of capital.

The change of the rating standards will induce the best response adjustment of the optimal targeted ratings by firms. This paper argues that in response to more stringent standards, firms may choose either to improve their credit quality, or to become more risky. The differential reaction to new standards can occur both within the same rating grade and across different ratings.

Consider first the adjustment of credit quality for firms within the same rating grade. The same rating grade pools companies with heterogenous credit quality. It implies that the new standard will have unequal effect on firms with the same credit rating. For firms on the top of the rating grade, the initial rating is unchanged under the new standard. For firms close to the lower boundary of the initial rating grade, the new standard translates into lower rating, unless a company raises more capital or reduces the exposure to catastrophic risks to adhere to new higher standard. 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 to the level optimal for the lower rating grade. In this case, under the new rating standard the firm becomes more risky.

Second, consider the adjustment of credit quality for companies with different initial ratings. The benefits of maintaining the same rating grade under a more stringent rating standard varies across the rating scale. Higher rated companies sell insurance contracts to buyers who have higher willingness to pay for credit quality. Following the rating standard change, these companies benefit from maintaining the rating more than poorer rated firms. It implies that under the new standard, better rated firms are more likely to improve their credit quality, while

lower rated firms are more likely to become more risky. Thus the new standard induces a more polarized distribution of credit risk in the industry.

We develop a sets of empirical tests to investigate the reaction of insurers to the change of the rating criteria after 2004-2005 hurricane seasons. Our analysis consists of two stages. First, we model the rating process in order to estimate the rating score for each firm and the rating boundaries. The estimation results are used to identify the position of each firm in the rating grade under the original rating standards. Second, we investigate the reaction to the standard change depending on the position of the firm in the rating grade, and the benefits and the cost of maintaining the rating.

We find that firms that are closer to the lower boundary of a given rating grade have adjusted their capital more compared to insurers closer to the higher boundary of the rating grade. At the same time, the direction of the adjustment differs across the rating grades and for firms with different benefits of defending the rating. In the insurance industry, firm's credit quality matters more for buyers of commercial insurance rather than personal insurance.[4] We find that higher credit quality companies concentrated in commercial insurance increase the amount of capital in response to new rating standards. The propensity to increase capital is especially pronounced around the A.M. Best A- rating which is viewed as an "investment grade" rating in the insurance industry. To the contrary, lower rated firms concentrated in personal insurance adjust to new standards by reducing the amount of capital. Also they increase concentration of their exposure to catastrophe risks.

Overall, our results suggest that the standards used by the credit agencies have an important effect on firms' credit quality. At the same time, more stringent rating standards need not imply higher credit quality for all companies and thus lead to an ambiguous aggregate effect for the industry. The results imply that the rating standards used by the rating agencies have a significant effect on the capacity of the industry to sustain catastrophic losses.

The rest of the paper is organized as follows. In the next section we analyze the model of pricing, capital and rating decisions of a firm. We use the model to derive the reaction of the industry to new standards in Section 3. Section 4 discusses the institutional setup and reviews the main changes that have been introduced by major credit rating agencies regarding the capital requirements for catastrophic exposures in 2006. Section 5 provides the econometric analysis of the change in the US property-casualty industry using the data between 2001 and

[4]See Section 3.1.1.

2008.

2 How do firms adjust to more stringent rating standards?

The question would be irrelevant in the world with perfect financial markets. The seminal Modigliani-Miller result implies that firm's adjustments of credit quality do not alter its value. Investors can change the exposure to firm's credit risk themselves by buying or selling firm's stock. Consequently, the rating standards do not matter for corporate decisions and the distribution of risks in the economy. However, the very existence of CRAs as information intermediaries suggests market imperfections, in particular, information asymmetries between investors and firms. In order to answer the question in the world with imperfect financial markets, we develop a theoretical framework that is built on the literatures on corporate risk management and on the role of credit ratings in the economy.

The corporate risk management literature has developed several explanations why firms and outside investors care about firm's credit quality when conditions of Modigliani-Miller do not hold.[5] Our theory is built on the results of Froot, Scharfstein and Stein (1993). They propose a general framework where the optimal risk management strategy coordinates firm's corporate investment and financing policies. In their setting, firm's cash flow is uncertain and external finance has increasing marginal costs. The paper demonstrates how firm's optimal level of hedging, and, consequently, the volatility of cash flow and the credit risk, depend on the correlations between investment opportunities, the cost of external financing and the availability of internal funds. Then the firm's current assets, the quality of its management, its position relative to competitors and the growth opportunities of the industry determine these correlations, and, consequently, the optimal choice of credit risk. It implies that firms in the same industry will differ in terms of their credit risk.

We follow the framework of Froot, Scharfstein and Stein (1993) and assume that a firm can choose its credit quality ρ, where $\rho \in [\underline{\rho}, \overline{\rho}]$ and higher value of ρ stands for higher credit quality. We do not specify the scale for the credit quality parameter ρ that, depending on the

[5] Smith and Stultz (1985) argue that lower credit quality reduces firm's debt capacity. Myers (1977) and Stultz (1990) shows that higher credit quality reduces investment distortions. DeMarzo and Duffie (1992) suggest that managers may have incentives to reduces the volatility of firm's performance in order to decrease the noise of a signal about their ability to the labor market. Smith and Stultz (1985) explain how reducing the volatility of firms earnings lightens tax liabilities under a convex tax schedule. These theories suggest that if a firm has a mechanism to change its credit risk, for example, by hedging the market risk, the firm will choose to reduce the risk to minimum.

application, can be a measure of volatility of cash flow, the risk of firm's debt, or a tail risk measure like value-at-risk. The individual characteristics of a firm are summarized by its type θ, where $\theta \in [\underline{\theta}, \overline{\theta}]$. Higher value of θ corresponds to better firm's quality and, other things equal, translates in higher profits $\pi(\rho, \theta)$, with $\pi_\theta > 0$. We assume that firm's profit function $\pi(\rho, \theta)$ obtains an interior maximum $\rho^*(\theta) \in (\underline{\rho}, \overline{\rho})$, where

$$\rho^*(\theta) \in \arg \max_{\rho \in [\underline{\rho}, \overline{\rho}]} \pi(\rho, \theta).$$

Also we assume that better firms choose higher credit quality,

$$\frac{\rho^*(\theta)}{d\theta} > 0.$$

Our motivation for this assumption is that better quality firms have access to more profitable investment opportunities, and will be more willing to reduce their credit risk and have lower cost of doing so. The same result can be obtained in the scope of Froot, Scharfstein and Stein (1993) model.

The ratings matter because outside investors do not perfectly observe firm's type θ and its choice of credit risk $\rho^*(\theta)$. Information aggregation because information production is costly (references) and the CRA have incentives to produce imprecise ratings (Kartasheva and Yilmaz (2011), Goel and Thakor (2010)) Thus, in addition to (ρ, θ), the firm's profit depends on a rating R. We consider a setting where firms are rated by a monopoly CRA and the rating fee is normalized to zero. The CRA employs a rating scale with two ratings R_2 and R_1 such that a firm obtains a higher rating R_2 when $\rho^*(\theta) \in [\rho_s, \overline{\rho}] = R_2$ and a lower rating R_1 when $\rho^*(\theta) \in [\underline{\rho}, \rho_s] = R_1$. Parameter $\rho_s \in [\underline{\rho}, \overline{\rho}]$ characterizes the rating standard of the CRA, and higher ρ_s is interpreted as more stringent rating standard. The profit of a firm rated $R \in \{R_1, R_2\}$ is $\pi(\rho, R, \theta)$. Other things being equal, higher rating yields higher profits, $\pi(\rho_s, R_2, \theta) > \pi(\rho_s, R_1, \theta)$. The difference $\Delta(\rho_s, \theta) = \pi(\rho_s, R_2, \theta) - \pi(\rho_s, R_1, \theta)$ measures the value of higher rating R_2 to type θ, and it increases as the rating standard becomes more stringent, $\Delta_{\rho_s}(\rho_s, \theta) > 0$.

The firm's optimal credit quality is obtained in two steps. First, given a target rating R_i, the firm chooses the optimal credit quality compatible with the rating. That is, it chooses $\rho^*(R_i, \theta)$ such that

$$\rho^*(R_i, \theta) \in \arg \max_{\rho \in R_i} \pi(\rho, R_i, \theta). \tag{1}$$

Again, we assume that optimal credit quality is increasing in firm's type,

$$\frac{\rho^*(R_i, \theta)}{d\theta} > 0.$$

This assumption emphasizes the idea that firm's choice of credit quality is a result of the interaction between its corporate investment and financing policies, rather than a need to satisfy a particular rating standard. In an extreme case where the firm's profit depends only on its rating and raising credit quality is costly, the firm's optimal choice of credit quality would be the lowest required for a particular rating, either $\underline{\rho}$ for rating R_1 or ρ_s for rating R_2.

Second, a firm selects the optimal target rating $R^*(\theta)$. It aims to obtain a rating R_2 if and only if

$$\pi(\rho^*(R_2, \theta), R_2, \theta) > \pi(\rho^*(R_1, \theta), R_1, \theta), \tag{2}$$

and a rating R_1 otherwise. The assumptions about the profit function $\pi(\rho, R, \theta)$ imply the following result.

Result 1. There is a type θ_s such that types $\theta < \theta_s$ have credit quality $\rho^*(\theta) \in [\underline{\rho}, \rho_s] = R_1$ and types $\theta > \theta_s$ have credit quality $\rho^*(\theta) \in [\rho_s, \overline{\rho}] = R_2$.

We use this simple framework to evaluate the effect a more stringent rating standard on firm's choice of credit quality. In order to do so, we consider the following comparative statics experiment. Suppose that the CRA increases the stringency of the standard from ρ_s to $\rho'_s > \rho_s$. Under the new standard, the firm's credit quality $\rho'(R'_i, \theta)$ and the target rating R'_i are obtained analogously to the solution (1) and (2). Denote θ'_s the lowest types rated R'_2 under the new stringency standard.

Result 2. As the rating standard becomes more stringent, $\rho'_s > \rho_s$, the set of types that targets higher rating R'_2 becomes smaller, $\theta'_s > \theta_s$.

In order to evaluate the effect of a more stringent rating standard, we compare the outomes under the two regimes. In our simple framework with two ratings, the change of the rating stringency results in two groups of firms. The first group are firms for which the new rating standard is not binding, with credit quality $\rho^*(\theta) < \rho_s$ and $\rho^*(\theta) > \rho'_s$. These firms maintain the same level of rating under the new rating standard. As more stringent rating standard improves the signal about their quality to the market, the profit of these types increases. Furthermore, they will adjust their credit quality to a level that optimizes their profits under the new standard. If higher credit quality signal increases firm's investment opportunities, $\pi_{\rho\rho_s} > 0$, then the adjusted level of credit quality of these firms increases, $\rho'(\theta) > \rho^*(\theta)$.

The second group are firms for which the new standard is binding, with $\rho_s < \rho^*(\theta) < \rho_s'$. These firms face a choice between a downgrade to a lower rating R_1' or maintaining a high rating R_2', at cost of increasing their credit quality to higher level $\rho'(\theta) > \rho_s'$. The optimal strategy for this group depends on the benefits of a higher rating R_2' and the costs of increasing the credit quality. The first possible scenario is that the benefit of high rating is relatively low. Then the optimal strategy for the firm is to accept the downgrade. The downgrade also implies that the firm will adjust downwards the credit quality, due to the assumption $\pi_{\rho\rho_s} > 0$. The alternative scenario is that the benefit of high rating is relatively high, and thus the firm prefers to increase its credit quality to comply with a new rating standard. In this case the firm's credit quality is adjusted upwards, $\rho'(\theta) \geq \rho_s'$.

In summary, the analysis suggests that firms will adjust their credit quality in response to the change in the rating standard. The size and the direction of the adjustment will depend on (i) the extent to which the new standard is binding upon the firm, and (ii) the sensitivity of the firm's profit to rating. The closer is the distance to the lower boundary of the rating, the more likely it is that the new standard triggers the rating change. Thus firms that are closer to the lower rating boundary and desire to maintain their rating level are more likely to increase their capital. The decision to maintain the rating will depend on sensitivity of firm's profits to rating. If the profits have low sensitivity and improving credit quality is costly, a firm may prefer to accept the rating downgrade instead of increasing credit quality to defend the rating.

3 Institutional Setting and Data

We explore the adjustment of firms to more stringent rating standards using the data on ratings of U.S. property-casualty insurance companies with exposure to catastrophic risks. The hypotheses developed in the previous section imply that new rating standards induce firms to adjust their capital depending on the extend to which the new standard is binding to the insurer and the benefits of defending the letter grade rating under the new standards. We use the natural experiment of hurricane Katrina in 2005 which induced the major rating agencies to change the rating standards for catastrophic losses. The main empirical tests examine the asymmetric reaction of firms to new standards by regressing the measure of change in equity capital on variables that describe the position of the insurer relative to the boundary of the rating grade, the exposure to catastrophic risks and the costs and benefits of defending the rating.

In this section, we describe the institutional setting and the data. In the following section

we discuss the empirical tests and results. The empirical analysis proceeds in two steps. First, we estimate the location of the firm in the rating grade and construct a variable that measures the distance between the firm's location and the rating boundary. Then we use the results of the estimation to conduct the main empirical tests of the asymmetric reaction of firms' to new standards.

3.1 Ratings in insurance market

3.1.1 Why financial strength ratings matter?

Both practitioners and academics agree that ratings are important for insurers and reinsurers. The main reason is that the value of an insurance contract to the buyer depends on the insurer's insolvency risk. 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 contract sold by a firm with higher ratings. Cummins and Danzon (1997) find evidence that the price of insurance is positively related to insurer's financial quality. Sommer (1996) estimates a negative relationship between insurance prices and insurer's insolvency risk.

A distinct feature of the property-liability insurance industry is that there two groups of insurance buyers with different sensitivity to credit risk. The first group consists of individual buyers who purchase personal insurance to cover automobile and homeowners risks, and small businesses who purchase commercial insurance for property and liability damages. In the event of insolvency of the insurance firm, these buyers are protected by the state guarantee funds. The motivation for state insurance guarantee fund protection is that individuals and small business may fail to provide private monitoring of the insurance firm's risk taking.[6] Also insurance contracts for this group are highly standardized and have low switching costs.

The second group includes large corporate buyers that purchase protection for physical damage to property, business interruption and liability proteciton. These contracts require substantial underwriting efforts from the insurance firm, are highly customized for each corporate buyer and are sold through insurance brokers. Also commercial insurance contracts are not protected by state guarantee funds. These factors make the second group more sensitive to the firm's credit risk. Indeed, Epermanis and Harrington (2006) find that commercial lines experience a more pronounce decline in the volume of insurance sold following the rating downgrade.

[6]The guarantee fund protection in insurance is similar to deposit insurance in banking. See Cummins (1988) for the discussion of the optimal design of the guarantee fund protection. Downs and Sommer (1999) provide evidence that guarantee funds increase insurers risk taking.

The two groups of insurance buyers provide the identification for differential benefits of defending the rating. In the empirical analysis, we will distinguish between insurance firms with concentration in personal lines and commercial lines. The insurance firms with higher concentration in commercial lines are expected to have higher benefits of maintaining the rating.

3.1.2 Who rates insurers?

Financial strength ratings of the U.S. insurance firms are available from four major credit rating agencies, A.M. Best, Fitch, Moody's and Standard and Poor's. All these agencies have NRSRO status and together provide coverage of 97.48% of the insurance market measured by asset size in 2009.

Among the NRSRO CRAs, the insurance industry views A.M. Best rating agency as a benchmark. 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. As a result, A.M. Best ratings are widely incorporated in various local, state and federal regulations and are used by major insurance brokers to differentiate among insurance firms. A.M. Best provides almost full coverage of the insurance industry in the U.S. Indeed, 95% of companies measured by the asset size were rated by A.M. Best in 2009. At the same time, the number of companies that do *not* have A.M. Best rating but have at least one rating from another NRSRO CRAs[7] is only 1.95%. For the purpose of our study, we focus on the ratings of A.M. Best.

3.1.3 Rating standards for catastrophic risk exposures

Hurricanes, earthquakes, wind storms and floods can have a large, rapid and unexpected impact on the financial strength of an insurer. In 2011, the devastating earthquakes in Japan and New Zealand, and the tornadoes and floods in the U.S. and Australia, have resulted in insured losses of around $70 billion. The exposure to catastrophic losses has been increasing over time due to growing demographic concentration in urban and suburban areas, increasing property values in catastrophe prone areas, and the increased complexity of supply chains. Higher frequency and severity of losses are the main two reasons that CRAs use to justify the higher capitalization needed to support catastrophic risks.

[7]Beginning 1990s, the monopoly of A.M. Best was challenged by Standard and Poor's that established a solid position on the market of insurers ratings. The other two CRAs has also expanded their coverage of the insurance industry over time. In 2009, the market coverage of Fitch, Moody's and Standard and Poor's were 47.93%, 24.88% and 51.13%, respectively. Doherty, Kartasheva and Phillips (2001) analyze the effect of entry on the information content of ratings.

The charges for catastrophic exposures are significant components of the rating agencies methodologies of assigning ratings to insurance companies. Before the hurricane season of 2005, the evaluation of the insurer's risk adjusted capitalization was based on, depending on the firm's risk profile, the projected losses from a 100-year windstorm or hurricane or a 250-year earthquake, as well as its reinsurance program.

In the aftermath of hurricane Katrina in 2005, the major rating agencies have revised the property catastrophe insurance criteria[8] resulting in the increased amount of capital that an insurer needs to hold in order to maintain the current rating. In 2006, A.M. Best introduced a second event as an additional stress test. In the case of hurricane exposure, the second event is 100-year windstorm or hurricane; in case of earthquake exposure, the second event is a 100-year earthquake. The changes of the rating methodology had a significant impact on the amount of risk capital and reinsurance program needed to achieve a particular rating.[9]

3.2 Data

3.2.1 Data sources

We consider a sample of U.S. property-casualty insurance companies with exposure to hurricane catastrophic losses between 2001 and 2008. The data are collected from two sources. The ratings of the financial strength of the insurance companies are obtained from A.M. Best's annual Key Rating Guide. The financial quality, business strategy and corporate structure characteristics of the insurance companies are obtained from the SNL Financial database which uses the annual regulatory statements on insurance companies provided by the National Association of Insurance Commissioners (NAIC). We restrict attention to companies with hurricane risk exposures defined by the hurricane risk prone line of business and geographic location. It includes companies with direct premium written in homeowners, farm owners, auto physical damage, commercial multiperil (non-liability), and inland marine in the five southeastern coastal states, Florida, Louisiana, Mississippi, South Carolina, and Texas.

[8] Guy Carpenter (2006) report provides an excellent summary of rating standards changes on catastrophic risks of the major rating agencies.

[9] Ratings standards can also have impact on 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.

3.2.2 Financial Strength of Insurers with Hurricane Risk Exposure

In this section we describe insurers' financial strength during the 2000s. The industry reveals two main trends. First, while commercial insurers had stable ratings during the decade, the personal line insurers experiences rating downgrades following the hurricane season, and were not able to recover their financial quality. Second, the concentration of exposure to catastrophic risks is higher for property insurers, and it has been increasing during the sample period. Also, the concentration of catastrophic exposure in personal lines increases for lower rated firms, which raises concerns about the vulnerability of this market segment to catastrophic risks.

Table 3 and Figure 1 show the financial strength change of commercial and personal property casualty insurers with hurricane risk exposures from 2002 to 2008. Panel A of Table 3 shows the number of insurers by lines of business and A.M. Best Rating. Both the numbers of commercial and personal insurers with high ratings greater than A are stable during the sample period. The trend is quite different for insurers with ratings below A-. While the number of commercial insurers with lower rating has been decreasing, the number of personal insurers with lower rating has been increasing steadily.

After the 2004-2005 hurricane seasons, a few insurers went bankrupt and many others came into the market with new capital. Then, the trend found in Panel A of Table 3 could be due to the new entry of unrated or low rated firms. Figure 1 presents average A.M. Best ratings changes for the subsample of insurers with continuous ratings during 2002-2008. The average ratings for personal insurers dropped in 2004 and 2005, and they fail to recover from the downgrade in the following years. To the contrary, commercial insurers experienced less downgrades, and their average rating increases until 2007. For comparison, Figure 1 also provides an average rating for the entire sample of rated property-casualty insurers in U.S., not limited to insurers exposed to hurricane risks. The trend for all U.S. insurers resembles the trend for commercial insurers.

Panel B of Table 3 presents a rating distribution of commercial and personal insurers and hurricane risk exposure for each insurer group. Commercial insurers are more likely to be rated by A.M. Best[10], and have a higher average rating. They have lower concentration of exposure in catastrophic risks. The trend is striking in personal lines. The average exposure of low rated insurers is more than 50%.

[10] Unrated personal insurers are either new entrants or are rated by Demotech, a rating agency that focuses on smaller firms.

4 Econometric Analysis and Results

4.1 Modeling the rating standard change

Empirical strategy. We first aim to estimate the location of each insurance firm in the rating grade. To do so, we compute an unobserved continuous latent rating score for each insurer that is based on the information used by the credit rating agencies to assign ratings. The dependent variable of the Probit regression model is the numerical conversion[11] of the A.M. Best financial strength ratings from A++ to D. The ordered Probit regression results provide an estimate of the latent rating score of each firm as a function of the firm's characteristics. Also the results allow to identify the cut-off point of each rating grade.

We use the estimated rating score and the rating boundaries to construct the relative location of each insurer within each rating grade. A variable DIS is defined as the distance from the estimated upper boundary latent score of each rating grade to the estimated score of each insurer. A larger value of DIS means that the firm is closer to the lower boundary of a rating grade.

The change of the rating standard must translate in lower rating score for the same level of exposure. Then the estimation of the rating boundaries and the firm's location in the rating grade must account for the change in the rating standards for catastrophic risks in 2006. We expect that higher exposure to catastrophic risks reduces A.M. Best's ratings. To capture the rating standard change on catastrophic risk, we run two separate regressions for the periods before (2001-2005) and after (2006-2008) the standard change. More stringent rating standards on catastrophic risk are expected to increase the absolute value of the coefficient on exposure to catastrophic risks for the later period 2006-2008. The exposure is measured as a proportion of premiums written[12] in hurricane risk exposed lines of business to total direct premium written.

The explanatory variables used to estimate the model are the variables listed in A.M. Best Credit Rating Methodology (2009), as well as the variables considered in other insolvency and rating studies.[13] The variables describe the firm's capital adequacy, underwriting and investment profitability, ability to raise capital and corporate stability. The capital adequacy measure is the A.M. Best's Capital Adequacy Ratio (BCAR). BCAR is a quantitative score that A.M. Best

[11] After including all "+" and "-" qualifiers, we obtain fourteen rating grades. A numerical conversion of ratings is available in Table 1.

[12] In insurance, premiums written stand for the total volume of insurance sold.

[13] See Cummins, Harrington and Klein (1995), Doherty and Phillips (2002), Doherty, Kartasheva and Phillips (2011).

assigns to each rated insurer based on the capital adequacy relative to the overall asset and liability risk profile. We include firm size and firm age, expecting larger and older companies to be assigned higher ratings. We also include two variables that account for the ability to raise capital. The first variable is a dummy for the single unaffiliated insurer. While affiliated subsidiary insurers are likely to get capital aid from their affiliated company or holding company when an unexpected loss occurs, a single unaffiliated insurer will have to find external financing. The second variable is a dummy for publicly traded company. A publicly traded stock company has access to a wide pool of investors and thus needs to pay lower cost of external financing. We expect the public dummy to be positively related and the single unaffiliated insurer dummy to be negatively related to the firm's rating.

The final model includes the variables that have high statistical significance in explaining the rating score. The initial set of variables included all Financial Analysis and Surveillance Tracking (FAST) scores and the Risk Based Capital ratios that are used by the National Association of Insurance Commissioners in the solvency surveillance system of the insurance industry. However, several financial ratios are closely related and show high statistical correlation. Excluding the insignificant variables did not affect the coefficients of remaining variables, resolving the possible omitted variable problem.

The sample consists of all property-casualty insurance companies in the U.S. rated by A.M. Best. The initial sample has 15,703 firm-year observations. We lose 4,859 observations for which explanatory variables in the rating model regression were unavailable. The final sample has 10,844 firm-year observations. Table 4 reports descriptive sample statistics for the variables used in the rating process regression.

Results. Table 5 and Table 6 present the rating process model results using the ordered Probit model. The second column of Table 5 shows a whole sample result, and the third and fourth column shows the regression for the subsample period before and after the ratings standard change.

The coefficient estimates of the exposure to catastrophic risks, CAT variable, in the two subsample regression results are consistent with the ratings standard change. That is, an insurer with the same level of exposure to catastrophic risks is assigned a lower rating after the rating standard change. The CAT coefficient is -0.19 for the pre-standard change period and -0.72 after the standard change period.

All other coefficients are significant and have expected signs. The model predicts that an

insurer obtains a higher rating from A.M. Best when it has a higher investment yield, lower premium surplus ratio, lower reserve surplus ratio, higher premium growth, lower reinsurance recoverable, less junk bonds, a higher BCAR, and less catastrophic risks exposure. The variables added to capture the qualitative characteristics also have predicted signs. Larger and older insurers have a higher rating. A subsidiary of a publicly traded insurance company has a higher rating, and single non-affiliated companies have lower ratings, indicating that the ability to acquire and cost of raising capital is an important rating factor.

Table 6 displays the summary statistics of the estimated latent rating score by the actual rating assigned by A.M. Best. It shows that as a rating becomes stronger, the estimated score monotonically increases. The significant coefficients and monotonic estimated estimate suggest that the ordered probit model yields solid explanatory power.

Rating standard change has a significant effect on firms ratings. The mean and median score difference between rating grades is about 0.3 to 0.6. Holding everything else equal, before the rating standard change, an insurer with 100% business in hurricane exposed lines of insurance will be assigned a rating only one notch lower than an insurer with no exposure to catastrophic losses. After the rating standard change, the same insurer is penalized by two to three notches.

4.2 Capital adjustment to the rating standard change

Empirical strategy. We now investigate how the insurance firms adjusted their capital after the rating standards change. The specific regression model used is the following.

$$SARC_{t,t+1} = \alpha + \beta_1 CATDIS05 + \beta_2 CATDIS06 + \beta_3 DIS_t + \beta_4 CAT05 + \beta_5 CAT06 + \sum_i \gamma_i X_{i,t} + \varepsilon$$

The dependent variable SARC is a measure of change in equity capital, annual surplus asset ratio change. We investigate how the equity capital change depends on the position of the insurer in the rating grade prior to the change of the rating standard, its exposure to catastrophic risk and the benefit of defending the rating.

The main variables of interest, CATDIS05 and CATDIS06, measure the effect of the new rating standard on the equity capital. These variables are constructed by multiplying the relative location of the firm in the rating grade estimated in the previous section, DIS, by the year 2005 or 2006 dummy and the exposure of the insurer to hurricane risk, CAT. We include the CATDIS variable for two years, 2005 and 2006, in order to account for the possibility that the industry anticipated the standard change. Indeed, higher rating standards were applied to

reinsurance industry in 2005. Though Katrina events prompted the rating agencies to increase the stringency of standards for the insurance industry, it is possible that insurers expected the change prior to 2006. Our hypotheses suggest that the coefficient of CATDIS is positive among the insurers which have stronger incentives to defend their current ratings. These insurers include firms that are located closer to the rating boundary and have higher exposure to catastrophic risks. However, we expect that the reaction will be heterogeneous depending on the benefits of defending the rating. If the cost of raising capital outweigh the benefits of maintaining the rating, the coefficient of CATDIS is negative.

In order to identify the effect of the rating standard change on the change in equity capital, we control for the initial position of the insurer in the rating grade, DIS, and its exposure to catastrophic risks, CAT. The anticipated hurricane risk has been modified upwards after hurricane seasons. Thus change of the anticipated risk may lead hurricane risk-exposed insurers to increase their surplus asset ratio, regardless of the rating standard change. Without controlling this effect, the main variable of our interest, CATDIS, will also capture the capital adjustment due to the increased anticipated risk. We control for the level of hurricane risk exposure by adding the proportion of catastrophic risk premium to total premium in 2005 and 2006, CAT05 and CAT06. If the ratings standard change has an impact on insurers' capital decisions, the CATDIS05 and CATDIS06 must remain significant after controlling for the degree of the catastrophic risk exposure.

Similarly, we include DIS in order to control the capital adjustment behavior of a firm seeking to maintain their current rating. Without DIS control, the variables CATDIS05 and CATDIS06 will also capture the general capital adjustment behavior without any rating standard changes. Insurers close to the lower boundary of each rating grade may increase their surplus to secure their current rating. Thus we expect DIS to be positively related to the surplus change.

We include other control variables that can change the surplus asset ratio. The most important consideration for insurer capital decision is its risk. The overall credit risk profile of an insurer depends on various factors, not limited to the premium written in hurricane-related lines of business. Asset portfolio change, underwriting line of business changes, reinsurance, and other strategic changes will influence an insurer's risk profile. In order to capture the overall risk change of each insurer, we include the Risk Based Capital (RBC) change from year t to $t+1$. RBC is an overall risk charge imposed by the NAIC. It covers four areas: asset risk,

credit risk, underwriting risk, and growth and other form of off-balance sheet risk.[14] Therefore, RBC provides a summary of the overall risk profile of the insurer. We expect this variable to be positively correlated with capital ratio change.[15]

The next important control factor is the loss experience. A loss shock in year t can reduce the surplus asset ratio, and raising or recouping the depleted capital to the target level may take time. We include the change in combined ratio to control for the loss experience. It is defined as a ratio of total loss and expense to net premium written. Combined ratio is a standard underwriting profitability measure in the insurance industry.

The other control variables are log asset in year t, the A.M. Best rating in year t, and year dummy variables in the regression model. Table 2 panel B presents the definition of variables used in the analysis.

Our hypotheses are that the propensity to defend a current rating may vary depending on the benefits of maintaining the rating and the insurance company's initial rating. The benefits of maintaining the rating are higher for insurers concentrated in commercial lines versus those concentrated in personal lines. Also the current ratings matter if there is a threshold rating that triggers the demand change. In the insurance industry, A.M. Best's A- rating is viewed as an investment grade analog of bond ratings. The requirement to purchase insurance from a firm rated at least A- is incorporate in various private contracts and is widely used in regulation.[16] These features of the insurance industry suggest that the propensity to defend the current rating will be the highest for A- rated insurers concentrated in commercial lines.

Following this logic, we subdivide insurers in groups based on the predicted propensity to defend a current rating after the ratings standard change. First, we distinguish between insurers

[14] NAIC provides guideline formulas for RBC charges. RBC increases as risks in each category increase. For example, an investment in U.S. government bonds has zero charge, whereas junk bonds require an RBC factor up to 30 percent. Similarly, underwriting in catastrophic risk-prone lines of business or commercial liability has a higher factor than auto property. When aggregating each charge into one RBC, covariance structure is also considered (Cummins, Grace, and Phillips 1999; NAIC 1993).

[15] Companies near regulatory contraint of 200% RBC ratio may reduce their risks (Ellul, Pab and Lundblad 2011). This should not bias our result unless the low risk based capital ratio firms are distributed close to the lower boundary of each rating category. As a rebustness check, we run the same set of regressions including a dummy variable equal to one when a risk based capital ratio is within the lower 25% quartile (456% in our sample) and an interaction term of this dummy and CATDIS in unreported regressions. All of the interaction variables are insignificant and inclusion of these variable does not affect other coefficients.

[16] Insurance brokers and policyholders generally do not recommend commercial insurance provider rated below A-. Also Nini and Cheyne (2010) show that the majority of commercial insurance demand is associated with insurance requirements placed in loan and debt, and the requirements include at least A- rating. Epermanis and Harrington (2006) find that the insurance demand sensitivity is highest when a commercial insurer is downgraded from A- to B++.

concentrated in commercial and personal lines of business. An insurer is defined as a commercial insurer if the direct premiums written in commercial lines of business are more than 50% of the insurer's total premiums written. Second, we distinguish among three rating groups: highly rated insurers with a rating A or higher, A- rated insurers and lower rated insurers with a rating B++ or lower. Finally, we consider a full set of six groups based on line of business and the rating. If the hypotheses of heterogeneous reaction to rating change are correct, the effect of the rating standard change must the most pronounced for A- rated commercial insurers subgroup.

The number of firm-year observations for the hurricane exposed sample of firms is 5,801. We lose some observations due to the unavailable right hand side variables in the regression. The final sample consists of 3,067 firm-year observations.[17]

Results. Table 7 presents the surplus ratio change regression results. Panel A reports the regression results of all property casualty insurers with hurricane risk exposure, and the two subgroups of commercial and personal insurers. Panel B presents the coefficient estimate of the effect of the rating standard change, CATDIS05 and CATDIS06, for the six rating and line of business subgroups.

The results for the whole sample support the hypothesis that the rating standard change produce heterogenous effects on the insurance industry. Indeed, the main variable of interest, CATDIS06, is not significant in the whole sample regression. Furthermore, CATDIS05 is significantly negative, meaning that insurers affected by the ratings standard change decreased rather than increased their capital between 2005 and 2006. The results for the subgroups of personal and commercial lines in Panel A reveal that the negative result of CATDIS05 is driven by personal line insurers. For this group, CATDIS05 and CATDIS06 have significant negative coefficients. At the same time, the coefficient of CATDIS06 is insignificant for the commercial lines group.

In order to decompose the heterogeneous reaction to new rating standards of different types of insurers depending on their propensity to defend ratings, we compare the coefficients of CATDIS05 and CATDIS06 of six ratings-lines of business subgroups. The results are shown in Panel B of Table 7. In line with the hypotheses, the results reveal that there are dramatic differences among the subgroups.

The estimation results suggest that commercial insurers with an A- rating have the strongest incentive to defend their current A- rating. The commercial A- insurers reacted to the standard

[17] Most of the sample is lost due to the A.M. Best rating and Best's Capital Adequacy Ratio (BCAR) availability.

change by increasing the capital. The coefficient of 0.16 means that an insurer very close to the bottom of the A- rating increased the surplus asset ratio about 1.32% more compared to an insurer very close to the top of the A- rating, if both of them have the same 8.84% hurricane risk exposure. If both of the insurers had 20% hurricane risk exposure, the insurer at the bottom of the rating bin increased approximately 5.6% more than the top A- rated insurer.[18] At the same time, commercial insurers with either high or low ratings do not show strong response to the rating standard change.

The rating standard change produced a negative effect on personal line insurers. Highly rated personal insurers close to the bottom of their ratings categories significantly reduced their capital between 2006 and 2007. Lower rated personal insurers also reduced their surplus asset ratio between 2005 and 2006.

The regression results are aligned with the actual ratings change over the sample period shown in Table 3 and Figure 1. While the majority of commercial lines insurers maintained their ratings, some personal line insurers were downgraded after the hurricane seasons. This observation provides the support for our hypothesis that the cost of maintaining the rating following the rating standard change outweighed the benefits for personal lines insurers.

Other coefficients are economically significant and have the expected signs. The location of the insurer in the rating grade, DIS, is always strongly positive in all regression models. Firms adjust their capital upwards when they approach to the bottom of a rating grade in any year. The positive sign of the exposure to catastrophic risks,CAT05 and CAT06, means that insurers with more hurricane risk exposure increased their capital more than insurers with less hurricane risk exposure after the 2004-2005 hurricane seasons. The coefficient of the profitability measure, combined ratio change, is significant and negative. It means that as insurers experience more losses in year $t+1$ than year t, the capital in year $t+1$ is reduced compared to the capital year t. The asset size coefficient shows that larger insurers generally increased their surplus asset ratios more than smaller insurers during the sample period.

5 Conclusion

In this paper we explore the effect of more stringent rating standards on the credit quality of a firm. We argue that more stringent standard leads to heterogeneous reaction driven by the trade

[18] The summary statistics of the latent rating score of the A- group is shown in Table 6. The difference between p99 and p1 in the A- rating is 2.76. So we assume that the DIS difference between the top and bottom insurer is 2.76 in this computation.

off between the costs and the benefits of defending a rating. We use a natural experiment of the hurricane Katrina to explore the reaction of the U.S. property-casualty companies with exposure to hurricane risks to the more stringent rating standards for catastrophic exposures. Consistent with the theory, more stringent standards induced higher credit quality for highly rated firms concentrated in commercial insurance lines. These firms have higher benefits of maintaining the rating and relatively low costs of raising capital. At the same time, the rating standard change induced higher concentration of credit risk for the group of personal insurers.

Our results imply that it is important to account for the industry best response to more stringent rating standards. The new rating standards has affected the distribution of credit risk in the industry by increasing the concentration to catastrophic losses in personal insurance lines. It is possible that new standards has reduce ability of personal insurers to sustain big losses due to catastrophic events.

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Table 1. Rating conversion table

Table 1 shows A.M. Best ratings conversion.

A.M. 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

Table 2. Variable Names and Definitions

Table 2 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 returns based on average invested assets
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.
RBC	Risk Based Capital
BCAR	Best's Capital Adequacy Ratio
Reinsurance Recoverable/Surplus (%)	Reinsurance recoverable as a percent of surplus
Reserve/Surplus (%)	Loss and loss adjustment expense reserves as a percent of surplus
Single dummy	Dummy=1 if this firm is non-affiliated single company
Public dummy	Dummy=1 if the ultimate parent of this company is publicly traded company
AMBEST	AM Best rating
Net premium growth (%)	1 year net premium written growth
Premium/Surplus (%)	Proportion of direct premiums written to surplus
Junk bonds/Asset (%)	Proportion of junk bonds [NAIC 4-6] to total assets
Firm age	Firm age
CAT	Proportion of premiums written in hurricane risk-exposed lines of business to total direct premiums written
SARC	Surplus/Asset ratio change from year t to year t+1
DIS	Estimated latent rating score distance from the upper boundary of each rating bin: the larger the value, the closer the company to the lower boundary
CATDIS05	If year=2005, then DISTANCE * CAT in 2005, zero otherwise
CATDIS06	If year=2006, then DISTANCE * CAT in 2006, zero otherwise
CAT05	If year=2005, then CAT in 2005, zero otherwise
CAT06	If year=2006, then CAT in 2006, zero otherwise

Table 3. Hurricane Risk-Exposed Insurers' Rating Changes from 2002 to 2008 by Line of Business

Table 3 shows the number of insurers in hurricane risk-exposed states by lines of business and by A.M. Best Rating. We define an insurer as a commercial insurer if the direct premiums written in commercial lines of business are more than 50% of the insurer's total premiums written. A strong rating is a rating greater than or equal to A and a weak rating is a rating less than or equal to A-. A weak rating also includes those insurers without A.M. Best rating information.

Panel A. Number of insurers by type and rating from 2002 to 2008

Year	Commercial Strong	Commercial Weak	Personal Strong	Personal Weak
2002	397	241	89	72
2003	372	234	91	84
2004	377	222	85	89
2005	383	201	80	96
2006	386	191	77	101
2007	400	198	81	103
2008	414	208	85	109

Panel B. Median ratio of hurricane risk gross premiums written to total gross premiums written

Rating	Commercial			Personal		
	N	N (Percentage)	PCAT	N	N (Percentage)	PCAT
A++	256	6.06%	2.21%	64	5.15%	10.91%
A+	946	22.40%	2.13%	192	15.46%	6.12%
A	1527	36.15%	2.68%	332	26.73%	18.66%
A-	949	22.47%	2.71%	225	18.12%	36.40%
B++	186	4.41%	5.28%	46	3.70%	67.63%
B+ and below	237	5.61%	3.43%	137	11.03%	81.36%
Not Rated	123	2.91%	8.48%	246	19.81%	87.80%

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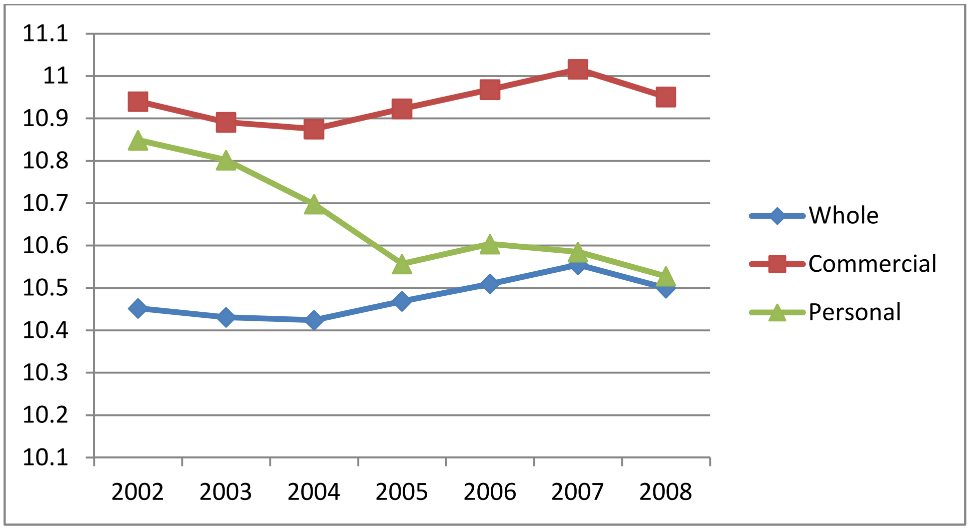

Figure 1. Rating Change: 2002-2008

Note: “Rating” is a numerical conversion of the A.M. Best rating. The conversion table is in Appendix I. “Whole” is the average rating of entire PC insurers in the U.S. “Commercial” is the average rating of Hurricane risk-exposed commercial line PC insurers, and “Personal” is the average rating of Hurricane risk-exposed personal line PC insurers.

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Table 4. Summary Statistics of Variables Used in the Regression Analysis

Table 4 shows the summary statistics of the variables used in the regression analysis. Sample includes Property Casualty insurers with an A.M. Best rating in the U.S. during 2001-2008.

Variable Name	N	Mean	Median	STD	P1	P99
Panel A. Variables used in ratings model ordered probit regression						
Investment Yield	10,910	4.11	4.00	1.72	1.00	8.00
Combined Ratio	10,910	103.41	98.00	67.14	8.00	258.00
Premium/Surplus	10,910	109.68	98.00	75.61	1.00	337.00
Net Premium Growth	10,910	19.56	5.00	100.53	-80.00	404.00
Reinsurance Recoverable/Surplus	10,910	46.12	12.00	89.75	-2.00	461.00
Reserve/Surplus	10,910	88.96	73.00	75.79	0	323.00
Junk Bonds/Asset	10,910	2.12	0	5.67	0	24.00
BCAR	10,910	241.05	198.20	152.00	73.20	999.90
Log[Asset]	10,910	11.67	11.55	1.79	8.06	16.00
Public Dummy	10,910	0.31	0	0.46	0	1
Single Dummy	10,910	0.14	0	0.35	0	1.00
Firm Age	10,910	51.59	34.00	41.19	8.00	177.00
CAT	10,910	0.044	0	0.14	0	0.92
Panel B. Variables used in capital ratio change regression						
Surplus/Asset ratio change		-0.0068	0.0045	0.1198	-0.4989	0.3368
DIS		1.5928	1.6128	0.7443	-0.0462	3.5503
CATDIS05		0.0235	0	0.1645	0	0.8481
CATDIS06		0.0306	0	0.1945	0	1.0402
CAT05		0.0131	0	0.0812	0	0.4313
CAT06		0.163	0	0.0899	0	0.4986
Asset		12.4627	12.3632	1.8050	8.3673	17.1647
Best Rating		10.6820	11.00	1.4983	6.00	13.00
Δ Combined Ratio		0.1192	-1.00	58.7065	-109.00	133.00
Δ RBC		94.7181	3.7762	2168.53	-1958.51	4715.13

Table 5. Ratings Model Regression Results

Table 5 shows the regression results of the rating model. The ordered probit regression model is adapted as an estimation method where the dependent variable is the numerical conversion of the A.M. Best rating. The numerical conversion for the Best rating is presented in Appendix I. The definition of variables is listed in Table 2 and the summary statistics is presented in Table 4. The sample includes all Property Casualty insurers with A.M. Best ratings in the U.S. during 2001-2008.

Variables	Expected Sign	Whole Sample		2001-2005		2006-2008	
Investment Yield	+	0.1019		0.1124		0.0647	
		[0.0083]	***	[0.0096]	***	[0.0170]	***
Combined Ratio	-	-0.0026		-0.0026		-0.0004	
		[0.0004]	***	[0.0004]	**	[0.0007]	***
Premium/Surplus	-	-0.0024		-0.0025		-0.0029	
		[0.0002]	***	[0.0002]	***	[0.0003]	***
Net Premium Growth	+/-	0.0013		0.0014		0.0006	
		[0.0002]	***	[0.0002]	***	[0.0003]	*
Reinsurance Recoverable/Surplus	-	-0.0028		-0.0029		-0.0030	
		[0.0001]	***	[0.0002]	***	[0.0003]	***
Reserve/Surplus	-	-0.0030		-0.0033		-0.0028	
		[0.0002]	***	[0.0002]	***	[0.0003]	***
Junk Bonds/Asset	-	-0.0169		-0.0187		-0.0193	
		[0.0025]	***	[0.0030]	***	[0.0051]	***
BCAR	+	0.0008		0.0007		0.0011	
		[0.0000]	***	[0.0000]	***	[0.0001]	***
Log[Asset]	+	0.3818		0.4046		0.3688	
		[0.0070]	***	[0.0092]	***	[0.0125]	***
Public Dummy	+	0.5653		0.5485		0.6067	
		[0.0236]	***	[0.0292]	***	[0.0407]	***
Single Dummy	-	-0.2873		-0.2362		-0.3763	
		[0.0315]	***	[0.0392]	***	[0.0530]	***
Firm Age	+	0.0014		0.0015		0.0010	
		[0.0002]	***	[0.0003]	***	[0.0005]	**
CAT	-	-0.3924		-0.2151		-0.7090	
		[0.0705]	***	[0.0878]	***	[0.1185]	***
Likelihood Ratio[LR]		5,774.8		3911.4		1,963.4	
Estrella pseudo-R2		0.4357		0.4484		0.4294	
McFadden's LRI		0.1451		0.1487		0.1499	
Number of Obs		10,910		7,118		3,792	

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

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Table 6. The Estimated Latent Rating Score from the Ordered Probit Regression

Table 6 displays summary statistics of the estimated latent rating score from the ordered probit regression by the actual assigned A.M. Best rating. The sample includes all Property Casualty insurers with A.M. Best ratings in the U.S. during 2001-2008.

Rating	Num	Mean	STD	p1	p25	Median	p75	p99
A++	529	5.372	0.841	3.627	4.722	5.381	5.951	7.373
A+	1800	4.912	0.751	2.977	4.427	4.899	5.418	6.701
A	3324	4.525	0.646	3.079	4.084	4.500	4.916	6.238
A-	2804	4.119	0.645	2.844	3.660	4.061	4.543	5.821
B++	1082	3.726	0.609	2.330	3.346	3.691	4.120	5.374
B+	671	3.415	0.703	2.079	2.941	3.325	3.804	5.378
B	388	3.299	0.670	1.478	2.897	3.290	3.743	4.803
B-	165	2.945	0.683	1.302	2.491	2.890	3.402	4.507
C++	85	2.844	0.775	1.376	2.243	2.713	3.386	4.898
C+	33	2.444	0.578	1.270	2.084	2.312	2.738	3.623
C	19	2.264	0.720	0.976	1.682	2.246	2.922	3.500
C-	10	2.082	0.504	1.419	1.599	1.999	2.503	2.855
Total	10910	4.285	0.885	2.169	3.704	4.272	4.842	6.482

Table 7. Capital Changes after the Rating Standard Change

Table 7 displays robust regression results where the dependent variable equals the change of surplus as a proportion of net admitted assets from year t to t+1. The sample includes Property Casualty insurance companies with Hurricane-risk prone lines of business, which are defined as direct premiums written for homeowners, farm owners, auto physical damage, commercial multiperil [non-liability], or inland marine in AL, FL, MS, SC, or TX. Panel A reports the regression results by line and by A.M. Best rating. We define an insurer as a commercial insurer if the direct premiums written in commercial lines of business are more than 50% of the insurer's total premiums written. Panel B presents the coefficient estimates of CATDIS05 and CATDIS06 from the six by line and rating sub-sample regressions. The full regression results are available upon request.

Panel A. By line of business and by rating groups

	By line of business			By A.M. Best Rating in year t-1		
	(1)	(2)	(3)	(4)	(5)	(6)
Model	All PC Insurers	Commercial Insurers	Personal Insurers	A and higher	A-	B++ and below
CATDIS05	-0.004	0.055**	-0.026	0.005	0.138***	-0.019
	(0.012)	(0.023)	(0.016)	(0.022)	(0.032)	(0.030)
CATDIS06	0.002	0.091***	-0.018	-0.025	0.039	0.028
	(0.011)	(0.032)	(0.015)	(0.018)	(0.034)	(0.029)
CAT05	0.025	-0.060	0.023	-0.005	-0.160**	0.008
	(0.024)	(0.050)	(0.034)	(0.050)	(0.074)	(0.051)
CAT06	0.028	-0.142**	0.068**	0.092**	-0.058	0.021
	(0.023)	(0.072)	(0.030)	(0.042)	(0.078)	(0.049)
DIS	0.009***	0.008***	0.012***	0.006***	0.016***	0.015**
	(0.001)	(0.002)	(0.004)	(0.002)	(0.004)	(0.006)
Log[Asset]	0.004***	0.004***	0.004**	0.002***	0.011***	0.010***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)
Best Rating in year t-1	-0.002***	-0.002***	-0.001	-0.000		-0.011***
	(0.001)	(0.001)	(0.002)	(0.002)		(0.003)
Δ Combined Ratio	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ RBC	0.000**	0.000	0.000**	0.000	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pseudo R-Square	0.300	0.242	0.186	0.324	0.371	0.309
F-value	98.966	60.653	10.612	29.320	85.192	14.748
Number of Obs.	3,437	2,806	631	830	2,145	462

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Panel B. Six line of business-rating subgroups

Model	(1) Commercial A and higher	(2) Commercial A-	(3) Commercial B++ and lower	(4) Personal A and higher	(5) Personal A-	(6) Personal B++ and lower
CATDIS05	0.089***	0.122***	0.007	0.000	0.204***	-0.051
	(0.034)	(0.041)	(0.074)	(0.032)	(0.052)	(0.045)
CATDIS06	0.026	0.176***	0.119	-0.040*	0.011	0.025
	(0.047)	(0.064)	(0.099)	(0.023)	(0.043)	(0.046)
CAT05	-0.166**	-0.141	0.078	-0.003	-0.316**	-0.039
	(0.076)	(0.095)	(0.146)	(0.076)	(0.126)	(0.087)
CAT06	-0.025	-0.346**	-0.161	0.130**	-0.010	0.046
	(0.096)	(0.158)	(0.233)	(0.056)	(0.101)	(0.100)
DIS	0.006***	0.011***	0.013**	-0.001	0.015	0.024
	(0.002)	(0.004)	(0.006)	(0.005)	(0.009)	(0.018)
Log[Asset]	0.003***	0.008***	0.013***	-0.002	0.013***	0.013*
	(0.001)	(0.002)	(0.003)	(0.002)	(0.004)	(0.007)
Best Rating in year t-1	-0.003		-0.008***	0.011**		-0.021**
	(0.002)		(0.003)	(0.005)		(0.010)
Δ Combined Ratio	-0.000***	0.000	-0.000***	-0.001***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ RBC	0.000	0.000	-0.000***	0.000***	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pseudo R-Square	0.183	0.190	0.414	0.161	0.706	0.067
F-value	27.429	12.528	16.989	5.706	24.813	1.570
Number of Obs.	1,776	689	341	369	140	121

Panel C. Without CAT05, CAT06 variables

		N	Pseudo R-Square	CATDIS05	CATDIS06
By Line	All	3,437	0.302	0.007	0.014**
	Commercial	2,806	0.244	0.028***	0.030***
	Personal	631	0.180	-0.017*	0.008
By Rating	A and above	2,145	0.375	0.003	0.008
	A-	830	0.326	0.062**	0.014
	B++ and below	462	0.314	-0.015	0.038**
Commercial	A and above	1,776	0.460	0.002	0.014
	A-	689	0.185	0.072***	0.037**
	B++ and below	341	0.425	0.042	0.055*
Personal	A and above	369	0.153	-0.001	0.006
	A-	140	0.685	-0.020	0.004
	B++ and below	121	0.082	-0.060	0.035

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