Competition among rating agencies and information disclosure*

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Abstract

The paper analyzes why a rating agency pools different credit risks in one credit grade, and how information disclosure depends on the value of information to the market. We build a model to analyze the optimal disclosure policy of a monopoly rating agency depending on the value of information to investors, and then describe the potential market and the strategy of the entrant. We find that entry of a symmetric rating agencies results in asymmetric rating scales. It justifies why some companies obtain multiple ratings and suggests that similar ratings from different agencies may mean different credit risks. We empirically test the qualitative predictions of the model. Standard and Poor's entry to the insurance market that was previously covered by a monopoly agency, A.M. Best, is used as a natural experiment to study the impact of competition on the information content of ratings.

Keywords: rating agency, competition, precision and disclosure of information, insurance.

JEL Codes: D8, G22, G28, L1, L43

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1 Introduction

Credit rating agencies has become increasingly important over the last 30 years. Ratings are widely used by investors as inputs to portfolio management decisions. They are embedded in various state and federal regulations. Also the rating agencies drive industry standards in that they may set, for example, the level of liquidity that a corporation should have to be a strong issuer.

In the United States, Securities and Exchange Commission (SEC) uses the term "Nationally Recognized Statistical Rating Organization" (NRSRO) to determine the agencies whose investment grade ratings allow for favorable regulatory treatment. However, the NRSROs themselves are not subject to substantive monitoring and till June 2007 there was little guidance on the designation of the NRSRO status.

Following recent failures of rating agencies to provide timely accurate information (Enron, Worldcom, Global Crossing, AB&B, AT&T, to name the big ones), rating agencies has been criticized for the potential lack of transparency about the rating process and significant concentration of power in a small number of rating agencies. In response to these criticisms, the U.S. House of Representatives passed the "Credit Rating Agency Reform Act of 2006" that aimed to substantially simplify the process of obtaining a NRSRO status. From June 2007 SEC has adopted rules to implement provisions of the Act. In particular, rating agencies who have issued ratings for 3 years and satisfy certain requirements have the option of registering as NRSROs. This policy has substantially diminished the regulatory barriers to entry. However, till now there is no agreement about the impact of competition on the quality of information provided by credit raters.

The current paper deals with one aspect of information quality, namely, incentives for information disclosure. Credit quality assessment implies that a rating agency produces an estimate of probability of default. However, with the exception of KMV^{TM}, major rating agencies do not disclose a numerical estimate of credit quality. Instead, they assign letter grades, where companies or issuers with similar credit risk characteristics have the same grade. Not surprisingly, pooling different credit risks within the same rating group reduces the amount of information disclosed to the market. We build a model to analyze how a profit maximizing monopoly rating agency designs the rating scale, and how the optimal rating scale changes when a new agency enters the market. We empirically test the qualitative predictions of the model using the data on ratings of creditworthiness of insurance companies.

In the model a rating agency decides how credit risk information is disclosed to the market. Lizzeri (1999) establishes a striking result in information intermediation literature: A monopoly rating agency's optimal rating scale is to pool all companies in one rating. Surprisingly, in spite the fact that de facto the agency discloses no information, all companies obtain a rating for a positive fee. The crucial assumption that leads to no disclosure result is that all parties are risk neutral. It implies that no party values the precision of information contained in rating. We relax this assumption and show that when precision of information has value to end users of ratings (investors, buyers of a product, etc.), no disclosure result no longer holds. Also we study how the marginal value for precision of information affects the optimal rating scale. As the value of information increases ratings become more precise.

The model has three groups of players - sellers (debt issuers, corporations, product producers), rating agencies, and buyers (investors, consumers). We assume that purchasing a rating is voluntary to a seller, and a rating agency cannot charge a fee contingent on the rating assigned. The optimal rating system of the agency is designed to trade-off the ability of high quality sellers to signal their quality by purchasing a rating and the benefits for the low quality companies to be pooled with better companies. This trade off determines the rating agency's disclosure policy to pool companies into rating categories and the optimal coverage of the market. We study how the market coverage and information precision depend on the value of information to buyers.

We use the basic model to analyze the entry strategy of a new rating agency. We show that a new agency can enter either by targeting high quality companies that derive substantial benefits from purchasing a second rating, or companies that benefit from finer information disclosure. Interestingly, entry results in asymmetric rating scales where the best ratings from two different companies imply different credit risks. Also the number of ratings each firm obtains depends on the credit quality of a rated company.

The theoretical model we develop yields a number of empirical predictions regarding the manner by which a new agency will enter the market for ratings, the types of companies that will demand to obtain a rating from the new agency, and the standard the entrant will use to assign ratings. We test these predictions using data on the U.S. property-liability insurance market. The insurance industry provides an ideal natural experiment to test our hypotheses for at least two reasons. First, unlike the market for credit ratings, there are no regulatory barriers to enter the market for insurance ratings. Thus, rating agencies can make entry decisions for purely economic reasons. Second, until recently the market for insurance ratings has largely been dominated by a single monopoly agency - the A.M. Best Company. Founded in 1899, A..M. Best has provided rating opinions on virtually all insurers operating in the U.S. marketplace for over 100 years. However, Best's became the object of much criticism in the late 1980's and early 1990's following a large increase in the number of insurer insolvencies as a result of the commercial liability insurance crisis during the mid-1980's and the large catastrophic events of Hurricane Andrew and the Northridge earthquake in the early 1990s. Following these difficulties Standard & Poor's entered the insurance ratings market in the late 1980's and dramatically increased the number of ratings it provided to insurers during the 1990's. For example, in 1992, S&P issued full rating opinions on only 23 property-casualty insurers and this number increased to over 340 insurers by the end of the decade. By year 2004, S&P is the second largest insurance rating agency and now rates almost 800 companies representing more than 90 percent of the industry's assets.

Our empirical objective is to investigate the strategies employed as the new entrant came into the insurance ratings business. We employ two methodologies. The first empirical test uses a hazard model (Shumway (2001)) to estimate a one-year probability of insolvency using publicly available data for all U.S. property-liability insurers and then use the results to compare the standards that were necessary for a firm to receive similar ratings from both the incumbent and the entrant agency.

The second empirical test is designed to investigate the differences in rating opinions across the incumbent and the entrant using a Heckman-style (Heckman (1979)) sample selection methodology. It allows to control for two limitations of hazard model analysis. First, the hazard model relies completely on publicly available information to determine the one-year probabilities of default. Therefore, we are unable to control for any private information that might be learned through the ratings process itself. Second, comparing the probabilities of default for insurers that receive a rating from both rating agencies ignores the possibility that firms will strategically decide whether to request a second rating from the new entrant.

By way of preview, we find that high quality insurers were attracted to receive a second rating from S&P and that S&P required higher standards in order for an insurer to achieve a similar rating. Both results are consistent with our theory.

The remainder of the paper is organized as follows. In the rest of the section we review the relevant literature. Section 2 presents the model. Section 3 analyzes the optimal rating scale of a monopoly rating agency. Section 4 analyzes which segments of the market are profitable for entry of a new agency and the strategy employed by the entrant to generate demand for an additional rating. We present our empirical analysis in Section 5 and conclude in Section 6.

Related Literature

The paper belongs to the growing literature on incentives of information intermediaries to manipulate information disclosed to interested parties. Since Akerlof (1970) seminal "lemon markets" paper it is recognized that information intermediaries may play crucial role for markets under adverse selection (see Biglaiser (1993)). However, if an intermediary cannot perfectly assess the quality of the good and/or it has discretion about how the results of the assessment are communicated to buyers, the incentive problems may reduce the amount and the precision of information disclosed to the market.

The theory we develop in this paper builds on Lizzeri (1999) who studies optimal disclosure policies of a perfectly informed information intermediary. The key distinction of this paper is that we assume that the end users of ratings care about the quality of information contained in rating, and thus relax the risk-neutrality assumption that leads to no disclosure result in Lizzeri's work.

Manipulation can also occur due to collusion between the intermediary and the seller. Strausz (2003) shows that honest certification is a natural monopoly. Peyrache and Quesada (2005) argue that mandatory certification makes intermediaries more prone to collusion by increasing participation of poor types.

When intermediaries compete for clients and are not certain about their ability as experts, reputation concerns may lead to misreporting of information. Scharfstein and Stein (2000) and Ottaviani and Sorensen (2006a, 2006b, 2006c) study the impact of reputation concerns on the reports of analysts. These papers consider cheap talk models in which intermediaries are concerned with establishing a reputation of being well informed. In order to signal its ability to provide information with high precision, the intermediary biases its private observation in favor of prior belief. Mariano (2006) addresses a similar issue in the context of rating agencies.

In spite the fact that most information intermediaries function in oligopolistic markets, there is no much research on the impact of competition on the disclosure of information. Lizzeri (1999) obtains that competition leads to full disclosure and zero fees for certification.

2 The model

We consider the following model of information intermediation. There are three groups of agents: Insurance companies, rating agencies, and buyers of insurance policies[1]. A unit mass of insurance companies are indexed by their financial strength, or quality, $v \in [0,1]$, which is private information of a company. Higher v corresponds to higher quality. Rating agencies and buyers share a common prior about the financial strength of a company. For simplicity, we assume that v is distributed uniformly on $[0,1]$.

There is a unit mass of identical buyers. Each buyer purchases one insurance policy. Buyer's willingness to pay for the policy depends on financial quality of a company and the accuracy of information about quality. We model risk aversion by assuming that buyers have mean-variance preferences. Given information I, buyers valuation of the policy is equal to

$$u(I) \equiv E[v|\, I] - aVar[v|\, I],$$

where $E[v|\, I]$ is the expected quality of the company, and $Var[v|\, I]$ is the variance of quality. $a > 0$ measures the marginal value of information accuracy to buyers. $u(I)$ is the maximum price that buyers are ready to pay for the policy given information I. Under the prior distribution of quality, buyers valuation is equal to

$$u_0 = \frac{1}{2} - \frac{1}{12}a.$$

If the value of information is low, $0 < a < 6$, the reservation price u_0 is positive. In this case providing new information is not essential for functioning of the market. When $a > 6$, a buyer would not purchase a policy unless it has some additional information about a company. Lizzeri (1999) is a special case of this model when $a = 0$.

We assume that an insurance company cannot credibly communicate its financial strength to buyers. A rating agency offers an evaluation service for a fee and can perfectly observe the quality of a company. We assume that the fee is universal for all companies purchasing the rating, and the rating agency cannot screen companies by demanding higher fee for more favorable rating. Also a rated company does not have an option to hide its rating[2]. A rating agency has discretion to decide its disclosure policy.

A disclosure policy of the agency defines how the estimates of the quality are communicated to buyers. One particular case is full disclosure, where a rating agency communicates the observed quality v. In general, a disclosure policy is a measurable function from the set of signals $[0,1]$ into the set of Borel probability distributions on real numbers. The disclosure policy that we show to be optimal in our model (Proposition ???) is very similar to the discrete system of ratings employed by the major rating agencies. Under this system an agency partitions the set of realization of v in subintervals, and discloses that its estimate of quality belongs to a subinterval.

[1] In order to be coherent with the empirical part of the paper, we frame the model within the insurance industry. However, our analysis of the incentives of the information intermediary to disclose information and the impact of competition on disclosure apply to other markets as well.

[2] Faure-Grimaud, Peyrache and Quesada (2005) show that firms may have incentives to hide their ratings only if they are sufficiently uncertain about their quality. In our setting firms have perfect information about their quality, and thus will not apply for rating if it does not increase their reservation price.

We assume that obtaining ratings is voluntary to insurance companies. An insurance company will purchase a rating only if it increases the expected reservation price of the buyers. Denote δ the demand for ratings. Then the payoff of the rating agency is equal to

$$V = \delta t.$$

The company's decision to obtain a rating is based on the cost of rating and its impact on the reservation price. The information content of the rating depends on the disclosure rule employed by the agency and on the types of companies that decide to be rated. The expected payoff of an insurance company v is equal to

$$\begin{array}{l} u_R(v) - t, \text{ if a company is rated,} \\ u_N(v), \text{ if a company is not rated,} \end{array}$$

where $u_R(v)$ and $u_N(v)$ are the expected payoffs of type v with and without a rating, respectively.

The game consists of four stages.

1. Insurance companies observe their types v.
2. A rating agency designs its disclosure policy.
3. The companies observe the disclosure policy of the rating agency and decide whether to purchase a rating. The participating companies are evaluated, and the results are disclosed to buyers according to the disclosure policy of the agency.
4. The buyers use the rating to update their beliefs about a company's quality, and pay the reservation price for the contract.

We study sequential equilibria of the game. Given its type v, the strategy of an insurance company is its decision to obtain a rating. The strategy of the rating agency is the disclosure rule. Buyers' strategy is the decision to purchase a policy. Buyers pay the reservation price conditional on all available information. Strategies of all players must be optimal given the beliefs about other players information. Beliefs must be consistent with the Bayes rule whenever possible.

3 Monopoly Optimal Rating Scale

3.1 Preliminary analysis: Full disclosure

This section describes the demand for ratings and the profits of the rating agency under full disclosure. Though this system is not optimal for the rating agency, the analysis can be useful to highlight the rating agency's gains from pooling different risk types in the same rating grade.

Proposition 1 *Suppose that a monopoly rating agency commits to full disclosure, and the fee for the rating services is such that $t < \frac{1}{2} + \frac{1}{12}a$. Then the unique sequential equilibrium of the subgame has a threshold structure: There is a type $v_F \in [0, 1]$ such that all types above v_F purchase a rating, and no type below v_F is rated.*

Proof. Let's consider some type $v \in [0,1]$ and assume that all types above v and no types below v are rated. Under full disclosure a rated type v is paid

$$u_R(v) \equiv v.$$

If type v is not rated, it is pooled with types $[0,v]$. The reservation price of non-rated companies is then equal to

$$u_N(v) \equiv \frac{1}{2}v - \frac{1}{12}av^2,$$

where $\frac{1}{2}v$ is the expected quality of non-rated types $[0,v]$ and $\frac{1}{12}v^2$ is the variance of the estimate. If this price is negative, the non-rated companies do not trade.

A necessary condition that type v purchases a rating is that it increases its reservation price net of the rating fee,

$$u_R(v) - t \geq \max\{u_N(v), 0\}. \tag{1}$$

Note that as v increases, the difference between the two prices increases,

$$\frac{d}{dv}(u_R(v) - u_N(v)) = \frac{1}{2} + \frac{1}{6}av > 0, \tag{2}$$

and

$$u_R(v) - u_N(v) = \begin{cases} 0 \text{ if } v = 0, \\ \frac{1}{2} + \frac{1}{12}a > 0 \text{ if } v = 1. \end{cases}$$

If the fee t is below $\frac{1}{2} + \frac{1}{12}a$, then there is a type $v_F \in (0,1)$ for which the participation constraint (1) is binding. (2) implies that all types above v_F strictly prefer to obtain a rating, and no type below v_F obtains a rating. The buyers' beliefs that the company's quality is above v_F if it is rated and below v_F if it is not rated are consistent with the equilibrium. The proof of the uniqueness is devoted to the Appendix. ■

Under full disclosure the fee charged by the rating agency is $t = u_R(v_F) - \max\{u_N(v_F), 0\}$. It is equal to the amount that the lowest quality company is willing to pay for the rating. The demand for ratings is $\delta = 1 - v_F$. So the profit of the rating agency writes

$$\max_{v_F}(1 - v_F)(u_R(v_F) - \max\{u_N(v_F), 0\}).$$

Since increasing the fee reduces the demand for ratings, the optimal fee and the resulting coverage of the market, $1 - v_F$, are derived from the trade off between the size of the fee and the demand for ratings.

Proposition 2 *The optimal market coverage, $1 - v_F$, with*

$$v_F = \begin{cases} \frac{a-6+\sqrt{a^2+6a+36}}{3a}, \; a \leq 10, \\ \frac{6}{a}, \; 10 \leq a \leq 12, \\ \frac{1}{2}, \; a \geq 12. \end{cases}$$

is decreasing in the value of information for $a < 10$ and increasing for $a > 10$. The profit of the rating agency is

$$\pi_F = \begin{cases} \frac{(a+12)(a+3)(a-6)+(6a+a^2+36)^{\frac{3}{2}}}{162a^2}, \; a \leq 10, \\ \frac{6(a-6)}{a^2}, \; 10 \leq a \leq 12, \\ \frac{1}{4}, \; a \geq 12. \end{cases}$$

It is increasing in the value of information a.

Suppose that instead of reporting the type v_F, the rating agency announces that this type is from an interval $[v_F, v_F + \Delta]$, $\Delta > 0$. Then v_F is pooled with better types, and it may be able to charge a higher price than under full disclosure if

$$v_F + \frac{1}{2}\Delta - \frac{1}{12}a\Delta^2 > v_F.$$

Pooling is beneficial to the rating agency becasue it allows to charge higher fee without reducing demand for ratings. If the marginal value of information is zero, $a = 0$, one obtains Lizzeri (1999) limit result that all types should be pooled and assigned the same rating grade. When precision of information matters, pooling is not without cost because it leads to more coarse information contained in ratings.

3.2 Monopoly rating system

In this section we analyze the optimal disclosure policy of the monopoly rating agency. Let's consider a rating system where the agency assigns two ratings, A and B. We will show below that this disclosure policy is optimal in for $a < 21$, and considering $a > 21$ does not yield qualitatively new results[3]. Denote v_M the lowest type that purchases a rating. If the rating agency observes type $v \in [v_M, v_M + b_M]$, the company is rated B. If the type is $v \in [v_M + b, 1]$, the company is rated A. The prices charged by rated companies are

$$\begin{aligned} u_A &= \frac{1}{2}(1 + v_M + b_M) - \frac{1}{12}a(1 - v_M - b_M)^2, \\ u_B &= v_M + \frac{1}{2}b_M - \frac{1}{12}ab^2, \end{aligned}$$

for ratings A and B, respectively. The price charged by a non-rated company is

$$u_N = \max(\frac{1}{2}v_M - \frac{1}{12}av_M^2, 0).$$

Purchasing a rating is beneficial for the company if

$$u_A - t \geq \max\{u_N, 0\}, \tag{3}$$
$$u_B - t \geq \max\{u_N, 0\}. \tag{4}$$

The right hand side of these constraints is the reservation price of a company if it does not purchase a rating. It is determined endogenously depending on whether a non-rated company is able to charge a positive price. It can be shown that $u_A > u_B$ for $a < 21$. Thus the fee charge by the rating agency is

$$t = u_B - \max\{u_N, 0\}.$$

[3]Higher values of information $a > 21$ will require higher number of rating grades. However, the profit of the rating agency is only determined by the price that can be charged by the lowest rating company as this is the price that defines the fee for rating. The only restriction that defines higher rating grades is that they must correspond to an increasing sequence of prices.

In equilibrium, companies $v \in [0, v_M]$ must be better off without a rating. If a company $v \in [0, v_M]$ deviates and purchases a rating, the rating agency announces that the company's financial strength is from the interval $[0, v_M]$. Thus the deviation is not profitable and purchasing a rating cannot increase the reservation price charged by these companies.

The optimal rating system of the rating agency solves

$$\max_{(v_M, b_M)} (1 - v_M)(u_B - \max\{u_N, 0\}).$$

If a company is able to sell at a positive price without purchasing a rating, $u_N > 0$, the value of the rating is the increase in price from u_N to u_B. As the value of information increases, a non-rated company cannot trade, $u_N < 0$. In this case the fee charged by the rating agency is equal to the price of the lowest rated company, u_B.

In the next proposition we characterize the optimal rating system of a monopoly rating agency.

Proposition 3 *The monopoly rating system is summarized in the following table.*

a	A	B	$profit\ of\ RA$	u_N
$2 \leq a \leq 6$	$[\frac{3}{4} - \frac{1}{2a}, 1]$	$[\frac{3}{4} - \frac{1}{2a}, 1]$	$\frac{(a+2)(a+10)}{96a}$	$\frac{(a-\frac{2}{3})(\frac{26}{3}-a)}{192a}$
$6 \leq a \leq \frac{21}{2}$	$[\frac{2}{3} + \frac{2}{a}, 1]$	$[\frac{2}{3} - \frac{1}{a}, \frac{2}{3} + \frac{2}{a}]$	$\frac{(a+3)^3}{81a^2}$	$\frac{(a-\frac{3}{2})(\frac{21}{2}-a)}{108a}$
$\frac{21}{2} \leq a \leq \frac{51}{4}$	$[\frac{9}{a}, 1]$	$[\frac{6}{a}, \frac{9}{a}]$	$\frac{27(a-6)}{4a^2}$	0
$a \geq \frac{51}{4}$	$[\frac{1}{2} + \frac{21}{8a}, 1]$	$[\frac{1}{2} - \frac{3}{8a}, \frac{1}{2} + \frac{21}{8a}]$	$\frac{(4a+3)^2}{64a^2}$	0

When the value of information is relatively low, $2 \leq a \leq 6$, all rated firms $v \in [\frac{3}{4} - \frac{1}{2a}, 1]$ are assigned the same rating. For higher values of information, $a \geq 6$, the rating agency assigns two ratings. The market coverage $1 - \underline{v}$ is non-monotone in the value of information. When the value of information is so low that the non-rated companies can sell at a positive price, the market coverage is decreasing in a; it is increasing for higher values of a.

The value of information has the major effect on the design of the optimal rating system. When a is relatively low, the optimal disclosure policy of the rating agency is to announce that the company's quality is above a minimum standard. In this case the price charged by the rated companies is equal to the expected valuation of companies in $[v_M, 1]$. Recall that the valuation by customers is composed of two components, the expected quality and the variance of quality. Since the value of accuracy of information is relatively low, rating is not necessary for selling at a positive price. The rating system of the agency is a trade-off between the higher coverage of the market and the higher expected valuation of the contract.

As the value of information increases, providing precision becomes more valuable than increasing expected quality by pooling. As a result, the price u_B that can be charged when a subset $[v_M, v_M + b_M]$, $v_M + b_M < 1$, is pooled in one rating grade B is higher than the price that can be charged when all rated companies $[v_M, 1]$ are pooled in one rating, the set $[v_M, 1]$ has higher expected quality.

The profit of the rating agency is non-monotone in the value of information. For relatively low values, the rating agency can benefit from its unique ability to screen the companies and selectively disclose the results. However, as the value of information increases, the optimal rating system requires finer information disclosure, and reduces the fee that can be charged for the rating.

Figure 1 shows the boundaries for ratings A and B as a function of a. Companies below the green line are not rated. Companies between the green and the red lines get rated B. Companies above the red line are rated A. Interestingly, the lower boundary for rating B is increasing for low information values.

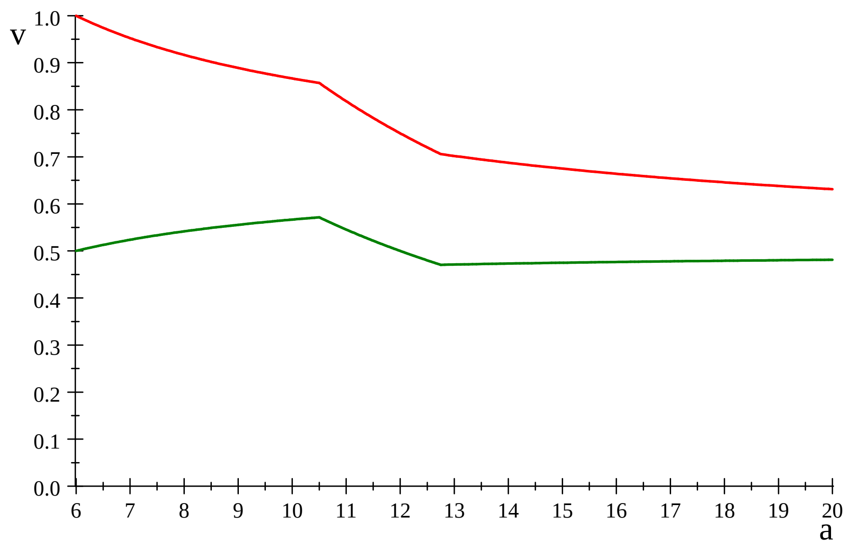

Figure 1: Optimal rating scale of a monopoly rating agency

In the next Corollary we compare the rating scale with two ratings to the full disclosure rating scale.

Corollary 1 *A rating system with two ratings provides higher profit to the rating agency than full disclosure rating system.*

4 Entry Strategy of a New Rating Agency

In this section we study the optimal entry strategy of a new rating agency. We consider the following timing of entry. After an insurance company has been rated by the incumbent rating agency (or refused to be rated), a new agency offers its ratings for a fee. If it obtains a second rating, its quality is reassessed by buyers. If it decides not to be rated by the entrant, its quality may also be re-assessed depending on the demand for ratings by the other companies. In this setup we assume that the disclosure policy of the incumbent is taken as given. Our motivation for this assumption is that the industry structure does not change overnight, and companies and the incumbent rating agency exhibit inertia in designing and understanding rating standards.

The reservation price of the company can be increased either when the second rating allows to signal higher quality, or when it improves the information of the buyers. In any event, if a company is rated by the entrant, it must be that

$$\begin{aligned} u(R_m, R_e; v) - t_m - t_e &\geq u(R_m; v) - t_m, \\ u(R_m, R_e; v) - t_m - t_e &\geq 0, \end{aligned}$$

where $u(R_m, R_e; v)$ and $u(R_m; v)$ are the payoffs of company v rated by both agencies and only by the incumbent, respectively, and t_m and t_e are the fees for ratings by two rating agencies.

In the next proposition we show that the demand for the second rating comes from the companies with the highest financial strength.

Proposition 4 *An entrant can always design a rating system that attracts the best companies within each rating interval of the incumbent. The rating standard of the entrant is more stingent than that of the incumbent.*

A limit example of such rating system is the one where the entrant attracts only the highest type $v = 1$. This system unambiguously creates some positive surplus for the insurance company, and all additional surplus can be extracted by the new rating agency. In general, the entry strategy of a new agency depends on the value of information to customers. In the next proposition we characterize the optimal entry strategy depending on the value of information a.

The rating system of the incumbent aims to maximize the market coverage but is constrained by the fact that the fee that can be charged to firms on the bottom of the distribution is limited. Compared to this system the optimal strategy of the entrant is to target the firms on the top of the distribution.

5 Empirical Analysis

The theoretical model presented above yields several empirical predictions regarding the optimal strategies a profit-maximizing entrant will employ as it attempts to successfully enter the market for ratings. In this section we seek to test these predictions taking advantage of data on the U.S. property-liability insurance industry during the years 1992 - 2000. The insurance industry during the time period of the late 1980's and through the decade of the 1990's is uniquely suited to test our hypotheses as Standard & Poor's, the well-respected bond rating agency, invested significant resources to expand their influence and entered the market for insurance ratings. Prior to this time period, the market for insurance ratings was largely dominated by the A.M. Best Company. Incorporated in 1899, A.M. Best has published ratings on virtually all U.S. insurers and, for a majority of their history, they were the only agency doing so. The monopoly position Best's enjoyed, however, began to erode after Best's was criticized following the liability insurance crisis of the mid 1980's and after several natural catastrophes in the early 1990's that bankrupted numerous insurers. The most aggressive agency to enter the market was Standard & Poor's (S&P) who began publishing ratings on property-liability insurers in 1983 and then expanded coverage once 1987 and then another time in 1991 (Standard & Poor's 1987; A.M. Best 1992). Today, S&P provides ratings on insurers that represent in excess of 80 percent of the assets of the industry - more than any other new entrant except Weiss Research.[4]

[4] Like A.M Best, Weiss Research provides ratings on almost every insurer that operates in the U.S. marketplace. However, the process Weiss uses in the assignment of their ratings is fundamentally different than the process used

5.1 Hypothesis Development

There are two distinct hypotheses that we derive directly from the theoretical model presented in this paper. The first hypothesis comes from Proposition **??** where we predict

Hypothesis 1 *New entrant agency will find the greatest demand for its services from the high quality insurers seeking to differentiate themselves from other insurers that have a rating similar to their own.*

More specifically, we predict higher-than -average quality insurers within a rating class who are bundled together with lower-than-average insurers in that same class will self-select and seek to differentiate themselves by obtaining a new rating.

In a related hypothesis, taken from Propositions 1 and **??**, we predict

Hypothesis 2 *New entrant rating agency will require higher standards, on average, in order for a firm to receive a rating similar to the one they received from the incumbent agency.*

Thus firms that seek a rating from the new agency may not receive higher ratings but instead, for each rating class, the newly rated insurers should have higher average financial quality.

In addition to the two hypotheses we generate directly from our model, there are two other hypotheses from the prior literature regarding the value of information contained in ratings that we need to control for in order to isolate the effects we test in this paper. First, consistent with Ramakrishnan and Thakor (1984) and Millon and Thakor (1985), we expect more opaque insurers or insurers for which market participants have a more difficult time assessing the true financial strength of the firm will be more likely to seek an additional rating. Second, conditional on the amount of information available to market participants, insurers whose customer base is more averse to the insolvency risk of the insurer will have greater demand to resolve that uncertainty. Stated alternatively - consumers unconcerned with the financial quality of their insurer will not reward the firm with higher prices and therefore there is little incentive for firms to attempt to differentiate themselves by purchasing a rating.

5.2 Methodology

We conduct several tests using two different econometric methodologies to investigate the hypotheses stated above. In the first set of tests we seek to empirically compare the stringency of the ratings assigned by the incumbent firm (A.M. Best) relative to the entrant (S&P). More stringent ratings standards are said to exist when the average/median probability of default for insurers in a particular rating class is lower for one agency than the other. The tests are designed to analyze the following questions. How do the ratings assigned by S&P compare to the ratings of A.M. Best for firms that are jointly rated by both companies? What is the average financial quality of the insurers in each rating category across the two agencies? Answering these questions requires us to develop a summary statistic of the financial quality of the insurers and then to use that statistics to compare the ratings systems of the two agencies. The benchmark we use is the one-year probability of default for each firm in our data set. We argue the one-year probability of default is a reasonable benchmark since both agencies state the primary objective of their rating systems is to provide an opinion about the insurer's ability to meet its contractual

by Bests and S&P. We consider S&P to be the more influential new entrant into the market for property-liability insurance ratings given their established reputation in the bond rating market.

obligations to policyholders. We use these probabilities to examine the stringency of the rating system by comparing either the median or mean probability of default for a given rating class.

The second set empirical tests we conduct seeks to better understand the determinants of differences in the ratings that are assigned by the incumbent versus the new entrant rating agency. The methodology we employ largely follows the work of Cantor and Packer (1997) who use a Heckman-style sample selection model to investigate differences in the ratings that an insurer receives when they choose to be rated by both agencies. We add to the literature since, unlike Cantor and Packer , the theory developed in this paper provides strong guidance for the control variables that we should use to explain these differences.

5.3 Estimating Default Probabilities

A variety of methods can be used to forecast the likelihood of bankruptcy for an insurance company. U.S. regulatory authorities use three univariate models to forecast bankruptcy. The Insurance Regulatory Information System (IRIS), the oldest system, utilizes a series of twelve audit ratios based upon financial statement data filed with the regulators. The newer Financial Analysis and Surveillance Tracking (FAST) system uses an expanded set of audit rations, approximately thirty, where each ratio is given a corresponding score. Regulators multiply each individual ratio by its corresponding score and then sum over all ratios to produce a FAST score. Insurers with higher FAST scores are more likely to become financially distressed and are subject to greater regulatory scrutiny. Finally the risk-based capital system defines a minimum amount of capital insurers must hold. The individual capital charges depend on the riskiness of the assets and the businesses in which the insurer participates.

In addition to the univariate regulatory models discussed above, economists have developed and implemented a variety of solvency prediction models based upon multivariate statistical techniques. Insolvency forecasting models based upon multiple discriminant analysis (Trieschmann and Pinches (1973)), or logistic regression (Cummins, Grace and Klein (1999)) are common in the literature. In addition, bankruptcy prediction models based upon neural networks (Brockett et al., 1994) and dynamic cash flow simulation models (Cummins, Grace and Phillips 1999) have also been discussed.

The limitation of these methods is that they are based on static models implemented using data that spans only one or just a few years. As a result, these static models are inadequate for the long-term panel data that we assembled for the study[5].

In this study we use the discrete-time hazard model suggested by Shumway (2001) to overcome the biases of the static models and to take advantage of our panel data. The hazard model approach has at least two primary advantages over the more traditional static models. First, hazard models allow for time-varying covariates that explicitly recognize that the financial health of some firms will deteriorate over time even though the firm may not declare bankruptcy for many years. Static models only make comparisons between firms that are classified as healthy or not healthy at just one point in time and they therefore ignore firms that are at risk of bankruptcy even though they have not yet become bankrupt. Shumway (2001) shows that ignoring this information creates a selection bias which leads to inconsistent parameter estimates.

[5] In addition, Theodossiou (1993) suggests that arbitrarily choosing when to observe each firm's characteristics leads to unnecessary selection bias problems and reduced forecasting ability.

Intuitively, hazard models correct this problem by allowing to extract useful information from the times series data on each individual firm. In addition, it can be shown that the parameter estimates from hazard models are unbiased and consistent.

The second reason the hazard model may be preferred to static models is that it allows to exploit all available information about the firm rather than just the last year's observations. Thus, the models are more efficient because the increased amount of data increases efficiency which yields more reliable parameter estimates and better out-of-sample forecasting results.

Implementing the discrete-time hazard model is rather straightforward. Shumway (2001) shows that the likelihood function of a discrete time hazard model is identical to the likelihood function for a multiperiod logit model. Thus, estimating the hazard model is equivalent to estimating the traditional static logistic model except the coding of the dependent variable is slightly different. Specifically, the dependent variable for the hazard model, y_{it}, is a binary indicator set equal to 1 if firm i is declared bankrupt in year $t+1$ and equals 0 otherwise. In other words, the dependent variable equals 0 for each year the firm does not exit the system and each bankrupt firm contributes only one failure observation, i.e., $y_{it} = 1$, in the last year the firm has data. Time varying covariates are easily incorporated by using each firm's annual data.

5.3.1 Data

The data to estimate the hazard model comes from the annual regulatory statements of all property-liability insurers maintained in electronic form by the National Association of Insurance Commissioners (NAIC). We include all firms that meet our data requirements (discussed below) over the years 1989-2000. Consistent with the literature, we define the year of insolvency as the year that the first formal regulatory action is taken against a troubled insurer. We identify the year of first regulatory against insurers through a variety of sources including the NAIC's *Report on Receiverships* (various years) and the *Status of Single-State and Multi-State Insolvencies* (various years). We also obtained the list of insolvent insurers provided in a report by A.M. Best Company which lists all property-liability insurers that failed from 1969-2001 (A.M. Best, 2002). From these sources we identified 300 property-liability insurers that failed between 1990 and 2001.

The explanatory variables we use to estimate the hazard model are the nineteen balance sheet and income statement ratios that make up the NAIC's FAST solvency tracking system. Grace, Harrington and Klein (1995) conclude that there are diminishing marginal returns to incorporating additional balance sheet and income statement ratios not already included in the FAST system. Thus, the FAST system seems to capture as much predictive power as can be gleaned from financial statement ratios alone. We also include controls for firm size equal to the natural logarithm of the real assets of the firm where the price deflator we use is the Consumer Price Index; and an organization form control variable which is an indicator set equal to 1 if the insurer belongs to a mutual or reciprocal group of insurers.

As discussed above, we estimate the hazard model using all insurers for which we have data to calculate the FAST ratios. Thus, not only do we include insurers rated by A.M. Best and/or S&P, but we also include insurer firm-year observations that do not receive ratings from either of these two agencies. The only insurers we delete from the analysis are those with insufficient data needed to calculate the nineteen FAST variables or those who do not have data available in the year prior to their first event year. In an effort to include as many insolvent observations in the analysis, we include insurers who report data two years prior to their first event year but who do not report in the year prior to their first event year. We delete any bankrupt firms for which we were unable to locate data within 2 years of their first event year. The final data set contains 24,062 solvent firm-year observations and 214 insolvent firm-year observations.

5.3.2 Empirical Results

Summary statistics for the solvent and insolvent company observations are shown in Table 1. Not surprisingly, tests between the means of the solvent and insolvent samples suggest the two groups of insurers differ significantly across a number of dimensions. Insolvent insurers carry significantly higher leverage ratios (the Kenney Ratio and the reserves to policyholder surplus ratio) than do solvent insurers.[6] Insolvent insurers are significantly smaller in terms of asset size than are solvent insurers and are less likely to be members of a mutual. Insolvent insurers pay out significantly more cash relative to premiums collected than do solvent insurers and they much more reliant on reinsurance (see the surplus aid to policyholder surplus ratio).[7]

The results of the discrete-time hazard model are shown in Panel A of Table 2. Overall the explanatory power of the model is reasonable as the pseudo R^2 statistic is 26 percent. The results are consistent with many of the inferences that were discussed after reviewing the summary statistics shown in Table 1. For example, the estimated coefficients suggest highly levered firms, rapidly growing firms, and firms that rely more heavily upon reinsurance to support their capital positions are associated with higher failure rates. Larger firms and insurers that are part of mutual organizations are relatively less likely to default. Finally, firms that have high cash outflows relative to inflows and who experience adverse reserve development are more likely to fail.

Panel B of Table 2 shows summary statistics of the estimated one-year probabilities of default for solvent and insolvent insurers. The average/median probability of default for the healthy firms is 0.8/0.2 percent while the average/median statistics for the firms in the year before they become bankrupt is 9.4/4.5 percent. Thus, the average estimated one-year probability of default for firms that become bankrupt in the next year is over 10 times larger than the average probability for healthy firms. Clearly the model does a reasonable job assigning high default probabilities to firms that ultimately fail and low probabilities to healthy firms. We also note here A.M. Best reports the average annual probability of default for property-liability insurers from 1991-2002 was 0.95 percent - a result very consistent with the probabilities produced by our model (A.M. Best, 2004).

With the one-year probabilities of default estimated, we can now begin to investigate our hypotheses. However, before we do so we first need to define a mapping between the different rating categories used by the two agencies. Unfortunately a single one-to-one mapping between

[6] The Kenney Ratio equals the net premiums written by the insurer divided by the insurer's policyholder surplus. Policyholder surplus is the traditional name used in the insurance industry to represent the equity capital of the insurer under statutory (i.e., not GAAP) accounting rules.

[7] Surplus aid is a statutory accounting item which is equal to the increase in the amount the equity capital of the insurer due to the purchase of reinsurance.

two systems does not exist and prior research investigating insurance ratings across agencies have used different definitions.[8] For this study we reviewed the verbal descriptions each agency ascribes to their individual rating classes and decided to use the five rating categories shown in Table 3. Numerical values, also shown in the table, were assigned to each rating category to facilitate comparisons across agencies and over time.

Table 4 shows the extent of the coverage each agency provided of the property-liability insurance industry over the time of this study. The total number of insurance companies in the NAIC data base ranged from a low of 1897 firms in year 1990 to a high of 2100 firms in year 1996. The total assets of the industry grew from $534 billion in 1989 to almost $940 billion by the end of 2000. Of these companies, A.M. Best assigned ratings to approximately 70 – 80 percent of the firms where these firms held approximately 93 percent of the assets of the industry. Obviously during the period of the 1990's, A.M. Best was providing almost complete coverage of the property-liability insurance industry. By comparison, S&P provided ratings on only 18 percent of the firms in the industry in 1992 - 360 insurers - and the number grew to 590 insurers by the end of 2000. Based on assets, S&P does provide greater coverage as they were rating firms that represented almost 70 percent of the assets of the industry by the end of the 2000 up from a low of 24 percent in 1993.

In addition to the coverage statistics, Table 4 also displays the average rating each agency assigned to the firms it oversaw. The difference across the two firms is dramatic. The average rating assigned to insurers A.M. Best declined slightly over the time period and ranged from a high of 2.8 in 1989 and fell to 2.4 by the end of the time period. S&P stands in stark contrast in two ways. First, unlike Best's, there was a monotonic increase in the average rating assigned by S&P over the time period 1992 – 2000. In 1992, the average rating assigned by S&P was only 0.6 and it more than tripled by 2000 to be 2.1. Second, S&P appears dramatically more pessimistic about the overall financial health of the property-liability insurance industry over this time period than did A.M. Best – especially during the early part of the 1990's.

One possible explanation for the difference of opinion regarding the average health of the industry across the agencies could be because the firms tracked by A.M. Best were, on average, of higher financial quality than the firms tracked by S&P. An empirical result that would be inconsistent with the hypotheses we develop based upon the model presented in this paper. To consider this possibility, we calculated the average and median probability of default using the results from the hazard model for insurers tracked by A.M. Best and by S&P over the time period of this study. The results are shown in Table 5 suggest the average and median probability of default statistics are always lower for S&P than they are for A.M. Best suggesting the firms tracked by S&P were typically of higher financial quality firms – not lower. The non-parametric Wilcoxon-Mann-Whitney test rejects the null hypothesis of equal medians for all nine years and the parametric t-test rejects the null hypothesis of equal means in seven out of nine years. Thus, it appears that, on average, S&P is providing rating opinions on insurers of higher average quality and requiring higher standard in order to obtain any particular rating. However - before

[8] For example, Pottier and Sommer (1999) use a four category system to map the individual ratings assigned by each agency. Both the GAO (1994) and Doherty and Phillips (2002) use a five level system but the individual ratings assigned to the five categories differ slightly. In work not shown here, we compared the results of the five level categorization system we adopted with the four level system suggested by Pottier and Sommer. The primary conclusions are similar regardless of which categorization is used.

we can make that conclusion we need to consider the manner by which S&P entered the market for insurance ratings.

Prior to 1991, S&P provided coverage to only a small number of property-liability insurers (approximately 100). However, in 1991, S&P dramatically expanded their coverage by introducing a service they called "Insurance Solvency Review." The primary enhancement in the new service was that S&P increased the number of firms it covered by offering "qualified ratings" in addition to their traditional ratings. The methodology S&P used to determine a qualified rating for an insurer differed in at least three important ways from the traditional manner. First, qualified ratings were solely based upon publicly available data. Thus, unlike the traditional method, S&P analysts did not interview or speak to the management of an insurer prior to issuing the qualified rating. Second, individual insurers were not required to request the rating nor pay a fee to receive the qualified rating. Finally, when the system of qualified ratings was introduced, S&P maintained a policy which said no insurer could receive above a BBB rating – regardless of the characteristics of the company. S&P ultimately relaxed this position following significant criticism from the industry and began to issue qualified ratings above BBB in 1994.

Table 6 shows summary statistics regarding the types of ratings, qualified versus unqualified, given by S&P over this time period. In 1992, S&P issued 360 ratings of which 337, or 94 percent, were determined using the qualified rating system. Only 23 firms received a full rating in 1992. Over time more firms agreed to obtain a full rating and by 2000 over 300 property-liability insurers paid to receive an unqualified rating. Similar to Best's, the average full rating declined slightly over time from a high of 3.2 in 1992 to 2.8 by the end of the time period. The average qualified rating increased over time from a low of 0.5 in 1992 to 1.2 by year 2000. However, even after 1994 when S&P removed the restriction that firms could not receive a rating above BBB on a qualified basis, the average qualified rating is always significantly less than the average rating given using the traditional methodology.

We know from Table 6 the average ratings issued by S&P differ significantly across the two rating methodologies (qualified vs. unqualified). But does financial quality of the insurers in each category differ significantly? In Table 7 we report summary statistics regarding the default probabilities of firms rated by A.M. Best's and those rated by S&P's on a qualified and unqualified basis. Table 7 clearly display a natural ordering within each rating technology: firms that received higher ratings had, on average, lower probabilities of default. For example, the average probability of default for firms rated by A.M. Best increases monotonically by rating category from a low of 0.25 percent for firms rated "Extremely Strong" to a high of 3.11 percent for firms that received the lowest rating "Marginal." A similar pattern can be seen for S&P firms that received either a full or qualified rating. The results suggest that at least, on average, each of the three technologies required firms to be less likely to default in order to receive a higher rating.

Now consider the standards necessary to achieve a rating across each technology.

Figure 5.1
Average Probability of Default by Rating Category
A.M. Best vs. Standard & Poor's Full Rating vs. Standard & Poor's Qualified Rating

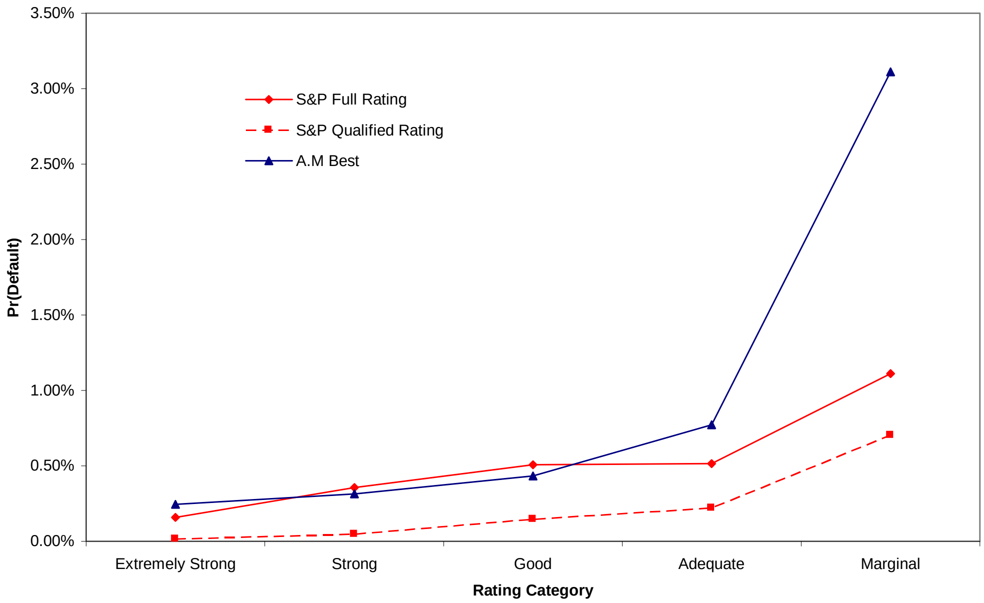

Figure 4.1 graphically displays the average probability of default of the firms over the time period of this study by rating category across each of the three rating technologies (the data can be seen in Table 7). It is easy to see the stringency employed by A.M. Best and S&P is similar when S&P issued a full unqualified rating although in three of the five categories the standards to achieve a rating are slightly more strict. The average probability of default for firms was slightly lower (and statistically significant) in the Extremely Strong, Adequate and Marginal categories. In the Good and Strong categories, the average probability of default for S&P rated companies was slightly higher than the average A.M. Best company (note - these differences are also statistically significant). These results stand in stark contrast, however, to the case where S&P issued an unqualified rating. In this case we find the average probability of default was substantially lower in each rating category relative to Best's and even relative to the standard S&P's employed on its own full ratings. For example, firms that received an Adequate rating (BBB) from S&P on a qualified basis had an average probability of default equal to 0.22 percent. A firm with a default probability of 0.22 percent likely would have received either an Extremely Strong (AAA) or a Strong (AA) rating if S&P was using their full rating standards.

5.4 Selection Bias Model to Explain Rating Differences

The results so far suggest insurers that opted to receive a fully unqualified rating from S&P were, on average, of higher financial quality. In addition, we have also shown the average probability of default of insurers in each rating class was slightly lower for S&P in three of the five rating categories consistent with the hypothesis the new entrant agency would maintain higher standards. Unfortunately the analysis thus far has two shortcomings. First, we've only been able to compare the two rating systems for firms that received a rating from both agencies. Thus, we have not ruled out the possibility that differences in the assigned ratings may be under or over stated because of a potential selection bias between insurers that chose to be rated by the new entrant and those that did not. Second, the hazard model used to calculate the one-year probabilities of default was estimated using publicly available information only. Presumably one of the advantages of a rating system is the ability of the agency to learn private information that is shared with the agency during the rating process. Thus, it would be advantageous to design an empirical methodology allows us to capture some of this private information. In this section we present a methodology that attempts to control for both shortcomings.

To begin the discussion, assume the following model is used by the incumbent rating agency to determine the rating for a particular firm:

$$r_{if} = \alpha_i + \boldsymbol{\beta}_i' \mathbf{X}_f + \varepsilon_{if} \quad (5)$$

where

r_{if} = rating issued firm f by the incumbent agency

α_i = constant term for the incumbent agency

β_i = vector of coefficients summarizing the incumbent agency's rating technology

X_f = vector of observable information for firm f

ε_{if} =error term of the incumbent agency's rating of firm f

In addition, assume the new entrant has a model of similar structure. We want to explain differences between the new entrant's ratings and the incumbent's, that is

$$r_{ef} - r_{if} = (\alpha_e - \alpha_i) + (\beta_e - \beta_i) X_f + (\varepsilon_{ef} - \varepsilon_{if}), \quad (6)$$

where all variables subscribed with an e represent the rating and/or the technology of the new entrant firm. As discussed by Cantor and Packer (1997), estimating equation (6) directly using OLS will lead to biased results if the decision to seek a second rating from the new agency is correlated with the ratings assigned by that agency. Failure to correct for this selection bias will make it impossible to understand if the differences we see between the two rating systems are due to actual differences between the two the systems or because the sample of firms that choose to get a rating from the new entrant have a common set of characteristics. In particular, the theory presented in this paper suggests that firms which elect to receive a full unqualified rating from S&P will be those that are of higher than average financial quality and have some belief that are likely to obtain a favorable outcome from the new entrant. Thus, the average rating difference that we see may underestimate the true difference in standards across the two rating systems.

We employ a standard Heckman two-stage regression methodology to control for this potential sample selection bias (Heckman 1979). The Heckman methodology is ideal in this setting because it not only allows us to control for the possibility of selection bias, but we can also incorporate private information garnered in the ratings process by including the insurer's A.M. Best rating as explanatory variables. The empirical procedure is as follows: we first estimate a Probit regression that models the insurer's decision to request a second rating by S&P; second, we use the results of the Probit regression to estimate an additional regressor, known as an inverse Mill's ratio, that, when included in the ratings difference model, will control for the selection bias. Thus, in the second stage we estimate via OLS,

$$r_{ef} - r_{if} = \alpha + \gamma IMR_f + n_f,$$

where the constant term measures the mean difference in ratings standards across the two agencies and the inverse mills term (IMR) captures the sample selection effect.[9] We hypothesize α will be negative consistent with our theory that the new entrant, on average, will employ higher rating standards than the incumbent firm. In addition, we predict the estimated coefficient γ will be positive consistent with the hypothesis that insurers who believe they will receive a favorable rating from S&P will self-select to receive that rating.

We have several hypotheses why an insurer would seek a second rating from S&P that we test using in the Probit model. First, consistent with our theory, we predict higher quality firms have a stronger demand to receive a second rating from S&P. To test this hypothesis we include indicator variables for each rating category assigned by A.M. Best (we omit the indicator for the Marginal rating class to avoid singularity). Including the Best's rating variables also allows us to control for the private information that Best's learns during the rating process.

We include three variables designed to test the Millon and Thakor (1985) hypothesis that more opaque or complex firms have a stronger demand for ratings. Specifically, we hypothesize larger firms and insurers with more diverse operations will be more likely to seek a second rating. Our proxy for firm size is the natural logarithm of the firm's assets. Firm complexity is proxied by geographical concentration of the insurer's business. Namely, we use a Herfindahl index of the premiums written across each state in which the insurer operates. We expect a positive coefficient on the firm size variable and a negative coefficient on the Herfindahl index.

We control for the organizational form of the insurer by including an indicator set equal to one if the insurer is a mutual or reciprocal insurer and zero if it is a stock insurance company. We have two competing hypotheses this variable. First, the managerial discretion literature predicts mutual insurers should underwrite less risky lines of insurance and have more transparent business models due to the reduced ability of a diffuse set of owner/policyholders to monitor management (Mayers and Smith 1987). Consistent with that literature, we hypothesize a negative relationship between the insurer being organized as a mutual and demand for a second rating. An alternative to the managerial discretion hypothesis suggests a positive relationship between mutual ownership form and the desire to seek a second rating because the only information available for potential customers to judge the financial quality of a mutual consists of regulatory accounting data. Under this rationale, stock insurers would have reduced incentives to seek an additional rating since presumably the amount of information about the insurer is readily available given the additional information available to policyholders due to analysts issuing reports that follow stock companies and because of information conveyed to the market through movements in the insurer's share price.

[9] Note, differences in rating standards can be due to a shift in the cardinal ranking across the two systems (i.e., differences in the intercept terms) or due to different weightings employed by the two agencies (i.e., differences in the beta coefficients). We are unaware of any theory that can guide us in selecting exogenous variables that might explain why two agencies might place different weighting on rating factors. Therefore, we only include an intercept term and a control for sample selection bias in the second stage rating difference regressions.

The final control variable we include tests the hypothesis that the risk aversion of the insurer's primary customer base provides incentives for the monopoly agency to disclosure more or less information about the true financial quality of the insurer. Recall our theory predicts that rating agencies have incentive to reveal more information to the market when the participants are more sensitive to differences in financial quality. To test this hypothesis we include a variable equal to the percentage of the insurer's premiums in retail lines of insurance.[10] We expect a positive sign on this variable consistent with the hypothesis that state guaranty funds provide greater protection to the retail policyholders of insurers that become bankrupt. Thus, retail policyholders should place less value on information and therefore the monopolist agency's optimal strategy should be to design a system that reveals little information to market participants. Based upon our theory, a new entrant has more value to add to the process due to the incumbent agency's incentive to withhold information.

5.4.1 Data and Empirical Results

The data for the rating difference tests includes any insurer that received a rating from A.M. Best over the time period 1994 - 2000. We eliminate the years 1992 and 1993 from the analysis due to S&P's policy of not assigning any firm a rating above BBB on an unqualified basis. We estimate both the first stage probit regression and the second stage OLS regressions separately for insurers that receive qualified vs. unqualified ratings from S&P since our earlier work suggests the standards across the two methodologies differs quite substantially. There are 6587 insurer-year observations in the Best's sample, 1925 observations in the S&P qualified rating sample, and 1439 observations in the S&P full rating sample.

Table 8 displays summary statistics for all the variables used in the rating differences tests. The average rating for A.M. Best companies over this time period was 2.18. For S&P firms, the average full rating was slightly higher at 2.77 and significantly lower, 1.22, for firms that received an unqualified rating. Although the average rating was higher for the sample of firms that receive a full rating from S&P, the average difference in rating for insurers that receive an opinion from both firms, S&P vs. A.M. Best, was 0.598 notches lower. On an unqualified basis, S&P assigned an average 1.57 lower rating grade relative to A.M. Best.

We also see from Table 8 that over 50 percent of the insurers that requested a full rating from S&P already had the highest rating from A.M. Best - a result consistent with our hypothesis that high quality companies have the greatest demand to further differentiate themselves in the marketplace. It also interesting to note that the greatest proportion of insurers that received a qualified rating from S&P were not the highest rated Best's companies but instead were just below the highest letter grade. One possible explanation for this results is that S&P knew the greatest demand for their services would come from the highest quality companies so S&P targeted unqualified ratings towards firms with more marginal demand for their services.

The statistics in Table 8 also reveal that larger insurers had greater demand to obtain a new rating from S&P and mutual insurers had little demand for S&P services on a full rating basis - both results consistent with our hypotheses. Interestingly, S&P appeared to target mutual insurers to receive unqualified ratings. Finally, the average insurer that received a full rating

[10] The lines of insurance we considered to be retail lines included personal automobile insurance (both liability and property damage), homeowners insurance and farmowners insurance.

from S&P had less business in retail lines of insurance relative to the average A.M. Best insurer. This last result is inconsistent with our hypothesis - at least on a univariate basis.

The first-stage probit regression results are shown in Table 9. The results for the full rating sample largely confirm the univariate tests and are consistent with many of our prior hypotheses. Focusing on the marginal effects panel, we find support for the hypothesis that higher quality firms are more likely to request a new rating from S&P. For example, based upon the model shown in column 3 of Table 9, a firm rated Extremely Strong by A.M. Best was 36.8 percent more likely to request a full rating from S&P relative to a firm rated Marginal by A.M. Best (recall – the A.M. Best rating Marginal is the reference category). We also note the likelihood that an insurer requests a full rating from S&P is monotonically increasing in A.M. Best rating category. Also consistent with our theory, large insurers, insurers in more retail lines of business, and insurers with more complex businesses are all more likely to seek an additional rating. Finally, mutual insurers are less likely to request a full rating from S&P consistent with the managerial discretion hypothesis.

Turning now to the Probit regression results based upon qualified rating sample, the first conclusion we draw is that the exogenous variables used to explain why a firm received a qualified rating from S&P have significantly less explanatory power as the pseudo R^2 statistics for these regressions are much lower than the corresponding statistics for the full rating sample. Obviously the theory developed in this paper, which takes as a fundamental assumption that firms voluntarily will choose to seek an additional rating, does not adequately explain the manner by which S&P targeted firms to receive a qualified rating. Therefore, although the pattern among many of the estimated beta coefficients is similar in the qualified sample relative to the full rating sample, the overall explanatory power of the model is much weaker. That being said, it is reasonable to expect S&P would target insurers to receive a qualified rating in the hopes they ultimately would have demand to purchase a full rating at some point in the future. For example, insurers among the top two A.M. Best rating categories are still the most likely receive a qualified rating by S&P. In addition, more complex insurers, as proxied by the geographical concentration of their business, were also more likely to receive a qualified rating. However, there are notable differences across the two samples including mutual insurers being more likely to receive a qualified rating than stock insurers and insurers with more commercial business also more likely to receive a qualified rating.

The results from the second stage OLS regressions are shown in Table 10. Our first conclusion is that we find strong evidence of selection bias as the coefficient on the inverse Mill's ratios are always positive and significantly different than zero. Therefore, insurers more likely to request a rating expect, on average, to receive a favorable outcome from S&P holding the amount of publicly available information about the company constant and controlling for the private information revealed through Best's rating process. More specifically, based upon the results shown in Model 2 for the unqualified rating methodology, insurers, on average, expect to receive a 0.33 higher rating from S&P relative to the standards used by A.M. Best. For firms that receive a qualified rating, our results suggest firms should have received a 1.20 increase in rating on the A.M. Best scale. Both results are consistent insurers with better than average quality, holding the Best rating class fixed, seeking to differentiate themselves.

The second conclusion we draw is that S&P maintained significantly higher standards relative to Best's as the intercept term in each model is negative and significantly different than zero.

Focussing on Model 2 for the unqualified ratings, we see the estimated mean difference in rating standards is -0.92 grades lower on the S&P scale versus A.M. Best. This result provides strong evidence consistent with our theory that, conditional upon the rating provided by the incumbent agency, insurers sought to differentiate themselves by seeking an additional rating from a new entrant agency that had a rating system that required higher standards in order to maintain the same rating. We see a similar pattern for the unqualified rating methodology although the ratings scale for the new entrant on this basis was much more stringent.

6 Conclusion

The objective of the paper is twofold. First, it analyzes optimal information disclosure of a monopoly rating agency depending on the marginal value of information to buyers. Second, it characterizes the optimal entry strategy of a new rating agency to the market dominated by the incumbent. The qualitative results of the paper are that information disclosure choice of the rating agency significantly depends on the value of information to its end users. As the value of information increases, the ratings become more precise. The entry strategy of a new agency is to target the companies of the highest financial quality in each rating class. This policy is beneficial for companies who voluntarily obtain the second rating. However, it decreases the payoff of the companies that are on the bottom side of each rating class. These results are strongly supported by our empirical analysis of the insurance industry.

An interesting question for further research is the optimal information disclosure in the industry whether the two agencies offer ratings simultaneously. Lizzeri (1999) establishes that a simultaneous one -shot competition between information intermediaries results in full information disclosure and zero fee for rating. However, agencies offer ratings repeatedly, and the nature of the repeated relation may allow companies to sustain positive profits.

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Appendix A: Proofs

Proof of Proposition 1. To prove uniqueness, consider a set of types V_N who do not go to the intermediary. Then the reservation price of these types is

$$E(v|V_N) - aVar(v|V_N),$$

where

$$E(v|V_N) = \frac{1}{|V_N|}\int_{V_N} vdv,$$

$$Var(v|V_N) = \frac{1}{|V_N|}\int_{V_N} (v - E(v|V_N))^2 dv.$$

If $V_N = [0,1]$, then this reservation price is equal to $max(0, \frac{1}{2} - \frac{1}{12}a)$. If type $v = 1$ is the only one rated, it is paid a reservation price equal to 1. When $t < 1 - max(0, \frac{1}{2} - \frac{1}{12}a) = \max(1, \frac{1}{2} + \frac{1}{12}a)$, among the non-rated types there are types that prefer to be rated. Denote v_r any of these types. Then all types above v_r prefer to be rated. Also the benefits of rating are decreasing for types below v_r, and there is a type $v_F < v_r$ that is indifferent between being rated or not. ■

Proof of Proposition 2. We distinguish between two cases, $u_N > 0$ and $u_N < 0$. $u_N > 0$ is equivalent to

$$\frac{1}{2} - \frac{1}{12}av_F > 0. \tag{7}$$

If $u_N > 0$, the agency charges the fee $t = v_F - u_N$, and the problem of the rating agency writes

$$(1 - v_F)(\frac{1}{2}v_F + \frac{1}{12}av_F^2)$$
$$\text{subject to (7).}$$

Denote $\lambda \geq 0$ the Lagrangian multiplier of (7). Suppose first that $\lambda > 0$. Then $v_F = \frac{6}{a}$, and

$$\lambda = \frac{12}{a}(\frac{3}{2} - \frac{15}{a}),$$

so $\lambda > 0$ when $a > 10$. In this case the profit of the agency is $\frac{6(a-6)}{a^2}$. Now suppose that (7) is not binding, $\lambda \geq 0$. Then $v_F = \frac{a-6+\sqrt{a^2+6a+36}}{3a}$, and (7) is satisfied when $a < 10$. The profit is $\frac{a^3+9a^2-54a-216+(6a+a^2+36)^{\frac{3}{2}}}{162a^2}$.

Consider the case $u_N < 0$. In this case the agency charges the fee $t = v_F$, and the problem of the rating agency writes

$$(1 - v_F)v_F$$
$$\text{subject to } -\frac{1}{2} + \frac{1}{12}av_F > 0.$$

Denote $\lambda \geq 0$ the Lagrangian multiplier of the constraint. If $\lambda > 0$, then $v_F = \frac{6}{a}$ and $\lambda = \frac{12}{a}(\frac{12}{a} - 1)$, implying $a < 12$. The profit in this case is $\frac{6(a-6)}{a^2}$. Now assume that the constraint is not binding. Then $v_F = \frac{1}{2}$, the profit is $\frac{1}{4}$, and the constraint is satisfied when $a > 12$.

To find the optimal v_F, compare the solutions in cases $u_N > 0$ and $u_N < 0$ for different values of a. When $a < 10$, the global solution is $v_F = \frac{a-6+\sqrt{a^2+6a+36}}{3a}$, resulting in profit $\frac{(a+12)(a+3)(a-6)+(6a+a^2+36)^{\frac{3}{2}}}{162a^2}$. When $10 < a < 12$, solutions in the two cases are the same, $v_F = \frac{6}{a}$, and the profit is $\frac{6(a-6)}{a^2}$. Finally, when $a > 12$, the global solution is $v_F = \frac{1}{2}$ and the profit is $\frac{1}{4}$. ■

Proof of Proposition 3. Let's consider the optimal rating system when the rating agency assigns two ratings, $A = \{v | v \in [\underline{v} + b, 1]\}$ and $B = \{v | v \in [\underline{v}, \underline{v} + b]\}$. The prices charged by the companies are

$$\begin{aligned} u_A &= \frac{1}{2}(1 + \underline{v} + b) - \frac{1}{12}a(1 - \underline{v} - b)^2, \\ u_B &= \underline{v} + \frac{1}{2}b - \frac{1}{12}ab^2, \\ u_N &= \frac{1}{2}\underline{v} - \frac{1}{12}a\underline{v}^2. \end{aligned}$$

We distinguish between two cases, $u_N > 0$ and $u_N < 0$.

Consider a rating system with $u_N > 0$. The problem of the rating agency writes

$$\max_{(b,\underline{v})} (1 - \underline{v})(u_B - u_N) = (1 - \underline{v})(\frac{1}{2}\underline{v} + \frac{1}{12}a\underline{v}^2 + \frac{1}{2}b - \frac{1}{12}ab^2)$$

$$\frac{1}{2} - \frac{1}{12}a\underline{v} \geq 0, \quad (8)$$

$$1 - b - \underline{v} \geq 0. \quad (9)$$

Constraint (8) is equivalent to $u_N > 0$, and (9) is a feasibility condition for the disclosure policy with two ratings. Denote $\lambda \geq 0$ and $\mu \geq 0$ the Lagrangian multipliers of these constraints. The first order conditions of the problem are

$$\begin{aligned} b: &\quad (1 - \underline{v})(\tfrac{1}{2} - \tfrac{1}{6}ab) - \mu = 0, \\ \underline{v}: &\quad -\tfrac{1}{4}a\underline{v}^2 + \tfrac{1}{6}(a - 6)\underline{v} + \tfrac{1}{2} - \tfrac{1}{2}b + \tfrac{1}{12}ab^2 - \tfrac{1}{12}a\lambda - \mu = 0. \end{aligned}$$

Suppose that $\lambda > 0$ and $\mu > 0$. Then $\underline{v} = \frac{6}{a}$ and $b = 1 - \frac{6}{a}$. It implies that $\mu = \frac{(a-6)(9-a)}{6a}$ and $\lambda = \frac{3(a-10)}{a}$. $\mu > 0$ when $6 < a < 9$, and $\lambda > 0$ when $a > 10$. A contradiction.

Suppose that $\lambda > 0$ and $\mu = 0$. Then $b = \frac{3}{a}$ and $\underline{v} = \frac{6}{a}$. It implies that $\lambda = \frac{9(2a-21)}{a^2}$, and $\lambda > 0$ when $a > \frac{21}{2}$. $\mu = 0$ implies that (9) must be satisfied, $\frac{6}{a} + \frac{3}{a} < 1$, or $a > 9$. Then this case is possible when $a > \frac{21}{2}$. The profit of the rating agency in this case is $\frac{27(a-6)}{4a^2}$.

Suppose that $\lambda = 0$ and $\mu > 0$. Then $b = 1 - \underline{v}$, and $\mu = (1 - \underline{v})(\frac{1}{2} - \frac{1}{6}a(1 - \underline{v}))$. The first order condition with respect to $\underline{v}$ writes $\frac{1}{4}a - \frac{1}{3}av - \frac{1}{2} = 0$, and $\underline{v} = \frac{3}{4} - \frac{1}{2a}$. $\underline{v} > 0$ when $a > 2$. $\mu = \frac{36-a^2}{96a}$, and $\mu > 0$ when $a < 6$. $\lambda = 0$ implies that (9) must be satisfied, $\frac{3}{4} - \frac{1}{2a} \leq \frac{6}{a}$, or $a < \frac{26}{3}$. Then this case is possible when $2 < a < 6$. The profit of the rating agency in this case is $\frac{(a+2)(a+10)}{96a}$. If $a < 2$, then $\underline{v} = 0$, and $b = 1$. The profit of the rating agency in this case is $\frac{1}{2} - \frac{1}{12}a$.

Suppose that $\lambda = \mu = 0$. Then $b = \frac{3}{a}$, and the first order condition with respect to $\underline{v}$ writes $-\frac{1}{4}a\underline{v}^2 + \left(\frac{1}{6}a - 1\right)\underline{v} + \frac{1}{2} - \frac{3}{4a} = 0$ implying that $\underline{v} = \frac{2}{3} - \frac{1}{a}$. $\lambda = 0$ implies that $\frac{2}{3} - \frac{1}{a} \leq \frac{6}{a}$, or

$a \leq \frac{21}{2}$. $\mu = 0$ implies that $\frac{3}{a} + \frac{2}{3} - \frac{1}{a} \leq 1$, or $a \geq 6$. Then this case is possible when $6 \leq a \leq \frac{21}{2}$. The profit of the agency in this case is $\frac{(a+3)^3}{81a^2}$.

The next table summarizes the case $u_N > 0$.

a	$\underline{v}$	b	$profit$
$2 \leq a \leq 6$	$\frac{3}{4} - \frac{1}{2a}$	$\frac{1}{4} + \frac{1}{2a}$	$\frac{(a+2)(a+10)}{96a}$
$6 \leq a \leq \frac{21}{2}$	$\frac{2}{3} - \frac{1}{a}$	$\frac{3}{a}$	$\frac{(a+3)^3}{81a^2}$
$a \geq \frac{21}{2}$	$\frac{6}{a}$	$\frac{3}{a}$	$\frac{27(a-6)}{4a^2}$

Consider the alternative system with $u_N < 0$. The problem of the rating agency in this case writes

$$\begin{aligned} \max_{(b,\underline{v})} (1-\underline{v})u_B &= (1-\underline{v})(\underline{v} + \frac{1}{2}b - \frac{1}{12}ab^2) \\ -\frac{1}{2} + \frac{1}{12}a\underline{v} &\geq 0 \text{ and } (9). \end{aligned}$$

Again, denote $\lambda \geq 0$ and $\mu \geq 0$ the Lagrangian multipliers of the constraints. The first order conditions of this problem write

$$\begin{aligned} b: &\quad (1-\underline{v})(\tfrac{1}{2} - \tfrac{1}{6}ab) - \mu = 0, \\ \underline{v}: &\quad 1 - 2\underline{v} - \tfrac{1}{2}b + \tfrac{1}{12}ab^2 + \tfrac{1}{12}a\lambda - \mu = 0. \end{aligned}$$

Suppose that $\lambda > 0$ and $\mu > 0$. Then $\underline{v} = \frac{6}{a}$ and $b = 1 - \frac{6}{a}$. It implies that $\lambda = -\frac{3(a^2-12a+12)}{a^2}$, and $\lambda > 0$ when $6 - 2\sqrt{6} < a < 6 + 2\sqrt{6}$. $\mu = \frac{(9-a)(a-6)}{6a}$, and $\mu > 0$ when $6 < a < 9$. Then this case is possible when $6 < a < 9$. The profit of the rating agency is $\frac{(a-6)(18-a)}{12a}$.

Suppose that $\lambda > 0$ and $\mu = 0$. Then $\underline{v} = \frac{6}{a}$ and $b = \frac{3}{a}$. It implies that $\lambda = \frac{3(51-4a)}{a^2}$, and $\lambda > 0$ when $a < \frac{51}{4}$. $\mu = 0$ implies that (9) must be satisfied, $\frac{6}{a} + \frac{3}{a} \leq 1$, or $a \geq 9$. So this case is possible when $9 \leq a < \frac{51}{4}$. The profit of the rating agency in this case is $\frac{27(a-6)}{4a^2}$.

Suppose that $\lambda = 0$ and $\mu > 0$. Then $b = 1 - \underline{v}$, and $\mu = (1-\underline{v})(\frac{1}{2} - \frac{1}{6}a(1-\underline{v}))$. The first order condition with respect to $\underline{v}$ becomes $a\underline{v}^2 - 2(a+2)\underline{v} + a = 0$, implying that $\underline{v} = \frac{a+2-2\sqrt{a+1}}{a}$. Then $\mu = \frac{7\sqrt{a+1}-2a-7}{3a}$, and $\mu > 0$ when $4a^2 + 21a + 42 < 0$. A contradiction.

Suppose that $\lambda = \mu = 0$. Then $b = \frac{3}{a}$ and $\underline{v} = \frac{1}{2} - \frac{3}{8a}$. $\lambda = 0$ implies that $\frac{1}{2} - \frac{3}{8a} \geq \frac{6}{a}$ must be satisfied, or $a \geq \frac{51}{4}$. $\mu = 0$ implies that $\frac{1}{2} - \frac{3}{8a} + \frac{3}{a} \leq 1$ must be satisfied, or $a \geq \frac{21}{4}$. So this case is possible when $a \geq \frac{51}{4}$. The profit of the rating agency in this case is $\frac{(4a+3)^2}{64a^2}$.

The next table summarizes the case of $u_N < 0$.

a	$\underline{v}$	b	$profit$
$6 \leq a \leq 9$	$\frac{6}{a}$	$1 - \frac{6}{a}$	$\frac{(a-6)(18-a)}{12a}$
$9 \leq a \leq \frac{51}{4}$	$\frac{6}{a}$	$\frac{3}{a}$	$\frac{27(a-6)}{4a^2}$
$a \geq \frac{51}{4}$	$\frac{1}{2} - \frac{3}{8a}$	$\frac{3}{a}$	$\frac{(4a+3)^2}{64a^2}$

The global solution to the problem can be found by comparing the profit of the rating agency under the two alternative rating systems. The next table summarizes the global solution.

a	$\underline{v}$	b	$profit$
$a \leq 2$	0	1	$\frac{1}{2} - \frac{1}{12}a$
$2 \leq a \leq 6$	$\frac{3}{4} - \frac{1}{2a}$	$\frac{1}{4} + \frac{1}{2a}$	$\frac{(a+2)(a+10)}{96a}$
$6 \leq a \leq \frac{21}{2}$	$\frac{2}{3} - \frac{1}{a}$	$\frac{3}{a}$	$\frac{(a+3)^3}{81a^2}$
$\frac{21}{2} \leq a \leq \frac{51}{4}$	$\frac{6}{a}$	$\frac{3}{a}$	$\frac{27(a-6)}{4a^2}$
$a \geq \frac{51}{4}$	$\frac{1}{2} - \frac{3}{8a}$	$\frac{3}{a}$	$\frac{(4a+3)^2}{64a^2}$

It completes the proof. ■

Proof of Proposition 1. Recall that under full disclosure the fee for the rating is defined by the willingness to pay of the lowest rated type $\underline{v}$. Under discrete rating system, it is the average willingness to pay of the types rated B, $v \in [\underline{v}, \overline{v}]$. Since the gains of the rating are higher for higher types, the second system will provide higher profit to the rating agency. Indeed, let's compare the profit functions of the rating agency under the two systems for any values of $(\underline{v}, \overline{v}, \beta)$. Denote π^F and π^D the profits of the rating agency under these systems.

$$\begin{aligned}
\pi^D - \pi^F &= (1-\underline{v})(u_R(B) - u_R(\underline{v})) \\
&= (1-\underline{v})(\beta(\frac{1}{2}(\underline{v}+\overline{v}) - \frac{1}{12}a(\overline{v}-\underline{v})^2) + (1-\beta)(\frac{1}{2}(1+\underline{v}) - \frac{1}{12}a(1-\underline{v})^2) \\
&\quad -(\beta\underline{v} + \frac{1}{2}(1-\beta)(1+\underline{v}) - \frac{1}{12}a(1-\beta)(1-\underline{v})^2)) \\
&= \beta(1-\underline{v})(\overline{v}-\underline{v})(\frac{1}{2} - \frac{1}{12}a(\overline{v}-\underline{v})) > 0.
\end{aligned}$$

In words, for any values of $(\underline{v}, \overline{v}, \beta)$ the profit under discrete rating system is higher than under full disclosure. Thus it also holds for the optimal points. Denote by $(\underline{v}^i, \overline{v}^i, \beta^i)$, $i = F, D$ the optimal points. Then

$$\pi^F(\underline{v}, \overline{v}, \beta) \leq \pi^D(\underline{v}, \overline{v}, \beta) \leq \pi^D(\underline{v}^D, \overline{v}^D, \beta^D) \text{ for } \forall(\underline{v}, \overline{v}, \beta).$$

In particular, this condition holds for $(\underline{v}^F, \overline{v}^F, \beta^F)$, and therefore $\pi^F(\underline{v}^F, \overline{v}^F, \beta^F) \leq \pi^D(\underline{v}^D, \overline{v}^D, \beta^D)$.
■

Proof of Proposition 4. We characterize the optimal rating system of the entrant for different rating systems of the incumbent depending on a characterized in Proposition (monopoly). Similarly to the incumbent's behavior, in general the entrant will have incentives to aggregate information. We focus on the case of two ratings. Denote v_e the lowest type that demand the 2^{nd} rating and b_e the mass of companies that obtain rating B from the entrant.

A necessary condition for a company to purchase the 2^{nd} rating is that it increases the price, that is

$$u_2(R, R_e) - t_e \geq u_1(R),$$

where $u_2(R, R_e)$ denotes the price charged by a company rated R by the entrant and R_e by the incumbent, and $u_1(R)$ is the price of a company rated R by a monopoly rating agency. Also a company rated R by the incumbent must be better off with two ratings than with a single rating,

$$u_2(R, R_e) - t_e \geq u_2(R, N),$$

where $u(R, N)$ is the price of a company that is rated R by the incumbent and has no rating from the entrant. These two constraints imply that

$$t_e \leq u_2(R, R_e) - \max\{u_1(R), u_2(R, N)\}. \quad (10)$$

The optimal rating system of the incumbent solves the following program.

$$\max_{\{v_e, b_e\}} (1 - v_e)t_e$$
$$\textit{subject to } (10).$$

In what follows we characterize the solution to this program depending on the rating system of the incumbent described in Proposition (monopoly).

!!!! The strategy of the entrant should satisfy two following constraints.

$$\begin{aligned} u(R_m, R_e) - t_e - t_m &\geq u(R_m) - t_m, \quad (11) \\ u(R_m, R_e) - t_e - t_m &\geq 0. \quad (12) \end{aligned}$$

The first constraint ensures that a company is better-off with two ratings. The second constraint guarantees that a rated company has non-negative profit.

We characterize the optimal entry strategy for each optimal rating system of the incumbent.

Case $a \leq 2$. $v_m = 0$, $b_m = 1$, and $t_m = \frac{1}{2} - \frac{1}{12}a$.

$$\begin{aligned} u(R_m, R_e) &= v_e + \frac{1}{2}b_e - \frac{1}{12}ab_e^2, \\ u(R_m) &= \frac{1}{2} - \frac{1}{12}a. \end{aligned}$$

Since $u(R_m) = t_m$, constraints (11) and (12) become $t_e \leq v_e + \frac{1}{2}b_e - \frac{1}{12}ab_e^2 - (\frac{1}{2} - \frac{1}{12}a)$. The optimal disclosure policy of the incumbent solves

$$\max_{v_e, b_e} (1 - v_e)(v_e + \frac{1}{2}b_e - \frac{1}{12}ab_e^2 - (\frac{1}{2} - \frac{1}{12}a))$$
$$s.t. \ 1 - v_e - b_e \geq 0 \text{ and } v_e \geq 0.$$

Denote λ and μ the positive Lagrangian multipliers of the constraints. The first order conditions of this problem are

$$\begin{aligned} b_e: &\quad (1 - v_e)(\tfrac{1}{2} - \tfrac{1}{6}ab_e) - \lambda = 0, \\ v_e: &\quad -(v_e + \tfrac{1}{2}b_e - \tfrac{1}{12}ab_e^2 - (\tfrac{1}{2} - \tfrac{1}{12}a)) + 1 - v_e - \lambda + \mu = 0. \end{aligned}$$

If $\lambda = 0$, then $b_e = \frac{3}{a} > 0$. A contradiction.

If $\lambda > 0$ and $\mu > 0$, then $v_e = 0$ and $b_e = 1$, resulting in $\pi_e = 0$.

If $\lambda > 0$ and $\mu = 0$, then $b_e = 1 - v_e$ and v_e solves $\frac{1}{4}av_e^2 - (\frac{1}{2}a + 1)v_e + \frac{1}{6}a + \frac{1}{2}$ resulting in $v_e = 1 + \frac{2}{a} - \frac{1}{a}\sqrt{\frac{1}{3}a^2 + 2a + 4}$. $\lambda = (1 - v_e)(\frac{1}{2} - \frac{1}{6}a(1 - v_e)) > 0$ and $0 < v_e < 1$ for all $a \leq 2$.

Case $2 \leq a \leq 6$.$v_m = \frac{3}{4} - \frac{1}{2a}$, $b_m = 1 - v_m$, and $t_m = \frac{1}{24}a + \frac{5}{12}$.

First note that an entrant cannot attract companies $v \in [v_m, v_m + \Delta]$ by disclosing more information about these companies, $u(v_m, v_m + \Delta) < u(v_m, 1)$ for any $0 \leq \Delta < 1 - v_m$. Thus it must offer a disclosure policy $v_e > v_m$.

In this case the incumbent assigns the same rating to all companies $v \in [\frac{3}{4} - \frac{1}{2a}, 1]$, and

$$\begin{aligned} u_A &= u_B = \frac{164a - a^2 - 52}{192a}, \\ u_N &= \frac{84a - 9a^2 - 52}{192a}. \end{aligned}$$

An entrant designs a rating system with $A_e = [v_e + b_e, 1]$ and $B_e = [v_e, v_e + b_e]$. The profit of the new rating agency in this case writes

$$\max_{v_e} (1 - v_e)(v_e + \frac{1}{2}b_e - \frac{1}{12}ab_e^2 - \max\{u_B, \frac{1}{2}(\underline{v} + v_e) - \frac{1}{12}a(v_e - \underline{v})^2\}),$$
$$\text{subject to } 1 - v_e - b_e \geq 0.$$

Denote $\lambda > 0$ the Lagrangian multiplier of the constraint. Assume that $v_e > \underline{v}$ and $\max\{u_B, \frac{1}{2}(\underline{v} + v_e) - \frac{1}{12}a(v_e - \underline{v})^2\} = u_B$. We check ex-post that the constraints are satisfied for the solution.

The first order conditions write

$$\begin{aligned} b_e: &\quad (1 - v_e)(\tfrac{1}{2} - \tfrac{1}{6}ab_e) - \lambda = 0, \\ v_e: &\quad 1 - 2v_e - \tfrac{1}{2}b_e + \tfrac{1}{12}ab_e^2 + u_B - \lambda = 0. \end{aligned}$$

Suppose $\lambda = 0$. Then $b_e = \frac{3}{a}$ and $v_e = \frac{1}{2}(1 - \frac{3}{4a} + u_B)$. $\lambda = 0$ implies $1 - \frac{3}{a} - \frac{1}{2}(1 - \frac{3}{4a} + u_B) \geq 0$, or $\frac{a^2 + 28a - 956}{384a} > 0$, which is not satisfied for $2 \leq a \leq 6$. A contradiction.

Suppose $\lambda > 0$. Then $b_e = 1 - v_e$ and $\lambda = (1 - v_e)(\frac{1}{2} - \frac{1}{6}a(1 - v_e))$. Solving for v_e and λ yields

$$\begin{aligned} v_e &= \frac{12(a + 2) - \sqrt{3(a^2 + 28a + 244)}}{12a}, \\ \lambda &= \frac{28\sqrt{3(a^2 + 28a + 244)} - (a^2 + 28a + 724)}{288a}. \end{aligned}$$

It is straightforward to verify that $0 < v_e < 1$, $v_e < \underline{v}$ and $\lambda > 0$ for $2 \leq a \leq 6$. Also $u_B > \frac{1}{2}(\underline{v} + v_e) - \frac{1}{12}a(v_e - \underline{v})^2$ is equivalent to $\frac{1}{2} - \frac{1}{12}a(1 - \underline{v} + v_e - \underline{v}) > 0$ which is satisfied for $2 \leq a \leq 6$. The profit of the entrant in this case is

$$\pi_e = \frac{\sqrt{3}(a^2 + 28a + 244)^{\frac{3}{2}} - 36(a^2 + 28a + 180)}{3456a^2},$$

and it is decreasing in a.

Case $6 \leq a \leq \frac{21}{2}$. ■

Table 1: FAST Ratio and Control Variable Summary Statistics: Solvent versus Insolvent Insurers 1989 - 2000

The table displays summary statistics of the variables used to estimate the one year default probabilities using the discrete-time hazard model. The statistics are shown separately for the solvent insurers and the insolvent insurer samples. All insurers are included in the analysis except insurers that have insufficient data or those that fail for which data is not available either one year or two years prior to the first regulatory action being taken against the firm. There are 214 firm-year observations in the insolvent sample and 24,062 in the solvent sample.

	Solvent Insurers		Insolvent Insurers		Test Statistic
Variable	μ_{sol}	σ_{sol}	μ_{ins}	σ_{ins}	H_0: $\mu_{sol} = \mu_{ins}$
Kenney Ratio: NPW to Policyholder Surplus	1.13	0.85	1.87	1.12	9.591
Reserves to Policyholder Surplus	1.03	0.94	1.64	1.25	7.237
1 Yr. Growth in NPW (%)	11.87	41.62	11.69	61.21	0.042
1 Yr. Growth in GPW (%)	11.94	37.63	11.06	52.93	0.244
Surplus Aid to Policyholder Surplus	2.05	4.34	6.07	7.52	7.816
Investment Yield (%)	5.71	1.38	5.41	1.55	2.778
1 Yr. Growth in Policyholder Surplus (%)	8.82	16.30	-8.50	19.87	12.710
Two-year Reserve Development to Policyholder Surplus (%)	-2.73	10.80	4.00	11.62	8.449
Gross Expenses to GPW	0.58	0.76	0.55	0.64	0.843
1 yr. Change in Gross Expenses (%)	0.05	0.47	0.09	0.58	1.006
1 yr. Change in Liquid Assets (%)	1.17	2.66	0.37	1.79	6.518
Investments in Affiliates to Policyholder Surplus	0.58	1.32	0.94	1.74	3.038
Receiv's. from Affiliates to Policyholder Surplus	0.02	0.04	0.04	0.05	5.243
Misc. Recoverables to Policyholder Surplus	0.03	0.05	0.07	0.08	6.691
Non-investment Grade Bonds to Policyholder Surplus	0.65	2.37	0.68	2.49	0.183
Other Invested Assets to Policyholder Surplus	0.01	0.03	0.02	0.04	3.414
Dummy = 1 if insurer has a large single agent	0.12	0.33	0.22	0.42	3.480
Dummy = 1 if insurer has a large single agent they control	0.08	0.28	0.12	0.32	1.502
Losses, Exp's, Div's and Taxes Paid to Premiums Collected	1.29	0.73	1.59	0.84	5.205
Total Assets (000000's in 2000 $)	433.65	2215.43	100.76	519.92	8.691
Ind. = 1 if insurer is part of a mutual group	0.26	0.44	0.08	0.28	8.965

Table 2: Hazard Model Regression Results

Panel A:

Table displays the results of the discrete-time hazard model regression model. The dependent variable y_{it} = 1 for each insurer that has a formal regulatory action taken against the insurer in either year t+1. Otherwise y_{it} = 0 for all other observations. There are 24,062 healthy firm-year observations and 214 insolvent company observations.

Variable	Coefficient Estimate	Standard Error	χ^2 Statistic	
Intercept	-0.7577	1.1653	0.4228	
Kenney Ratio: NPW to Policyholder Surplus	0.0047	0.0015	10.3304	***
Reserves to Policyholder Surplus	189.3000	121.0000	2.4455	
1 Yr. Growth in NPW (%)	0.0055	0.0026	4.3943	**
1 Yr. Growth in GPW (%)	0.5068	0.2575	3.8733	**
Surplus Aid to Policyholder Surplus	0.0415	0.0128	10.5759	***
Investment Yield (%)	-0.0117	0.0646	0.0328	
1 Yr. Growth in Policyholder Surplus (%)	-0.0390	0.0063	38.6798	***
Two-year Reserve Development to Policyholder Surplus (%)	0.0311	0.0086	13.0963	***
Gross Expenses to GPW	0.2654	0.1796	2.1834	
1 yr. Change in Gross Expenses (%)	-0.1195	0.1961	0.3714	
1 yr. Change in Liquid Assets (%)	-0.0462	0.0517	0.7956	
Investments in Affiliates to Policyholder Surplus	0.0000	0.0000	10.9740	***
Receiv's. from Affiliates to Policyholder Surplus	3.3208	1.6962	3.8327	*
Misc. Recoverables to Policyholder Surplus	2.1060	1.2641	2.7755	*
Non-investment Grade Bonds to Policyholder Surplus	0.0556	0.0317	3.0818	*
Other Invested Assets to Policyholder Surplus	6.7624	2.2026	9.4257	***
Dummy = 1 if insurer has a large single agent	0.6341	0.2205	8.2740	***
Dummy = 1 if insurer has a large single agent they control	-0.3205	0.2870	1.2477	
Losses, Exp's, Div's and Taxes Paid to Premiums Collected	0.6960	0.1589	19.1885	***
Ln(Total Assets in $2000)	-0.4707	0.0665	50.0860	***
Ind. = 1 if insurer is part of a mutual group	-0.8337	0.2709	9.4694	***
Log Likelihood Function Value	-908.617			
Pseudo R^2	25.86%			

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

The pseudo R^2 equals 1 minus the ratio of the log likehood function value divided by the log likelihood function value where all coefficients are constrained to be zero (see Greene 1997 p. 891).

Panel B:

Table displays summary statistics of the predicted one-year probability of default for solvent firm-year observations and for bankrupt firm-year observations.

Firm Type	Num	Ave.	Median	Standard Deviation	1st Percentile	99th Percentile
Solvent	24,062	0.81%	0.20%	2.46%	0.01%	11.08%
Insolvent	214	9.35%	4.46%	12.78%	0.09%	66.45%

Table 3
Insurer Rating Categories: A.M Best vs. Standard & Poor's

Number	Description	A.M. Best	S&P
4	Extremely Strong	A++,A+	AAA
3	Strong	A	AA
2	Good	A-	A
1	Adequate	B++,B+	BBB
0	Marginal	B and below	BB and below

Table 4
Number of Companies Rated and Average Rating
A.M. Best vs. Standard & Poor's 1989 - 2000

Table displays the number of companies in the NAIC database, the number of firms rated by A.M. Best and Standard & Poor's over the years 1989 - 2000.* The table also displays the total assets of the industry and the total assets of the firms rated by A.M. Best and Standard & Poor's. The final two columns display the average rating of the companies rated by agency.

	Number of Companies			Total Assets ($ billions)			Average Rating	
Year	NAIC	A.M. Best	S&P	NAIC	A.M. Best	S&P	A.M. Best	S&P
1989	1903	1110 (58.3%)		534.6	491.6 (91.9%)		2.840	
1990	1897	1175 (61.9%)		566.5	511.6 (90.3%)		2.750	
1991	1968	1261 (64.1%)		615.2	565.1 (91.9%)		2.604	
1992	2012	1352 (67.2%)	360 (17.9%)	659.3	597.5 (90.6%)	218.9 (33.2%)	2.583	0.664
1993	2061	1437 (69.7%)	349 (16.9%)	698.2	635.8 (91.1%)	164.5 (23.6%)	2.555	0.693
1994	2065	1515 (73.4%)	391 (18.9%)	729.3	668.7 (91.7%)	177.9 (24.4%)	2.434	1.192
1995	2084	1551 (74.4%)	393 (18.9%)	783.9	724.0 (92.4%)	200.0 (25.5%)	2.386	1.417
1996	2100	1577 (75.1%)	572 (27.2%)	830.2	774.0 (93.2%)	554.6 (66.8%)	2.382	1.818
1997	2096	1598 (76.2%)	568 (27.1%)	911.0	860.9 (94.5%)	612.9 (67.3%)	2.416	1.871
1998	2096	1620 (77.3%)	587 (28.0%)	949.4	897.5 (94.5%)	644.1 (67.8%)	2.474	2.082
1999	2042	1620 (79.3%)	583 (28.6%)	953.0	903.1 (94.8%)	655.7 (68.8%)	2.500	2.163
2000	1952	1570 (80.4%)	590 (30.2%)	938.5	888.2 (94.6%)	645.4 (68.8%)	2.461	2.110

* - S&P provided ratings on property-liability insurers over the years 1989-1991. We were unable to locate this data in electronic format.

Table 5
Summary Statistics One-Year Probability of Default
A.M Best vs. Standard & Poor's: 1989 - 2000

Table displays the average and median probability of default of the firms that receive ratings by A.M. Best and Standard & Poor's. The T-test column reports the results testing the average proability of default for A.M. Best is different than S&P assuming unequal variances. The column labeled "Non-Par." reports the results of the non-parametric Wilcoxon-Mann-Whitney difference in medians test. The chart below displays the average and median statistics for each agency over time period of this study.

	A.M. Best				Standard & Poor's				Test Statistics $H_0: \mu_{Best} = \mu_{S\&P}$	
Year	Num	Mean	Median	Std. Dev.	Num	Mean	Median	Std. Dev.	T-Test	Non-Par.
1989	1110	0.40%	0.14%	1.39%						
1990	1175	0.60%	0.27%	1.25%						
1991	1261	0.50%	0.14%	1.80%						
1992	1352	0.64%	0.15%	2.55%	360	0.37%	0.11%	1.07%	3.050	4.427
1993	1437	0.47%	0.12%	2.15%	349	0.34%	0.09%	0.82%	1.767	4.027
1994	1515	0.46%	0.14%	1.18%	391	0.41%	0.10%	1.57%	0.601	4.953
1995	1551	0.42%	0.10%	2.14%	393	0.24%	0.06%	0.89%	2.604	5.744
1996	1577	0.88%	0.19%	3.44%	572	0.41%	0.14%	0.88%	4.988	5.028
1997	1598	0.52%	0.15%	1.72%	568	0.32%	0.11%	1.35%	2.771	4.767
1998	1620	0.69%	0.16%	2.91%	587	0.28%	0.12%	0.48%	5.421	5.108
1999	1620	0.80%	0.20%	2.55%	583	0.45%	0.16%	1.49%	3.935	3.898
2000	1570	0.68%	0.20%	2.05%	590	0.36%	0.17%	0.78%	5.129	3.548

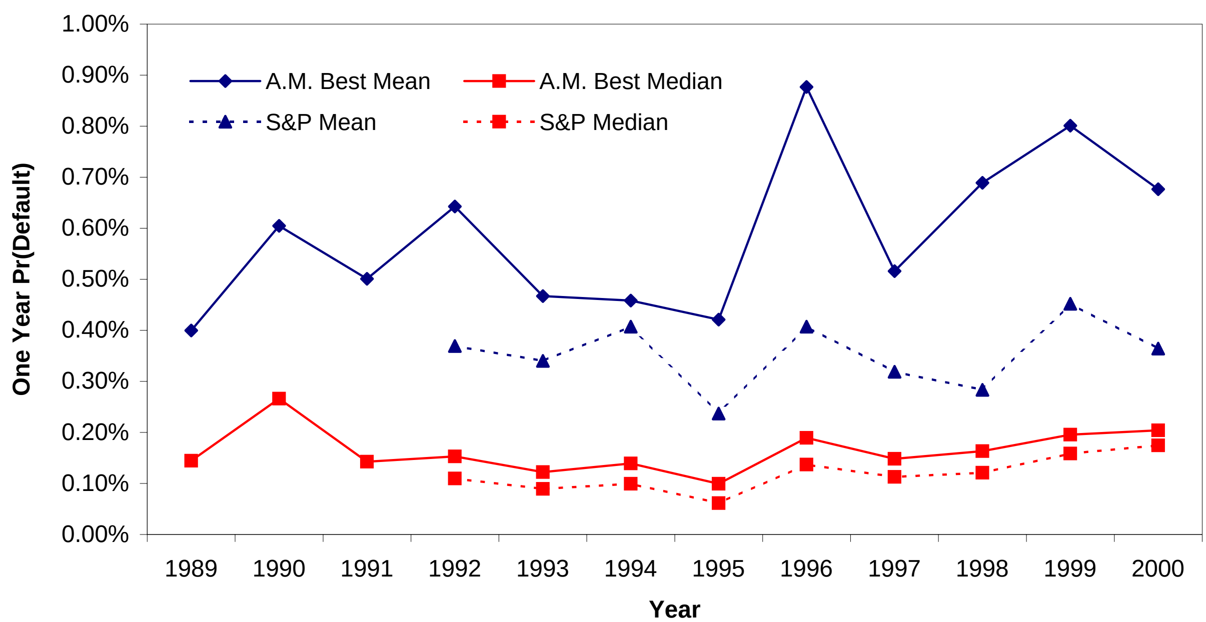

Table 6
Standard & Poor's Qualified vs. Full Ratings: 1992 - 2000

Table displays summary statistics of ratings S&P issued property-liability insurers using the qualified vs. the unqualified rating system over the years 1992 - 2000.

	Full Ratings						Qualified Ratings						Test Statistic $H_0: \mu_{full} = \mu_{qual}$	
Year	Num	Percent	μ_{full}	σ_{full}	Min	Max	Num	Percent	μ_{qual}	σ_{qual}	Min	Max	T-Stat	
1992	23	(6.4%)	3.22	0.74	1.00	4.00	337	(93.6%)	0.49	0.50	0.00	1.00	17.50	***
1993	25	(7.2%)	2.96	1.14	0.00	4.00	324	(92.8%)	0.52	0.50	0.00	1.00	10.67	***
1994	34	(8.7%)	3.03	1.03	0.00	4.00	357	(91.3%)	1.02	0.87	0.00	3.00	11.03	***
1995	55	(14.0%)	2.89	1.07	1.00	4.00	338	(86.0%)	1.18	0.91	0.00	4.00	11.27	***
1996	232	(40.6%)	2.78	0.91	1.00	4.00	340	(59.4%)	1.16	0.91	0.00	4.00	20.79	***
1997	255	(44.9%)	2.75	0.85	1.00	4.00	313	(55.1%)	1.16	0.85	0.00	4.00	22.09	***
1998	320	(54.5%)	2.78	0.81	1.00	4.00	267	(45.5%)	1.24	0.87	0.00	4.00	22.04	***
1999	343	(58.8%)	2.80	0.73	0.00	4.00	240	(41.2%)	1.25	0.81	0.00	4.00	23.64	***
2000	339	(57.5%)	2.77	0.77	0.00	4.00	251	(42.5%)	1.22	0.82	0.00	4.00	23.37	***

*** - significant at the 1 percent level

Number of Insurers that Received Qualified and Unqualified Ratings by Standard & Poor's 1992 - 2000

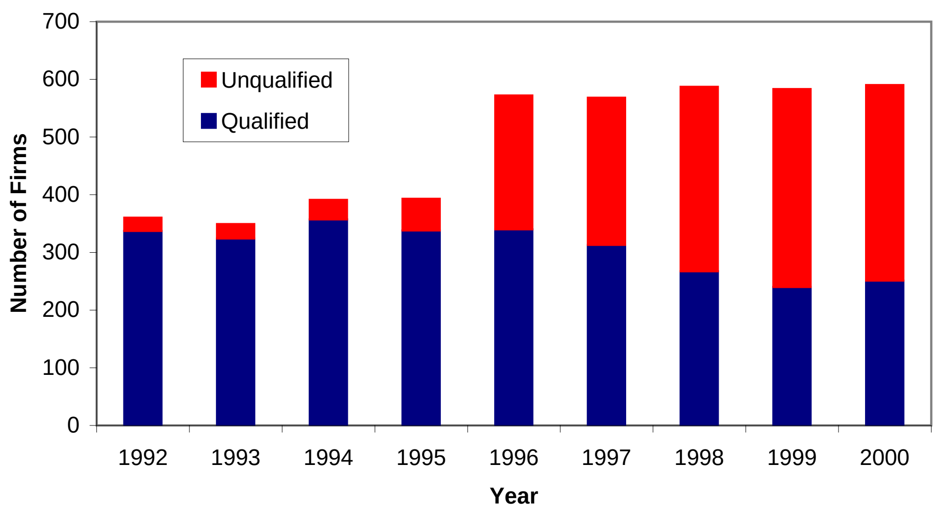

Table 7
Stringency and Accuracy of A.M. Bests vs. Standard and Poor's Ratings

Each panel shows the distribution of ratings issued by a particular rating agency over the time period of this study as well as summary statistics of the probability of default by rating category. Panel A displays statistics for firms that receive a full unqualified rating from S&P during the years 1992 - 2000. Panel B displays statistics for firms that received qualified ratings from S&P during the years 1992 - 2000. Panel C displays statistics for firms that received ratings from A.M. Best during the years 1989 - 2000.

Panel A: Firms that Receive a Full Rating from Standard & Poor's

					Percentiles			
Rating	**Num**		μ	σ	10^{th}	**Median**	90^{th}	$90^{th} - 10^{th}$
Extremely Strong	339	(20.8%)	0.16%	0.22%	0.01%	0.09%	0.33%	0.32%
Strong	697	(42.9%)	0.36%	1.40%	0.03%	0.13%	0.61%	0.58%
Good	515	(31.7%)	0.51%	0.72%	0.06%	0.29%	1.16%	1.10%
Adequate	69	(4.2%)	0.51%	0.93%	0.04%	0.22%	1.15%	1.11%
Marginal	6	(0.4%)	1.11%	1.94%	0.01%	0.43%	5.03%	5.02%
	1626							

Panel B: Firms that Receive a Qualified Rating from Standard & Poor's

					Percentiles			
Rating	**Num**		μ	σ	10^{th}	**Median**	90^{th}	$90^{th} - 10^{th}$
Extremely Strong	9	(0.3%)	0.01%	0.02%	0.00%	0.01%	0.06%	0.06%
Strong	92	(3.3%)	0.05%	0.06%	0.01%	0.02%	0.13%	0.12%
Good	673	(24.3%)	0.15%	0.46%	0.02%	0.06%	0.26%	0.24%
Adequate	1131	(40.9%)	0.22%	0.45%	0.02%	0.09%	0.44%	0.42%
Marginal	862	(31.2%)	0.70%	1.84%	0.03%	0.20%	1.62%	1.58%
	2767							

Panel C: A.M. Best Ratings

					Percentiles			
Rating	**Num**		μ	σ	10^{th}	**Median**	90^{th}	$90^{th} - 10^{th}$
Extremely Strong	4790	(27.6%)	0.25%	0.74%	0.02%	0.10%	0.48%	0.46%
Strong	4593	(26.4%)	0.31%	0.90%	0.03%	0.13%	0.64%	0.61%
Good	4067	(23.4%)	0.43%	1.06%	0.04%	0.18%	0.91%	0.88%
Adequate	2683	(15.4%)	0.77%	2.16%	0.06%	0.28%	1.66%	1.60%
Marginal	1253	(7.2%)	3.11%	6.61%	0.12%	0.89%	7.91%	7.79%
	17,386							

Table 8
Summary Statistics of Insurer's Receiving Full vs. Qualified Ratings from Standard & Poor's: 1994 - 2000

The sample includes insurer-year observations for all firms that receive an A.M. Best rating and any firm that receives a rating from S&P over the years 1994 - 2000. We eliminate all observations from 1992 and 1993 because of S&P's policy of not assigning any firm a rating above BBB when the insurer is being rated on a qualified basis.

	A.M. Best Only		Standard & Poor's Qualified Rating		Standard & Poor's Full Rating		Test Statistics		
	μ_a	σ_a	μ_q	σ_q	μ_f	σ_f	$H_0: \mu_a = \mu_q$	$H_0: \mu_a = \mu_f$	$H_0: \mu_q = \mu_f$
Ind. = 1 for Marginal A.M. Best Rating	0.089	0.285	0.035	0.183	0.001	0.026	10.0 ***	24.7 ***	8.1 ***
Ind. = 1 for Adequate A.M. Best Rating	0.216	0.412	0.115	0.319	0.015	0.122	11.5 ***	33.6 ***	12.6 ***
Ind. = 1 for Good A.M. Best Rating	0.284	0.451	0.193	0.395	0.153	0.360	8.6 ***	12.0 ***	3.1 ***
Ind. = 1 for Strong A.M. Best Rating	0.244	0.430	0.368	0.482	0.278	0.448	10.1 ***	2.7 ***	5.6 ***
Ind. = 1 for Ext. Strong A.M. Best Rating	0.166	0.372	0.289	0.454	0.553	0.497	10.9 ***	28.0 ***	15.9 ***
S&P Rating	-		1.215	0.862	2.770	0.806			53.9 ***
A.M. Best Rating	2.182	1.204	2.762	1.095	3.368	0.798	20.0 ***	46.3 ***	18.6 ***
S&P Rating - A.M. Best Rating	-		-1.547	1.016	-0.598	0.648			33.0 ***
Ind. = 1 if insurer is part of a mutual group	0.319	0.466	0.473	0.499	0.175	0.380	12.1 ***	12.4 ***	19.7 ***
Total Assets (000000's in 2000 $)	352.3	1861.7	414.9	885.9	1,860.4	5,963.9	2.0 **	9.6 ***	9.2 ***
% NPW in Retail Lines of Insurance	0.360	0.368	0.356	0.360	0.322	0.328	0.4	3.9 ***	2.8 ***
Ind. = 1 if year = 1994	0.154	0.361	0.166	0.372	0.020	0.140	1.2	23.3 ***	15.8 ***
Ind. = 1 if year = 1995	0.163	0.370	0.162	0.368	0.036	0.185	0.2	19.2 ***	13.0 ***
Ind. = 1 if year = 1996	0.138	0.345	0.163	0.369	0.150	0.357	2.6 ***	1.2	1.0
Ind. = 1 if year = 1997	0.133	0.339	0.146	0.353	0.160	0.367	1.4 *	2.6 ***	1.1
Ind. = 1 if year = 1998	0.136	0.343	0.126	0.332	0.197	0.398	1.2	5.4 ***	5.5 ***
Ind. = 1 if year = 1999	0.137	0.344	0.116	0.321	0.220	0.414	2.5 ***	7.1 ***	7.9 ***
Ind. = 1 if year = 2000	0.138	0.345	0.122	0.327	0.217	0.413	1.8 **	6.9 ***	7.3 ***

*** - significant at the 1 percent level; ** - significant at the 5 percent level; * - significant at the 10 percent level. The number of firm-year observations that received only one rating from A.M. Best was 6587. The number of firm-year observations that received both an A.M. Best rating and a qualified/full

Table 9
Probit Regression Results Predicting Whether Insurer Received a Full or Qualified Rating from Standard & Poor's: 1994 - 2000

Table displays Probit regression results where the dependent variable for the first two regression models equaled 1 when insurer i was assigned a qualified rating by Standard & Poor's in year t and 0 otherwise. In the last two regressions the indicator variable equals 1 when insurer i requested a full unqualified rating from Standard & Poor's in year t. Panel A displays the estimated coefficients on the independent variables. Panel B displays the marginal effects.

Panel A: Regression Results	**Did Insurer Receive Qualified Rating from S&P?**		**Did Insurer Request Full Rating from S&P?**	
Independent Variable	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Intercept	-1.3994 ***	-2.6336 ***	-2.6467 ***	-5.6479 ***
	(0.076)	(0.199)	(0.283)	(0.387)
Ind. = 1 for Adequate A.M. Best Rating	0.1686 **	0.1193	0.6573 **	0.6428 **
	(0.077)	(0.079)	(0.293)	(0.323)
Ind. = 1 for Good A.M. Best Rating	0.2485 ***	0.1431 *	1.5896 ***	1.4644 ***
	(0.073)	(0.077)	(0.284)	(0.312)
Ind. = 1 for Strong A.M. Best Rating	0.6366 ***	0.5061 ***	1.8913 ***	1.6554 ***
	(0.071)	(0.075)	(0.283)	(0.311)
Ind. = 1 for Extremely Strong A.M. Best Rating	0.5344 ***	0.3426 ***	2.5311 ***	2.1789 ***
	(0.072)	(0.078)	(0.283)	(0.311)
Ln(Total Assets in $2000)		0.0673 ***		0.1915 ***
		(0.010)		(0.012)
Ind. = 1 if insurer is part of a mutual group		0.5300 ***		-0.6313 ***
		(0.033)		(0.047)
% NPW in Retail Lines of Insurance		-0.1455 ***		0.1701 ***
		(0.046)		(0.058)
State of Business of Herfindahl		-0.0900 **		-0.5681 ***
		(0.046)		(0.059)
Log-likehood function value	-4763.0	-4606.3	-3271.5	-3063.5
Pseudo R^2	2.64%	5.84%	21.18%	29.38%

Panel B: Estimated Marginal Effects				
Ind. = 1 for Adequate A.M. Best Rating	0.0452 **	0.0312	0.0955 **	0.0706 **
Ind. = 1 for Good A.M. Best Rating	0.0667 ***	0.0374 *	0.2310 ***	0.1608 ***
Ind. = 1 for Strong A.M. Best Rating	0.1708 ***	0.1322 ***	0.2749 ***	0.1817 ***
Ind. = 1 for Extremely Strong A.M. Best Rating	0.1434 ***	0.0895 ***	0.3679 ***	0.2392 ***
Ln(Total Assets in $2000)		0.0176 ***		0.0210 ***
Ind. = 1 if insurer is part of a mutual group		0.1384 ***		-0.0693 ***
% NPW in Retail Lines of Insurance		-0.0380 ***		0.0187 ***
State of Business of Herfindahl		-0.0235 **		-0.0624 ***

*** - significant at the 1 percent level; ** - significant at the 5 percent level; * - significant at the 10 percent level
The pseudo R^2 equals 1 minus the ratio of the log likehood function value divided by the log likelihood function value where all coefficients are constrained to be zero (see Greene 1997 p. 891).

Table 10

OLS Regression Results Explaining Rating Difference Between Standard & Poor's and A.M. Best Ratings: 1994 - 2000

Table displays OLS regression results where the dependent variable for the first two regression models equaled the difference between the qualified rating assigned by Standard & Poor's minus the rating assigned by A.M. Best in year t. The dependent variable for the last two regressions the indicator variable equaled the difference between the full rating assigned by Standard & Poor's minus the rating assigned by A.M. Best in year t.

	Did Insurer Receive Qualified Rating from S&P?		Did Insurer Request Full Rating from S&P?	
Independent Variable	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Intercept	-5.6029 ***	-2.7431 ***	-1.3142 ***	-0.9243 ***
	(0.150)	(0.116)	(0.049)	(0.040)
Inverse Mills Ratio	2.9075 ***	0.8959 ***	0.5807 ***	0.2981 ***
	0.1067	0.0852	(0.037)	(0.033)
R^2	27.44%	5.43%	13.73%	5.24%
Expected increase in rating due to selection bias	4.06	1.20	0.72	0.33