

# Information effect of entry into credit ratings market: The case of insurers' ratings\*

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## Abstract

This paper analyzes the optimal entry strategy of a credit rating agency (CRA) to a market served by the incumbent. We show that a monopolistic CRA pools sellers into multiple rating classes and has partial market coverage. This provides an opportunity for market entry. The entrant targets higher-than-average companies in each rating class of the incumbent's rating scale and employs more stringent rating standards. We use Standard and Poor's entry into the market for insurance ratings previously covered by a monopolist, A.M. Best, to empirically test the impact of entry on the information content of ratings.

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

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Significant debate exists regarding the role that competition should play in the market for credit ratings. Representatives from the credit rating agencies (CRAs) themselves argue that reducing barriers to entry would eventually lead to reduced disclosure of information as the new entrants engage in “race to the bottom” strategies in order to sell their services. Testimony by Mr. Raymond W. McDaniel, chairman and CEO of Moody’s Corporation, before the US Securities and Exchange Commission illustrates this line of reasoning:

Considering the unique dynamics of our market, historically new market entrants and marginal participants have sought to make their products more attractive to issuers by offering higher ratings than do more established market participants. Some new entrants might be inclined to try to compete in this manner because of the ease with which such a strategy could be implemented and the short-term benefits that might accrue to the entrant as a result. Therefore, Moody’s believes that the usefulness of credit ratings in the aggregate for market efficiency, transparency and investor protection would decline in the event that more Nationally Recognized Statistical Rating Organizations (“NRSROs”) are established and rating levels become a more important element of competition within the industry.<sup>1</sup> (McDaniel 2002)

Critics, on the other hand, argue that the lack of competition may be one of the factors that contributed to the inability of the CRAs to provide accurate and timely information in the recent credit crisis (SEC 2008) and to support the adoption of rules that promote competition. Recent regulatory changes have favored this point of view—most notably when Congress passed the “Credit Rating Agency Duopoly Relief Act” in 2006 that clarified the process of obtaining NRSRO status. Though market concentration

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<sup>1</sup>Primarily for the purposes of safety and soundness regulation, regulated investors including banks, thrifts, insurance companies, pension funds, and so on are required to follow with rules that in part restrict their investments to carry ratings issued only by an NRSRO. Thus, NRSRO status is viewed by many as regulatory approval of the rating agency. See White (2002) for background and discussion.

remains very high, several new CRAs have recently obtained NRSRO status.<sup>2</sup>

Although Congress has already moved in the direction of encouraging entry in the market for credit ratings, little theoretical or empirical research exists that would be helpful in this debate. We seek to address this shortcoming in this paper by theoretically and empirically analyzing how the entry of a new CRA affects the informational content of ratings. We begin by examining the information disclosure of a monopoly CRA. Our analysis suggests that it is optimal for the agency to pool information into letter grades, which results in the clustering of companies and issuers into fairly broad rating classes—a result consistent with common practice. This pooling of information, however, generates an opportunity for a new agency to offer additional ratings. Thus, the second objective we have is to analyze the entry strategy of a new CRA. If a company or an issuer decides to pay for a rating by a new CRA, it suggests that the entrant uses a different rating scale or that its rating contains additional information. Our third objective is to provide evidence of the effect of entry on the information content of the ratings of insurance companies. The insurance industry provides a unique natural experiment as it was served by the monopoly rating agency, the A.M. Best Company, for almost 100 years until it experienced the entry of Standard & Poor’s (S&P) at the end of the 1980s.

There are longer term issues as to how the rating market will reach an oligopolistic equilibrium after the monopoly is broken. For example, do oligopolists compete on the basis of product differentiation<sup>3</sup>; what are the equilibrium properties of an oligopolistic credit ratings market? However, in this paper we focus on the more immediate question of how information pooling by a monopolist presents an entry opportunity and what strategy is adopted by the entrant.

Optimal information disclosure was first addressed by Lizzeri (1999) who showed that when all parties are risk neutral a monopoly CRA’s optimal disclosure strategy is to pool

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<sup>2</sup>The Herfindahl-Hirschmann Index (HHI) for all NRSRO ratings outstanding is 3,778, which is equivalent to 2.65 equally sized firms. The current total number of NRSROs is 10, including A.M. Best, DBRS, Fitch, Japan Credit Rating Agency, Moody’s Rating and Investment Information, Standard & Poor’s, Egan-Jones, LACE and Realpoint. (SEC 2008)

<sup>3</sup>Kartasheva (2010) analyzes the equilibrium precision of CRAs in a duopoly setting.

all companies into one rate class. Surprisingly, all sellers pay to be rated in spite of the fact that a seller does not have to obtain a rating, and de facto the CRA discloses no information. At the same time, entry of a new CRA results in full disclosure of information.

Lizzeri's results contrast with practice. For example, as a monopolist CRA in the insurance industry for many decades, A.M. Best had multiple rating categories and did not have complete market coverage. Moreover, in most settings, multiple CRAs are in competition. In 2000, A.M. Best covered 80.5 percent of the insurance companies, while S&P's coverage was 27.5 percent. We present a model that explains these phenomena and addresses the impact of new entry.

We depart from Lizzeri by suggesting that buyers value the precision of information contained in ratings. Because rating-based guidelines are widely used in the conduct of business activities, buyers are ready to pay a higher price for a good with less ambiguous quality.<sup>4</sup> We consider a model where sellers have private information about the quality of a good, which they cannot communicate credibly to buyers. A CRA can learn what a seller's quality is, but it has discretion in how this information is communicated to buyers. The evaluation of a seller is reached in two stages. In the first stage, a CRA chooses and commits to a disclosure policy and the fee for its services behind a veil of ignorance. In the second stage, privately informed sellers decide whether to demand a rating from the CRA. Once the CRA evaluates the sellers who solicited a rating, buyers form a belief about each seller based on that seller's decision to be rated and, possibly, the seller's rating.

We derive four main results. First, when buyers care about the precision of information, Lizzeri's single rating result holds only as a special case. The optimal rating scale derived from the model resembles the interval disclosure rule actually employed by the major credit agencies. Pooling the lowest rated seller with better types has two counter-

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<sup>4</sup>For example, in a survey of 200 plan sponsors and investment managers in the U.S. and Europe (Cantor, Gwilym and Thomas 2007), 60 percent of fund managers and 47 percent of plan sponsors report that CRAs should put more emphasis on the accuracy of ratings.

vailing effects: the expected quality in the eyes of buyers increases, while the precision of information goes down. For a low value of information precision, the first effect dominates, and full pooling is optimal for the CRA. As the value of precision increases, the trade-off between the two effects defines the boundary of the lowest rating. The model results in multiple equilibrium disclosure policies for rated sellers of higher quality. However, in all equilibria, the payoff of rated sellers is non-decreasing in quality. Also, as the value of information precision goes to infinity, the optimal disclosure of a monopoly CRA converges to full disclosure. Hence, the CRA's incentives to provide information cannot be fully attributed to a competitive market structure.

Our second result is that the optimal disclosure policy of a CRA implies partial market coverage. The reason is that the presence of unrated companies widens the gap between the prices rated and unrated sellers receive on their products or securities. As a result, this permits the CRA to charge a higher fee.

The next two results are related to the optimal entry strategy of a new CRA to a market previously served by the incumbent. Our third result deals with the demand for entrant's ratings. For each incumbent's rating grade, sellers of higher-than-average quality are disadvantaged by pooling. We show that an optimal entry strategy for a new CRA is to target these sellers. Hence, the number of ratings each seller obtains depends on its position relative to other sellers in the rating interval of the incumbent. As a result, there is no congruency between the demand for the entrant's rating and the quality of the seller. High and low quality sellers can be rated by both agencies, while the intermediate quality seller obtains only one rating.

The final result is that the entrant will design a more stringent rating scale relative to that of the incumbent. A seller will purchase a second rating from the entrant only if this enables it to increase the price charged to buyers. This occurs when the entrant's rating increases the seller's expected quality by pooling it with better quality types or improves information precision by reducing the diversity of the pool. In both cases, an entrant will require that higher standards be met in order to provide a similar rating to that of the

incumbent. It also follows from our model that sellers are more likely to demand a second rating in markets where precision is of greater value.

We test our predictions on the entry strategy of a new CRA using data on the U.S. property-liability insurance market. The insurance industry provides an ideal natural experiment to study entry for two reasons. First, unlike the market for bond ratings, there are no regulatory barriers to entering the market for insurance ratings. Second, until recently, the market for insurance ratings has largely been dominated by a single monopoly agency—the A.M. Best Company. S&P made its initial foray into the insurance ratings market in the late 1980s and dramatically increased the number of ratings it provided to insurers during the 1990s.<sup>5</sup>

Insurance ratings measure an insurer’s financial strength and ability to meet its ongoing insurance policy and contract obligations. Prior research has shown that ratings in this market matter. For example, Epermanis and Harrington (2006) provide evidence that insurance buyers are sensitive to insurers’ ratings with lower rated insurers receiving lower prices for their policies in the marketplace.<sup>6</sup> Since policy liabilities are the primary source of capital for insurers, lower prices imply higher costs of capital. Also the importance of a rating for an insurer depends on the type of buyer. Corporate insurance buyers usually require that insurers are highly rated as their insurance policies are very detailed and tailored to a given company’s profile. These policies are mostly sold through insurance agents and brokers who often will not recommend an insurer with an A.M. Best rating below A- (e.g., see Bradford 2003). Personal automobile insurance and homeowners insurance, on the other hand, are protected by state-guarantee funds and sold to less sophisticated customers. As a result, prices and demand are less sensitive to an insurer’s financial strength.

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<sup>5</sup>For example, in 1992, S&P issued full rating opinions on only 25 property-casualty insurers, and this number increased to over 250 insurers by the end of the decade. By 2000, S&P was the second largest insurance rating agency and now rates over 800 companies, representing more than 45 percent of the industry’s assets.

<sup>6</sup>Epermanis and Harrington (2006) report that the rating downgrade of a property-liability insurer rated A or higher by A.M. Best results in an estimated abnormal premium growth of about -5 percent; for A- rated insurers, the estimated impact of a downgrade is -12 percent.

We employ two methodologies to examine the entry strategies of new CRA. First, we use a hazard model to estimate a one-year probability of insolvency using publicly available data for all U.S. property-liability insurers. We show that S&P applied higher standards compared to A.M. Best for an insurer to achieve a similar rating.

Comparing the probabilities of default for insurers that receive a rating from A.M. Best and S&P ignores the possibility that firms can decide strategically whether to request a second rating from the entrant. This strategic behavior potentially biases our results. To address this concern, our second empirical test is designed to investigate the differences in rating opinions between the incumbent and the entrant using the Heckman-style sample selection methodology (Heckman 1979). It allows us to correct for the strategic decision-making of firms and to decompose the sources of rating differences into two components: standards differences between the two agencies, and the insurer’s financial quality. We find that higher-than-average quality insurers in each rating category chose to receive a second rating from S&P and that S&P required higher standards for an insurer to achieve a similar rating. Both results are consistent with our theory.

The plan of the paper is as follows. The next section discusses related literature. Section 2 presents the model and examines the disclosure policy of the monopoly. Section 3 analyzes which market segments are profitable for an entrant. We discuss the institutional details of insurance ratings and describe the data in Section 4. Our empirical analysis is presented in Section 5, and the conclusion follows. All proofs and tables are provided in the Appendix.

## 1 Related Literature

This paper belongs to the growing literature on the incentives of information intermediaries to manipulate information disclosed to interested parties. Since Akerlof’s (1970) “lemons markets” paper, it has been recognized that information intermediaries may play

a crucial role for markets under adverse selection (see Biglaiser 1993).<sup>7</sup> Boot, Milbourn and Schmeits (2006) show that intermediaries can help to coordinate on a desired equilibrium. 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, incentive problems may reduce the precision of information disclosed to the market.

The theory we develop in this paper builds on Lizzeri (1999) who studied the optimal disclosure policies of an intermediary capable of perfectly ascertaining the quality of the seller and communicating it to the buyer. Lizzeri derives a unique equilibrium in which all sellers pay a positive fee for an uninformative rating. The logic of this result is as follows: the profit of a CRA is a product of market coverage and a uniform rating fee. The fee cannot exceed the willingness to pay of the lowest quality rated seller. By pooling this seller with better quality sellers into one rating, a CRA can charge a higher fee without reducing demand for its services.

Risk neutrality is essential for this result. It implies that the buyer is ready to pay the same price regardless of whether the quality is known for sure or is uncertain. In other words, the buyer does not value the precision of information disclosed by the intermediary. We change this assumption and assume that buyers care about the quality of information contained in the rating. In this respect, our analysis is related to the literature on information quality and ambiguity aversion (Veronesi 2000; Epstein and Schneider 2008).

There are other explanations of why an information intermediary might manipulate information. Manipulation can occur due to collusion between the intermediary and the seller; for example, Strausz (2005) shows that the threat of collusion makes honest certification a natural monopoly. Peyrache and Quesada (2005) argue that mandatory certification makes intermediaries more prone to collusion by increasing the participation

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<sup>7</sup>Grossman and Hart (1980), Grossman (1981) and Milgrom (1981) analyzed direct communication between the buyer and the seller. In their framework, a seller can disclose any information, but must include the true type in its report. Then, the conjecture of the buyer is that the true type is the most pessimistic element of the report, and full disclosure obtains. The key distinction of our approach is that a rating agency provides information about multiple sellers. It permits clustering different sellers into one rating class, and the unraveling need not happen.

of low quality sellers. Mathis, McAndrews and Rochet (2009) show that reputation is sufficient to discipline CRAs only when a large fraction of their incomes come from rating simple assets. Benabou and Laroque (1992) analyze the incentives of an intermediary to manipulate information when the intermediary also acts as a speculator on the market.

When intermediaries compete for clients and are not certain about their ability as experts, reputation concerns can lead to the misreporting of information. Scharfstein and Stein (1990) and Ottaviani and Sorensen (2006a, 2006b, 2006c) study the impact of reputation concerns on the reports of analysts. These papers consider cheap-talk models (Crawford and Sobel 1982) 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) applies the cheap talk model in the context of rating agencies.

The complexity of information and participation of naive buyers can lead to biases in information reporting. Skreta and Veldkamp (2008) study how the higher complexity of rated assets affects incentives for ratings shopping. They show that the ability of sellers to compare ratings from different CRAs before the ratings are disclosed to the market leads to ratings shopping and ultimately inflates ratings. Bolton, Freixas and Shapiro (2008) show that a CRA may overstate the seller's quality when there are more naive investors. Pagano and Volpin (2008) argue that the issuers of structured bonds (sellers) prefer coarse and opaque ratings to expand demand from sophisticated investors (buyers).

In spite the fact that most information intermediaries function in oligopolistic markets, there is little research on the impact of competition on the disclosure of information.<sup>8</sup> Lizzeri shows that competition leads to full disclosure and zero fees for certification. In this paper, we study the impact of entry into a previously monopolistic market for ratings.

Limited empirical literature exists that investigates the impact of competition in the

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<sup>8</sup>A few exceptions include Lerner and Tirole (2006) who study competition in standard settings; Farhi, Lerner and Tirole (2008) analyze the interaction between ratings shopping behavior and the transparency of certification; Morrison and White (2005) study banks' decisions to apply to regulators with different perceived abilities.

market for credit ratings. Closest to our own paper is that of Becker and Milbourn (2009) who analyze changes in the informativeness of corporate bond ratings as the presence of a third credit rating agency, Fitch, grew in a market previously dominated by Moody’s and S&P. Contrary to our work, the authors concluded that the greater presence of the new entrant led to a decrease in the overall informativeness of ratings. Kisgen and Strahan (2009) investigated another form of entry when the SEC assigned NRSRO status to a fourth credit rating agency in the mid 1990s. The authors showed that the SEC’s certification of the Dominion Bond Rating Service led to a statistically significant reduction in the cost of debt capital for the firms already rated by Dominion prior to its certification. The authors suggests that their results are driven not by an increase in the information available to market participants, but instead because there was an increase in demand for the debt issued by firms that received a bond rating from Dominion following the agency’s certification by the SEC.

## 2 Ratings of a Monopoly Credit Rating Agency

### 2.1 Model

A CRA provides services that can lower the information asymmetry between buyers and sellers. Sellers have private information about their quality,  $v$ . The CRA and buyers share a common prior about the quality of a seller. For simplicity, we assume that  $v$  is distributed uniformly on  $[0, 1]$  with a higher  $v$  indicating a higher quality.

A seller cannot credibly communicate its quality to buyers. A rating agency offers an evaluation service for a fee  $t$  and can perfectly observe the type  $v$  of a seller<sup>9</sup>. The fee is flat for all sellers purchasing a rating<sup>10</sup>, and a CRA cannot screen sellers by demanding a higher fee for a more favorable rating.<sup>11</sup>

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<sup>9</sup>Our results are robust to the specification where the rating agency observes the seller’s type with some noise. Since noisy signals do not affect the logic of the results, we focus on the case of perfect signals in the paper. Further results are available from the authors.

<sup>10</sup>In practice, CRA fees depend on the type of provided service, but do not depend on the assigned rating (Cantor and Parker 1994).

<sup>11</sup>A rated seller does not value an option to withhold its rating. Faure-Grimaud, Peyrache and Quesada

Having evaluated a seller, a CRA strategically communicates its results. The disclosure policy of the agency defines how rated sellers' quality types are communicated to buyers. For example, under full disclosure, a CRA 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.

There is a unit mass of identical buyers. A buyer purchases at most one unit of a good from one seller. The buyer's willingness to pay for the good depends on the expected quality and the precision of information about quality<sup>12</sup>. Precision is measured by the variance of quality conditional on the information available to buyers. For example, under full disclosure, the variance of quality of a rated seller is zero, and the precision is the highest. To model demand for precision, we assume that buyers have mean-variance preferences. Given information  $I$  available to buyers, the valuation of a good is equal to

$$u(I) \equiv E[v|I] - a\text{Var}[v|I],$$

where  $E[v|I]$  is the expected quality, and  $\text{Var}[v|I]$  is the variance of quality.  $a > 0$  measures the marginal value of information precision to buyers. Buyers are price takers, and  $u(I)$  is the price paid for the good. Under the prior distribution, the buyers' valuation is equal to

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

If the marginal 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 the functioning of the market. When  $a > 6$ , a buyer does not purchase a good unless he or she has some additional information about a seller. When  $a = 0$ , this model is equivalent to Lizzeri.

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(forthcoming) 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 they will not apply for a rating unless it increases their reservation price.

<sup>12</sup>The value of more accurate signals has been extensively analyzed in connection with earnings management. For example, earnings smoothing can increase the informativeness by enhancing the signal/noise ratio. Moreover, more informative earnings can command a stock price premium. See for example, Hunt, Moyer and Shelvin (2000) and Tucker and Zarowin (2006).

Obtaining ratings is voluntary to sellers. The decision to be rated is based on the cost of the rating and its effect on a buyer's valuation. The information impact of a rating depends on the disclosure rule employed by the agency and on the set of rated types. The expected payoff to a seller of type  $v$  depends upon a buyer's valuation and is equal to

$$\begin{aligned} &u_R(v) - t \text{ if it is rated, and} \\ &u_N(v) \text{ if it is not rated,} \end{aligned}$$

where  $u_R(v)$  and  $u_N(v)$  are the expected payoffs of type  $v$  with and without a rating, respectively. Denote  $\delta$  the mass of sellers demanding a rating. Then the payoff of the rating agency is equal to

$$V = \delta t.$$

The game consists of three stages.

- I. Sellers learn their types. A rating agency designs its disclosure policy and sets a fee.
- II. Sellers observe the disclosure policy of the rating agency and the fee. They decide whether to purchase a rating. The participating sellers are evaluated, and the results are disclosed to buyers according to the disclosure policy of the CRA.
- III. The buyers observe the disclosure policy and the rating if the seller is rated. They decide whether to purchase the credit sensitive product. Sellers receive a payoff, which depends on the rating status.

We study sequential equilibria of the game. The strategies of all players must be optimal at every stage of the game given the beliefs about other players' information. Beliefs must be consistent with the Bayes rule whenever possible.

## 2.2 Full Disclosure and the Benefits of Information Pooling

An analysis of full disclosure would be useful highlighting the CRA's benefits from pooling information. Under full disclosure, a rating is a perfect signal to buyers about a seller's type. If a seller  $\hat{v} \in [0, 1)$  decides to purchase a rating, better sellers  $v > \hat{v}$  do the same

because their payoff when rated is increasing in quality. Then, nonrated sellers must have a quality below  $\widehat{v}$ . Also, if a seller  $\widehat{v}$  is not rated, a rating does not benefit the sellers with a lower quality  $v < \widehat{v}$ . This intuition implies that, given a fee for ratings, there is a seller type indifferent between purchasing a rating or operating without a rating.<sup>13</sup> The demand for ratings comes from higher seller types. The optimal fee for the rating agency and the resulting coverage of the market are derived from the trade-off between the marginal benefit of charging a higher fee and the marginal cost of the reduced demand for ratings.

**Proposition 1** *Suppose that a monopoly rating agency commits to full disclosure, and the fee for the rating services is less than  $\frac{1}{2} + \frac{1}{12}a$ . 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.*

Is full disclosure optimal for the CRA? Suppose that, instead of reporting the type  $v_F$ , the rating agency announces that this type is from an interval  $[v_F, v_F + \Delta]$ ,  $\Delta > 0$ . Thus,  $v_F$  is pooled with better types, and the rating agency may be able to charge a higher fee without reducing the demand for ratings. This occurs when the valuation of pooled types is higher than the valuation of the lowest rated type; that is,

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

If the marginal value of information is zero,  $a = 0$ , Lizzeri's result holds: all types should be pooled and assigned the same rating grade. When the precision of information matters,  $a > 0$ , pooling imposes a cost in lost precision,  $\frac{1}{12}a\Delta^2$ . This intuition suggests that the optimal disclosure policy trades off the benefits of pooling due to higher fees with the cost of pooling due to reduced precision.

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<sup>13</sup>For this to hold, the fee should not exceed the gain of a rating to the highest type  $v = 1$  when it is the only rated type,  $1 - (\frac{1}{2} - \frac{1}{12}a) = \frac{1}{2} + \frac{1}{12}a$ .

## 2.3 Optimal Disclosure

We now analyze the profit maximizing disclosure policy of a monopoly rating agency. The CRA may fully disclose the seller's type, or it may pool a seller with other sellers and disclose that it belongs to a particular group. Formally, a disclosure policy is a correspondence  $s : [0, 1] \rightarrow [0, 1]$ . The expected quality  $\mu(s(v))$  and the variance  $\sigma^2(s(v))$  of type  $v$  rated  $s(v)$  depend on the set of types that obtain the same rating,

$$\begin{aligned}\mu(s(v)) &= E[v' : s(v') = s(v)], \\ \sigma^2(s(v)) &= \text{Var}[v' : s(v') = s(v)],\end{aligned}$$

which results in buyers' valuations of seller type  $v$  equal to

$$u(s(v)) = \mu(s(v)) - a\sigma^2(s(v)).$$

Denote  $V_R(s)$  the set of rated seller types,  $V_R(s) \subset [0, 1]$ , and  $V_N(s)$  the set of nonrated types,  $V_N(s) = [0, 1] \setminus V_R(s)$ . Sellers purchase a rating only if it has a positive return,

$$u(s(v)) - t \geq \max\{u(V_N(s)), 0\} \text{ for all } v \in V_R(s). \quad (1)$$

The right-hand side of the inequality reflects that a nonrated seller trades only if its valuation without a rating is positive. Given any distribution of types  $F(v)$ , a disclosure policy  $s(\cdot)$  generates demand

$$\delta(s) = \int_{V_R(s)} dF(v).$$

A strategy of the rating agency is a disclosure policy  $s(\cdot)$  and a fee for the rating  $t$ . A strategy of each seller type is the decision to be rated. We restrict attention to pure strategies and study sequential equilibria of this game. In equilibrium, the following two conditions must be met. First, the disclosure policy is optimal for the rating agency,

$$(s(\cdot), t) \in \arg \max_{\tilde{s}, \tilde{t}} \delta(\tilde{s})\tilde{t}.$$

Second, the decision to obtain a rating is optimal for a seller. That is, for any  $(s(\cdot), t)$  and strategies of sellers  $[0, 1] \setminus v$ , seller type  $v$  is rated if and only if (1) holds for this seller.

To analyze the optimal disclosure policy, we proceed in two steps. In the next proposition, we describe the structure of an optimal disclosure policy for any distribution of types  $F(v)$ . Then, in Proposition 3, we apply this result to solve for the policy in the context of our model where  $F(v)$  is uniform. Also we provide the results how the optimal disclosure depends on the marginal value of information  $a$ .

**Proposition 2** *An optimal disclosure policy of a monopoly rating agency has the following structure. There is a type  $v_M \in [0, 1]$  such that all types  $v \geq v_M$  are rated, and no type  $v < v_M$  is rated. Types  $[v_M, v_M + b_M]$ ,  $b_M \geq 0$  and  $v_M + b_M \leq 1$  are assigned the same rating. The fee charged for the rating is equal to the value of the rating of the lowest rated type,  $t_M = u([v_M, v_M + b_M]) - \max\{u([0, v_M]), 0\}$ .*

An optimal disclosure policy is similar to the discrete system of ratings employed by the major rating agencies. Under this system, a CRA partitions the set of realization of  $v$  in subintervals and discloses that its estimate of quality belongs to a subinterval.

The rating agency faces demand  $\delta_M = 1 - v_M$  and earns profits

$$(1 - v_M)t_M$$

Denote  $u(N)$  and  $u(L)$  the valuation of nonrated types  $N = [0, v_M]$  and the lowest rated types  $L = [v_M, v_M + b_M]$ , respectively. Then,

$$u(L) = v_M + \frac{1}{2}b_M - \frac{1}{12}ab_M^2, \quad (2)$$

$$u(N) = \max\left(\frac{1}{2}v_M - \frac{1}{12}av_M^2, 0\right),$$

$$t_M = u(L) - \max\{u(N), 0\}. \quad (3)$$

If a seller cannot trade without a rating,  $u(N) < 0$ , the fee is equal to the valuation of types in the lowest grade  $L$ . When  $u_N > 0$ , a CRA charges the difference between the valuations of the lowest grade sellers and nonrated sellers,  $u(L) - u(N)$ .

In equilibrium, nonrated sellers  $N$  must be better off without a rating. If a seller  $v \in N$  deviates and purchases a rating, the rating agency announces that the seller's quality is

from the interval  $N$ . Then, the deviation is not profitable and purchasing a rating cannot increase the reservation price charged by these sellers.

An optimal disclosure policy of the rating agency solves

$$\max_{(v_M, b_M)} (1 - v_M)(u(L) - \max\{u(N), 0\}).$$

In the next proposition, we summarize the solution to this problem.

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

$a$	$v_M$	$b_M$	$t_M$	$\pi_M$	$\max\{u_N, 0\}$
$0 \leq a \leq 2$	0	1	$\frac{1}{2} - \frac{1}{12}a$	$\frac{1}{2} - \frac{1}{12}a$	0
$2 \leq a \leq 6$	$\frac{3}{4} - \frac{3}{2a}$	$\frac{1}{4} + \frac{3}{2a}$	$\frac{1}{4} + \frac{1}{24}a$	$\frac{(a+6)^2}{96a}$	$\frac{3(10-a)(a-2)}{64a}$
$6 \leq a \leq \frac{21}{2}$	$\frac{2}{3} - \frac{1}{a}$	$\frac{3}{a}$	$\frac{(a+3)^2}{27a}$	$\frac{(a+3)^3}{81a^2}$	$\frac{(2a-3)(21-2a)}{108a}$
$\frac{21}{2} \leq a \leq \frac{51}{4}$	$\frac{6}{a}$	$\frac{3}{a}$	$\frac{27}{4a}$	$\frac{27(a-6)}{4a^2}$	0
$a \geq \frac{51}{4}$	$\frac{1}{2} - \frac{3}{8a}$	$\frac{3}{a}$	$\frac{3}{8a} + \frac{1}{2}$	$\frac{(4a+3)^2}{64a^2}$	0

When the marginal value of information is relatively low,  $a \leq 2$ , all seller types are rated and pooled in the same rating grade. As the value of information increases, the rating becomes more precise, that is, the mass of pooled types  $b_M$  decreases. The market coverage decreases in  $a$  when  $u(N) > 0$ , increases when  $u(N) = 0$  and decreases when  $u(N) < 0$ . The profit of the rating agency is non-monotone in the value of information  $a$ . It decreases when  $u(N) > 0$ , increases when  $u(N) = 0$  and decreases when  $u(N) < 0$ . Profit is the highest when the value of information is the lowest,  $a = 0$ . As  $a \rightarrow +\infty$ , the profit converges to  $\frac{1}{4}$ .

What is the mass of types pooled in the lowest rating? From (2), pooling  $db_M$  sellers in one rating increases the expected quality of  $u(L)$  by  $\frac{1}{2}db_M$  and reduces the precision of the rating by  $(-\frac{1}{6}ab_M)db_M$ . For low values of  $a$ , the increase in expected quality from pooling outweighs the precision cost and that leads to extensive pooling. For higher values of  $a$ , the interior solution obtained when the marginal increase in expected quality is equal to the marginal cost of reduced precision resulting in  $b_M = \frac{3}{a}$ . As the value of precision increases, the mass of types pooled in the lowest rating goes to zero.

The marginal value of information entails five disclosure policy regimes. When  $a$  is low,  $0 \leq a \leq 2$ , the optimal disclosure policy of the rating agency is to pool all sellers in the same rating grade. It shows that Lizzeri’s “no disclosure” result is more general. It also holds when buyers have a relatively low value for the information precision of the rating.

For moderate information values,  $2 \leq a \leq 6$ , a monopoly rating agency has partial coverage of the market,  $v_M > 0$ , but all rated sellers are still pooled in a single rating grade. This regime resembles a minimum standard setting. Reducing the coverage of the market is beneficial for the rating agency because it widens the difference between the valuation of rated and nonrated sellers, and allows the CRA to charge a higher fee for the rating. At the same time, the value of precision is too low to expand the number of rating categories, so all rated sellers are pooled in order to increase the expected quality of the lowest rated type.

As the value of information increases,  $a \geq 6$ , providing precision becomes more valuable than increasing expected quality by pooling. The distinction between the last three regimes for  $a \geq 6$  is the ability of nonrated sellers to trade. Higher demands for precision imply that rating becomes essential for trade, and the agency expands its coverage of the market for  $\frac{21}{2} \leq a \leq \frac{51}{4}$ . However, when the payoff of nonrated sellers is negative,  $u(N) < 0$ , precision becomes secondary to improving the pool of rated companies. Coverage is increasing for  $a \geq \frac{51}{4}$ .

The profit of the rating agency is non-monotone in the value of information. For relatively low values, the CRA can benefit from its unique ability to screen sellers and selectively disclose the results. However, as the value of information increases, the optimal rating system requires finer information disclosure, and the CRA cannot increase the fee by pooling types in one rating.

Figure 1 shows the boundaries for rating  $L$  as a function of  $a$ . Types located below the lower curve are not rated. Types located between the lower and the upper curves are pooled in the lowest rating grade  $L$ . As with full disclosure, the coverage of the market is

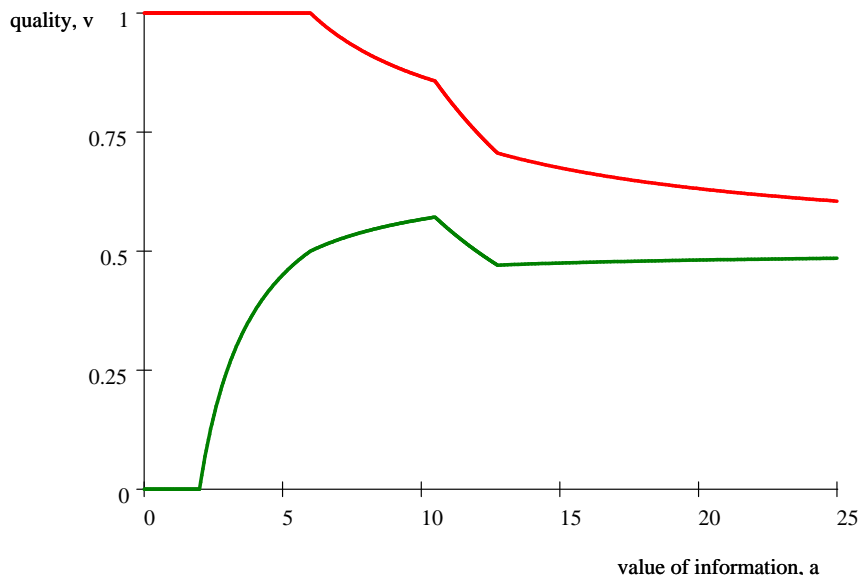


Figure 1: Optimal Rating Scale of a Monopoly CRA

non-monotone in  $a$  and depends on the ability of nonrated companies to trade. Coverage is decreasing in  $a$  for low information values because the rating agency has an incentive to widen the gap between the valuations of rated and nonrated sellers.

The optimal disclosure policy of the monopolist admits multiple equilibrium rating scales for types  $[v_M + b_M, 1]$ . As long as these sellers are willing to purchase a rating, the CRA is indifferent among all disclosure policies. We focus on one equilibrium type, that is, an interval disclosure that is employed by the majority of credit rating agencies. In the next proposition, we derive a necessary condition for an interval disclosure policy to be an equilibrium, and we show how the size of a rating interval changes with the marginal value of information.

**Proposition 4** *Any system of intervals  $(R_1, \dots, R_N)$ ,  $N \leq +\infty$  that satisfies  $b_{k+1} \leq b_k + \frac{6}{a}$  is consistent with the optimal disclosure policy. As the value of precision increases, the mass of types pooled in the same rating interval decreases.*

Interval disclosure policies are not equivalent from the seller's perspective. In each

pooling interval, the types at the bottom of the interval benefit from pooling at a cost of types on the top of an interval. It is immediate to show the following.

**Proposition 5** *In each pooling interval, the mass of types that prefer full disclosure is greater than the mass of types that prefer pooling, and the difference is increasing in the value of precision  $a$ .*

This result implies that the number of rated sellers that are willing to pay a positive price for a second rating that improves the precision of the signal about their quality is increasing in the value of precision to buyers. In the next section, we study entry under the assumption that the incumbent CRA uses interval disclosure. Our motivation is twofold. First, we show that there is an equilibrium that is consistent with industry practice. Second, we show that interval disclosure allows entry in multiple segments of the market. Indeed, if there are segments of the market where the incumbent makes sellers' types perfectly known to the buyers, a new rating agency receives no benefit from entering these segments.<sup>14</sup>

### 3 Entry of a New Credit Rating Agency

We analyze the entry strategy of a new agency on the following time line. After the ratings have been purchased from the incumbent, but before the transactions between buyers and sellers, a new agency offers an additional rating for a fee. If a new rating agency attracts any sellers, these are rated by the entrant. Then, buyers form their valuations based on all available sellers' ratings (i.e., from the incumbent and the entrant) and trade takes place.

The main focus of this section is the transition from a monopolistic to a duopolistic structure. Our objective is to find which segments of the market served by the incumbent CRA can be attractive for the entrant. In this setup, the incumbent does not adjust its

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<sup>14</sup>Note that if a rating agency's evaluation technology is imperfect, entry can be beneficial even in the case of full disclosure.

disclosure policy. Although understanding the long-term impact of competition is impossible without accounting for the incumbent's reaction to entry, our approach provides a clear intuition about the entry strategy of a new CRA<sup>15</sup>.

A seller will pay for an additional rating only if it increases its value in the eyes of the buyers. This occurs when the second rating allows the seller to signal that it has higher quality and/or when it improves the precision of information. If a seller is rated by the incumbent and the entrant, it must be that two ratings are better than one,

$$u(R_m, R_e; v) - t_m - t_e \geq u(R_m; v) - t_m,$$

where  $u(R_m, R_e; v)$  and  $u(R_m; v)$  are the payoffs of seller  $v$  when rated by both agencies and when rated only by the incumbent, respectively, and  $t_m$  and  $t_e$  are the fees of the two CRAs. If a seller is rated only by the entrant, then

$$u(R_e; v) - t_e \geq \max\{u(V_N), 0\}.$$

In the next proposition we characterize the demand for the entrant's ratings.

**Proposition 6** *Suppose that the incumbent CRA employs an interval disclosure rating system. The demand for ratings of the entrant comes from the sellers at the top of each rating interval of the incumbent. The interval disclosure rating system of the entrant is such that the average quality of a seller with an  $n$ th highest rating of the entrant is higher than that of a seller with the  $n$ th highest rating of the incumbent. The second rating increases the precision of information about the seller.*

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<sup>15</sup>The incumbent's reaction to entry is beyond the scope of the current paper. The main reason we do not address it here is that the incumbent's reaction cannot be analyzed without recognizing the repeated and long-term interaction between multiple credit rating agencies. Indeed, the equilibrium of the simultaneous one-shot game is fragile to the presence of entry: Lizzeri's analysis suggests that there is full disclosure in the market with multiple credit rating agencies. Building a model that is suitable for understanding how a new rating agency establishes a market presence in the environment where reputation is a big barrier to entry is left for further research. Reputation is not an issue in the application we analyze in the paper because S&P was a well-established agency in the ratings market before it started to rate insurers. At the same time, identifying the segments of the market where the entry has occurred is an interesting question that we focus on in this section.

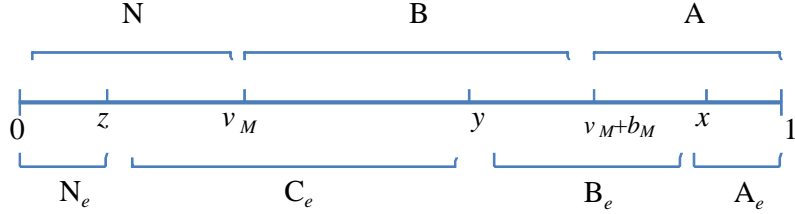


Figure 2: Demand for entrant's ratings

The first result implies that the decision to obtain a second rating need not be congruent with the quality of a seller. Higher-than-average sellers in each rating category of the incumbent CRA are the ones who can benefit from obtaining a second rating. The second result is that the rating scale of the entrant must be more stringent in the sense that a seller needs to meet higher standards to obtain a comparable rating. The intuition for this result is illustrated in Figure 2. In the figure, sellers  $v \in [v_M, 1]$  are rated by the incumbent, while sellers  $v \in [0, v_M]$  are not rated. The rating scale of the incumbent consists of two ratings,  $A$  and  $B$ . Lower quality sellers located in the interval  $N$  are not rated. In this example, there are three potential entry segments, each of which is located on the top of intervals  $A$ ,  $B$  and  $N$ . It implies that a rating scale of the entrant consists of intervals  $A_e = [x, 1]$ ,  $B_e = [y, v_M + b_M]$  and  $C_e = [z, v_M]$ . The relationship between the two scales is such that  $A_e \subset A$  and  $B_e \subset A \cup B$ . Hence, the average quality of sellers in each of these intervals is higher than the average quality under the incumbent's rating scale. As for the precision of the entrant's ratings, it is determined by the width of the rating interval. Interestingly, though the precision is always higher for the best entrant's rating  $A_e$ , it may be higher or lower for the entrant's lower ratings  $B_e$  and  $C_e$ . However, the ultimate precision of information about sellers with two ratings is always higher than the precision with a single rating prior to entry.

The mass of types that are disadvantaged by pooling is increasing in the marginal value of information (Proposition 5), so does the mass of potential entry segments for a new CRA. It implies that the entry is more profitable in certification markets where the

value of information is high.

The exact boundaries  $(x, y, z)$  of the entrant's rating scale depends on the rating scale of the incumbent and on the marginal value of information to sellers. The entrant can target multiple groups, including unrated sellers. An optimal entry strategy is a trade-off between the fee the entrant can charge and its coverage of the market. The highest quality rated sellers are willing to pay the highest price to refine the information about their quality. However, charging high fees to this group reduces the demand from other sellers.

Proposition 6 does not rest on any distributional assumption over seller types. The particular incumbent rating categories in which the entrant chooses to enter depends on how the incumbent formed its rating categories in the first place. The size, number and thresholds of rating categories depend on the distributional assumption and the value of information  $a$ . For example, when the market coverage of the incumbent is low, rating nonrated companies may provide the highest value to the entrant. However, when the incumbent has substantial market coverage, but pools rated companies in wide rate grades, the entrant's profitable strategy is to offer the second rating to disadvantaged rated companies<sup>16</sup>.

## 4 Institutional Setting and Data

In the remainder of the paper, we test the primary predictions of our theoretical model using the data on ratings of property-casualty insurance companies in the US. Proposition 6 implies that (i) the entrant CRA will have higher standards, on average, in order for a firm to receive a rating similar to the one received from the incumbent CRA; and (ii) the entrant CRA will obtain the greatest demand for its services from higher-than-average quality insurers within a rating class of the incumbent CRA. Proposition 5 means that

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<sup>16</sup>We can gain further insight into the qualitative nature of the entry strategy by following a particular case. In the supplementary material available from the authors we examine the entrant's strategy when the incumbent assigns at most two ratings.

(iii) 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. We take advantage of a natural experiment, which began in the late 1980's and continued through the 1990's, when the well-known bond rating agency S&P entered the market for insurance ratings.<sup>17</sup>

In this section, we present the institutional setting for our tests and describe our data sources. We then discuss our empirical tests and results from univariate comparisons of the stringency standards employed by S&P and A.M. Best. We conclude the empirical section by presenting an econometric analysis of the differences in the ratings assigned to insurers that opted to request a rating from both agencies.

## 4.1 Insurance Ratings and Standard & Poor's Entry

Before the end of 1980s, the market for insurance ratings was largely dominated by the A.M. Best Company. Incorporated in 1899, A.M. Best publishes "financial strength ratings" for the majority of U.S. insurers, and, for most of its history, it was the only agency doing so. A.M. Best's monopoly position began to erode after it was criticized following the liability insurance crisis of the mid-1980s and several natural catastrophes in the early 1990s bankrupted numerous insurers.<sup>18</sup> The most aggressive agency to enter the market

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<sup>17</sup>Although our theoretical results could be useful to analyze entry into the bond rating industry, none of new NRSROs has obtained a significant market share to perform the tests. As noted by White (2002): "A striking fact about the structure of the industry in the U.S. is its persistent fewness of incumbents. There have never been more than five general-purpose bond rating firms; currently there are only three. Network effects—users' desires for consistency of rating categories across issuers—are surely part of the explanation. But for the past 25 years, regulatory restrictions (by the Securities and Exchange Commission) on who can be a "nationally recognized statistical rating organization" (NRSRO) have surely also played a role." Becker and Milbourn (2009) argue the significant growth of Fitch Ratings during the 1990s through 2006 can be thought of an increasing competition in the market for corporate debt ratings and they conduct an analysis that attempts to document the effects thereof. The market for insurance company ratings differs quite substantially as Fitch Ratings, albeit a company with small market share at the beginning of the 1990s, had been providing rating opinions on corporate debt since the early 1900s. S&P's decision to begin offering insurance ratings truly represented a new entrant and thus is a more direct test of our model.

<sup>18</sup>Winter (1991) provides an overview of the crisis in U.S. liability insurance markets that occurred between 1984–1986. Lewis and Murdock (1996) describe the state of the U.S. property insurance markets following several large natural disasters that occurred in the early 1990's including Hurricanes Andrew

was S&P who entered in three phases.<sup>19</sup> As shown in Table 1 and graphically in Figure T1, S&P's initial entry occurred in the late 1980's when it announced it would publish "claims paying ability" ratings on property-liability insurers using methods similar to those employed by A.M. Best and also similar to the methodology it used to issue ratings on corporate debt. Both A.M. Best and S&P combine publicly available information and proprietary information from interviews with the management of the insurers to determine their ratings. In addition, and consistent with our theoretical model, A.M. Best and S&P both require that a company must request a rating and pay a fee to initiate the rating process.

Table 2 displays the number of property-liability insurers operating in the United States, the number of firms rated by A.M. Best Company, and the number of firms that requested a rating from S&P 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 S&P. The numbers in parentheses show the percentage of firms (or assets) of the industry receiving a rating from either firm.

Phase two of S&P's entry began in 1991 when it introduced its "qualified solvency rating" service to complement its traditional ratings. Qualified ratings were unsolicited ratings based upon publicly available data. An important feature of the service was that no insurer could receive above BBB rating. As a result, qualified ratings did not provide much new information to insurance buyers about individual companies. However, they advertised new ratings of S&P to the insurance industry that used to view A.M. Best as a sole ratings supplier for about a century.

The final phase of S&P's entry occurred in late 1994 when S&P decided to relax the rule that said insurers could not receive a qualified rating above BBB. As shown in Figure T1, this decision led to an increase in the demand for its services over the next couple of

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(in Florida) and Iniki (in Hawaii) in 1992 and the Northridge Earthquake in California in 1994.

<sup>19</sup>The three phases have been documented in the financial press. See PR Newswire, 27 August 1987, "S&P launches insurance rating service"; Risk Management, June 1991, "S&P launches service to rate solvency"; National Underwriter, 25 September 1995, "S&P expanding P-C range."

years. By the end of the 1990s, S&P provided full rating opinions to about 30–50 percent of insurers measured by the asset size.<sup>20</sup>

In the empirical analysis we focus on solicited ratings. An implicit assumption of the model is that insurance buyers could immediately appreciate the value of S&P ratings. However, we include time controls and provide evidence on how demand for entrants rating changed through the 1990’s. We explore the advertising role of unsolicited ratings in a separate paper.<sup>21</sup>

The key feature of the entry strategy discussed in Section 3 is that the entrant offers ratings to companies that have already decided whether to be rated by the incumbent CRA. Consistent with the model assumption, almost all insurers in the sample obtained S&P rating as their second rating. The average percentage of firm-year observations where the insurer had an S&P rating and no Best rating in the prior year and then had both an S&P and Best rating in the current year represents only 0.14% of our sample. At the same time, the percentage of firms that requested a new rating from S&P that already had an existing AM Best rating is 83%.

## 4.2 Data

We gathered two sets of data: the first documents the financial quality, business strategy and organizational characteristics of U.S. insurance companies, while the second data set reports the financial strength/claims paying ability ratings assigned to insurance companies by A.M. Best and S&P. Information on insurers’ financial quality and other relevant characteristics comes from the annual regulatory statements of all property-liability insurers maintained in electronic form by the National Association of Insurance Commissioners

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<sup>20</sup>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 its ratings is fundamentally different than the process used by Best and S&P. We consider S&P to be the more influential new entrant into the market for property-liability insurance ratings given its established reputation in the bond rating market.

<sup>21</sup>See Doherty, Kartasheva, Phillips (2010). We show that the assignment of a low unsolicited rating by the entrant increases the uncertainty about the quality of the seller and decreases its expected quality. This creates demand for firms with unsolicited ratings to receive a full rating which will be more informative of quality.

(NAIC). We include all firms that meet our data requirements (discussed below). The ratings information for A.M. Best comes from Best’s annual *Key Ratings Guide* (various years). We obtained the S&P ratings directly from S&P via a custom data order. Our data spans the years of S&P’s entry into this market—1989–2000.

## 5 Econometric Analysis and Results

### 5.1 Comparing Rating Stringency

*Empirical strategy.* In our first set of tests, we compare the stringency of the ratings assigned by the incumbent firm (A.M. Best) relative to the entrant (S&P). To do so, we need a statistic that summarizes the financial quality of each insurer in our data. Fortunately, for our purposes, a single metric is sufficient to conduct this comparison since both A.M. Best and S&P have similar objectives for their rating systems.<sup>22</sup> Thus, consistent with the ratings literature and with the agencies own stated objectives, the metric we use as a proxy for financial quality is the insurer’s one-year probability of default, which we estimate using the discrete-time hazard model of Shumway (2001). The hazard model has three advantages over more traditional static models (e.g., Altman Z-scores; Altman 1968). 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.<sup>23</sup> Second, hazard models allow us to exploit all available information about the condition of the firm rather than just the last year’s observations. Finally, the hazard model allows us to exploit fully our large panel data set of insurers.

Shumway shows that the likelihood function of a discrete time hazard model is identical

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<sup>22</sup>For example, A.M. Best describes its Financial Strength Rating as an “independent opinion of an insurer’s financial strength and ability to meet its ongoing insurance policy and contract obligations.” S&P describes their claims-paying ability rating as “an assessment of an operating insurance company’s financial capacity to meet its policyholder obligations in accordance with their terms.” See A.M. Best (2004) and Standard & Poor’s (1995).

<sup>23</sup>Shumway shows that ignoring this information creates a selection bias, which leads to inconsistent parameter estimates.

to the likelihood function for a multiperiod logit model. Thus, estimating the model is equivalent to estimating the traditional static logistic model except the coding of the dependent variable is slightly different. The dependent variable for the hazard model,  $y_{it}$ , is a binary indicator that is 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; that is,  $y_{it} = 1$ , in the last year that the firm has data. Time varying covariates are easily incorporated by using each firm's annual data estimated from a discrete-time hazard model. Consistent with the insurer solvency prediction literature, we classify the year of insolvency as the year that the first formal regulatory action is taken against a troubled insurer (e.g., Cummins, Harrington and Klein 1995). We identify the year of the first regulatory action through a variety of sources, including the NAIC's Report on Receiverships (various years), the Status of Single-State and Multi-State Insolvencies (various years) and from the list of insolvent insurers provided in a report by the A.M. Best Company, which lists all property-liability insurers that failed from 1969–2001 (A.M. Best, 2004). From these sources, we identify 300 property-liability insurers that failed between 1990 and 2001.

The explanatory variables we use to construct the probability of default are the 19 balance sheet and income statement ratios that make up the NAIC's Financial Analysis and Surveillance Tracking (FAST) system. These accounting-based variables are similar to those used to model corporate debt ratings (see, e.g., Altman 1968 or Shumway 2001), but there are more of them, and they are tailored to the specifics of this industry. Previous research by Grace, Harrington and Klein (1995) concluded that there were diminishing marginal returns to incorporating additional balance sheet and income statement ratios not already included in the FAST system, except to include a control for firm size and an organizational form indicator variable to control for whether the insurer belongs to a mutual or reciprocal group of insurers.<sup>24</sup>

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<sup>24</sup>Firm size is equal to the natural logarithm of the real assets of the firm where the price deflator is

The probability of default is estimated for all insurers for which we have data to calculate the FAST ratios. Thus, not only do we include insurers rated by A.M. Best 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 19 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 as possible, 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 two years of their first event year. The final data set contains 24,236 solvent firm-year observations and 217 insolvent firm-year observations.

To compare the strategies of the two CRAs, we need to define a mapping between their rating systems. Unfortunately, a single one-to-one mapping does not exist, and prior research investigating insurance ratings across agencies used different definitions.<sup>25</sup> For this study, we reviewed the verbal descriptions each agency ascribed to their individual rating categories at the time S&P began to enter the market for insurance ratings (A.M. Best 1991; Standard & Poor’s 1991). Identifying the upper- end of each agency’s ratings scale is straightforward, so we map S&P’s AAA rating into A.M. Best’s A++/A+ category.<sup>26</sup> Midway through each agency’s rating scale, we map S&P’s BBB rating into

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the Consumer Price Index.

<sup>25</sup>For example, Pottier and Sommer (1999) use a four-category system to map the individual ratings assigned by each agency. Both the Government Accounting Office (1994) and Doherty and Phillips (2002) use a five-level system, but the individual ratings assigned to the five categories differ slightly across the two papers. In work not shown here, we compared the results of the five-level and four-level categorization systems with the results shown in this paper. Some of the details are different, but the primary conclusions are similar regardless of which categorization is used. Namely, our primary conclusion that S&P required higher standards to achieve a similar rating is robust to the choice of mapping across the two rating systems.

<sup>26</sup>We consider the A++ and A+ rating categories of A.M. Best to be the same since, at the time of S&P’s entry in the late 1980’s, the highest category in the A.M. Best rating system was A+. In 1992, midway through our sample period, Best announced the expansion of its rating scale to add finer distinctions among certain categories. One rating that was divided was the A+ category, which was split into A++ and A+. The other category that was impacted was B+, which was split into B++ and B+. The release of additional information by Best through its adoption of a finer rating scale is anecdotal

Best's B++/B+ category as both agencies suggest these categories delineate the threshold between "Investment vs. Non-investment grade insurers" (using S&P's language) and between "Secure vs. Vulnerable" insurers (using A.M. Best's language). For the remaining ratings, we map all categories in between the upper and lower anchor points to each other (S&P's AA and A categories map into Best's A and A- categories), and we map each agency's categories below the investment grade/secure threshold to each other. Table 2 summarizes the mapping used in the study and also presents the verbal descriptions each agency uses to describe their system taken from their respective ratings manuals. Also shown in Table 2 are numerical values assigned to each rating category that will be used later.

Clearly, while A.M. Best and S&P may use similar descriptions of rating classes, the fact that they adopt different criteria, as predicted by theory, implies imperfect match between the two systems. The empirical analysis will explore the differences between the A.M. Best and S&P standards.

*Results.* Table 3 presents summary statistics comparing the solvent and insolvent samples of the data set used to estimate the hazard model. 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 217 firm-year observations in the insolvent sample and 24,236 in the solvent sample.

Table 4 Panel A displays the results of the discrete-time hazard regression model. The results are consistent with the summary statistics. For example, the estimated coefficients suggest highly leveraged firms, rapidly growing firms and firms that rely more heavily upon reinsurance to support their capital positions are associated with higher failure rates.

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evidence consistent with our story. That is, the additional competition in the market for insurance ratings, at least in part, may have encouraged Best to reveal additional information to consumers. See A.M. Best (1991,1992).

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 loss reserve development are more likely to fail. Overall the explanatory power of the model is reasonable as the pseudo  $R^2$  statistic is 26 percent.

Table 4 Panel B displays summary statistics of the predicted one-year probability of default for solvent firm-year observations and for bankrupt firm-year observations. That is, the 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 ten/twenty times larger at 9.2/4.4 percent. 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 that 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).

Table 4 Panel C is a classification table that displays the number of actual insolvent and solvent firm-year observations versus the number of predicted insolvent and solvent firm-year observations using the estimated hazard model. Observations were predicted to be insolvent (solvent) that had one-year probabilities of default estimated to be greater than the population average over this time period (0.89 percent).

We now consider differences in the average financial quality of the insurers rated by each agency. To do so, we calculate the average and median probability of default for the insurers that requested a rating by A.M. Best or by S&P over the time period of this study. The results are shown in Table 5, which displays the average and median probability of default of the firms that receive ratings by A.M. Best and S&P. The t-test column reports the results of the null hypothesis of equal means for the probability of default for A.M. Best rated insurers versus S&P rated insurers, assuming unequal variances against the alternative hypothesis average probability of default for S&P rated insurers is lower than the average for A.M. Best rated insurers. Figure T5 displays the average probability

of default time series for each agency over the time period of this study. Except for 1989, when S&P only rated three insurers, the average and median probability of default statistics for S&P rated firms that requested a rating are always lower than for the A.M. Best rated firms through 1998, and these difference are always statistically significant at a 1 percent p-value based on a one-sided t-test.<sup>27</sup> To give economic significance, the analysis suggests that from 1989 through 1998, the one-year default probability for the average insurer that requested a rating from S&P was 56 percent lower than the probability of default for the average firm that requested a rating from A.M. Best. It is also interesting to note from Table 5 that differences in average or median quality appear to converge over time as S&P's presence in this market grew more substantial. This result is most easily seen in the t-statistics, which generally decline over time and, in 2000, is insignificant.

Table 6 and the accompanying chart, Figure T6, show the average rating issued by each agency over the time period of our study where the numerical scores assigned to each category were shown in Table 2. The results stand in stark contrast to those reported in Table 5 because the average rating issued by A.M. Best over this time period was very similar to the average rating S&P issued, even though the probability of default for the average insurer that requested a rating from S&P was significantly lower. This result is consistent with our hypothesis that the entrant CRA has higher standards, on average, in order for a firm to receive a rating similar to the one it received from the incumbent CRA.

The final univariate comparison we make is shown in Table 7 where we compare the ratings assigned to insurers that requested a rating from both agencies. Table 7 displays summary statistics of the ratings assigned by A.M. Best and S&P to U.S. property-liability insurers over the years 1989–2000. The final two columns display t-statistics reporting the difference in means test assuming unequal variances. The data includes all firm-year observations over the years 1989–2000 that received a rating from both A.M. Best and

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<sup>27</sup>Table 5 only shows the statistics for the null hypothesis of differences in means. The statistics for the null hypothesis of differences in medians provide similar results and thus are not shown. The results are available from the authors upon request.

S&P. Each cell of the matrix,  $c_{ij}$ , equals the number of firm-year observations that receive rating  $i$  from A.M. Best and rating  $j$  from S&P, where  $i, j \in \{\text{Superior, Excellent, Good, Marginal}\}$ .

The results suggest that S&P generally agreed with the rating A.M. Best assigned to the same insurer as the two agencies issued the identical rating for 56.6 percent of the firm-year observations. Table 7 also suggests that, when S&P's opinion differed from A.M. Best's, it was generally more pessimistic, as 39.5 percent of the firm-year observations represent cases where S&P assigned a lower rating to the insurer than did A.M. Best. S&P assigned a higher rating to an insurer than did A.M. Best in only 3.9 percent of the firm-year observations. Again, this result is consistent with our theory.

## 5.2 Investigating the Differences in Ratings

The univariate results suggest that insurers who opted to receive an S&P rating were, on average, of higher financial quality, yet the average rating they received was either the same or lower than the rating they received from A.M. Best. Although consistent with our theory, this analysis suffers from two shortcomings. First, we have 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 distorted by 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 only publicly available information. Presumably, one of the advantages of a rating system is the ability of a CRA to learn private information. In this section, we investigate the determinants of differences in the ratings assigned by the incumbent versus the entrant CRA while controlling for the private information the agencies learn through the rating process and the strategic incentives of the insurer.

*Empirical Strategy.* Assume the following model is used by the incumbent rating agency to determine the rating for a particular firm:

$$r_{if} = \alpha_i + \beta_i' X_f + \varepsilon_{if} \quad (4)$$

where

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

$\alpha_i$  = constant term for the incumbent agency

$\beta_i$  = vector of coefficients summarizing the incumbent agency's rating technology

$X_f$  = vector of observable information for firm  $f$

$\varepsilon_{if}$  = 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,

$$r_{ef} - r_{if} = (\alpha_e - \alpha_i) + (\beta_e - \beta_i)' X_f + (\varepsilon_{ef} - \varepsilon_{if}), \quad (5)$$

where all variables subscribed with an  $e$  denote the new entrant agency. As discussed by Cantor and Packer, estimating equation (5) directly using OLS leads to biased results if the decision to seek a second rating is correlated with the ratings assigned by that agency. This selection bias makes it impossible to know if the estimated differences between the two rating systems are due to differences between the rating scales, or whether the sample of firms that choose to get a rating from the new entrant have a common set of characteristics. The theory presented in this paper suggests that firms, which elect to receive a full rating from S&P, are those with higher than average financial quality in their rating category and have some belief that they are likely to obtain a favorable outcome from the 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 sample selection bias (Heckman 1979). The Heckman methodology is ideal in this setting because it allows us to control for the possibility of selection bias and we can 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 inverse Mill’s ratio, which, when included in the ratings difference model, controls for the selection bias. Thus, in the second stage, we estimate

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

where the estimated constant term measures the mean difference in ratings standards across the two agencies, and the coefficient on the inverse Mill’s ratio (IMR) captures the sample selection effect.<sup>28</sup> We hypothesize  $\alpha$  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  $\gamma$  will be positive, consistent with the hypothesis that insurers who believe that they will receive a favorable rating from S&P will self-select to receive that rating.

We include the following variables to explain the demand for a second rating. First, our theory suggests that higher quality insurers within each rating category of the incumbent will have a stronger demand for a second rating from S&P. To test this hypothesis, we construct for each insurer a variable that is equal to the median probability of default of insurers within the same A.M. Best’s rating category as the insurer minus the insurer’s own estimated default probability. Insurers for which this variable is positive have lower expected default rates than the median insurer in their current A.M. Best rating class. We expect a positive estimated coefficient on this variable.

Second, we include a variable that interacts the “higher quality than the median insurer” variable with a time trend to control for differences in demand over time. We expect that insurers with the highest demand will choose a rating from the new entrant

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<sup>28</sup>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, like Cantor and Packer (1997), we only include an intercept term and a control for sample selection bias in the second-stage rating difference regressions.

first and this effect will dissipate over time. Thus, we expect a positive coefficient on the “higher than median insurer” variable and a negative coefficient on the interacted variable.

Third, the model predicts that rating agencies have incentives to reveal more information to the market when the buyers value information more highly. To test this hypothesis, we include a variable equal to the percentage of the insurer’s premiums in retail lines of insurance.<sup>29</sup> We expect that retail policyholders place less value on information for at least two reasons. First, state-guarantee funds provide greater protection to the retail policyholders of insurers that become bankrupt. Second, most consumer lines of insurance are amenable to objective data and modeling, and thus the insurer’s underwriting portfolio is relatively less opaque. Given both reasons, we expect that retail consumers value the additional information revealed by obtaining the second rating less relative to commercial buyers of insurance.

We include three variables to control for the insurer’s previous experience with S&P. The first is an indicator variable equal to one for any insurer that is part of a group that has corporate debt already rated by S&P. We also include an indicator equal to one if the insurer itself requested a claims paying ability rating from S&P in the previous year. We expect that insurers with an existing relationship with S&P would be more likely to request a second rating from the entrant for two reasons. First, the managers of the firm are already aware of the methodology employed by S&P and therefore can better forecast the outcome of the review process. Second, an existing relationship reduces the marginal cost of obtaining a rating relative to insurers with no previous experience with S&P.

Our third previous S&P experience variable equals one if the insurer was assigned a qualified rating by S&P in the previous year and zero otherwise. Recall, in 1991, S&P introduced its qualified rating service where they assigned ratings to the insurer, without the insurer’s consent, based upon quantitative analysis only. From 1991–1994, the highest

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<sup>29</sup>The lines of insurance we considered to be retail lines included personal automobile insurance (both liability and property damage), homeowners insurance and farmowners insurance.

qualified rating S&P would assign was BBB. In 1994, they relaxed this constraint and began issuing A, AA and AAA ratings on a qualified basis. Thus, we interact the qualified rating indicator with a dummy variable for 1990–1994 and another dummy for 1995–1999 to control for the differences in the qualified rating scheme across time. We do not have strong priors regarding the expected signs on these indicator variables because it is not clear if consumers viewed qualified ratings as informative since S&P only used publicly available information to determine the rating.

We include two variables to control for differences in firm complexity: a size variable (equal to the natural logarithm of the firm’s assets) and a variable measuring the geographical concentration of the firm’s premium writings (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 consistent with the hypothesis that larger and more geographically dispersed insurers are more complex.

The final insurer characteristic variable we include is an indicator variable for whether an insurer is organized as a mutual or reciprocal. We have two competing hypotheses for this variable. First, the managerial discretion literature predicts that mutual insurers underwrite less risky lines of insurance and have more transparent business models than stock insurers due to the reduced ability of a diffuse set of owner/policyholders to monitor management (Mayers and Smith 1987). This model suggests that mutuals should have a lower demand for a second rating. An alternative is that stock insurers have lower demand for an additional rating because their financial quality is already conveyed in share price.

Finally, we include indicator variables for each rating category assigned by A. M. Best to the insurer for two reasons. First, we wish to control for the private information that A.M. Best learns during the rating process and to control for any differences in the demand for a second rating based upon the insurer’s overall credit quality, as judged by A.M. Best. We do not have any prior hypothesis for these variables.

The data for the rating difference tests includes any insurer that received a rating

from A.M. Best over the time period 1990–2000 (we lose one year of data due to our inclusion of two lagged variables). We estimate the first-stage probit regression using all firm-year observations and the second-stage OLS regressions only for insurers that receive full ratings from S&P. There are 13,353 insurer-year observations in the A.M. Best sample of which 1,503 also obtained an S&P rating.

*Results.* Table 8 displays the summary statistics for all the variables used in the ratings differences tests. The columns labeled “A.M. Best and Standard & Poor’s” display summary statistics for just those insurer-year observations that were assigned ratings by both the incumbent and the new entrant agency. The columns labeled “A.M. Best Only” are insurer-year observations for firms that requested a rating only from A.M. Best. The most important statistic in this table is the average difference in rating assigned to an insurer by S&P relative to A.M. Best, which, over the time period of this study, was 0.35 notches lower. The results in Table 8 also suggest that insurers who requested a full rating were (i) less likely to be a members of a mutual group of insurers than the average A.M. Best insurer, (ii) were much larger than the average A.M. Best insurer (based on assets under management), and (iii) conducted less business in retail lines of insurance. All of these latter results are consistent with our prior hypotheses.

The results also suggest that insurers who requested a claims paying ability rating were more likely to have a previous relationship with S&P either due to the presence of a corporate debt rating or because the insurer previously requested a claims paying ability rating. Over 70 percent of the insurers that requested a claims paying rating in the current year already had a corporate debt rating, and close to 70 percent of the insurers already had a claims paying ability rating from the previous year. The corresponding percentages for insurers that only had a rating from A.M. Best were 19.6 and 1.7 percent, respectively.

The first-stage probit regression results are shown in Table 9. Panel A displays the estimated coefficients on the independent variables. Panel B displays the marginal ef-

fects.<sup>30</sup> The most important results concern the test that higher-than-median quality insurers in each rating category of the incumbent are more likely to demand a second rating. The variable measuring the difference between the median insurer's probability of default in the A.M. Best rating category and the estimated default probability for the insurer, is both positive and significant as predicted. At the same time, the interaction of this variable with the time indicator is negative. This suggests that the importance of S&P's entry strategy to target the best companies in each rating category declined over time.

The insurer characteristic variables suggest that larger insurers, those writing across geographical locales, firms organized as stock insurers and those writing a greater percentage of their business in commercial lines of insurance are more likely to request a second rating from S&P. These results are all consistent with our theory that more complex insurers and insurers whose customers place a higher value on information have a greater demand to communicate their financial strength to the market place.

The previous S&P relationship variables are also consistent with our prior hypotheses as the estimated coefficients on both the corporate debt rating indicator and the previous claims paying ability rating indicator are positive and significant. The indicator variables for S&P assigning a qualified rating to an insurer are largely insignificant consistent with the hypothesis that the insurers' management viewed these ratings as having little ability to reveal new information to market participants.

The results for the indicator variables controlling for A.M. Best rating classes reveal the likelihood of requesting a second rating from S&P increases as the quality of the insurer (as rated by A.M. Best) also increases. Note, however, the economic significance of these effects are relatively small as the estimated marginal increase in probability for an Excellent or Superior rated A.M. Best insurer (over a Marginal insurer) is only 1.5 or 1.7 percent, respectively.

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<sup>30</sup>The model also contains year indicator variables, but the results are suppressed to save space. The full results with the estimated coefficients for the year indicator variables are available upon request.

The results from the second stage OLS regressions where the dependent variable is the difference between the rating assigned by S&P minus the rating assigned by A.M. Best in year  $t$  are shown in Table 10. The inverse Mill's terms in each model were calculated using the results of each Probit regression shown in Table 10, respectively.

Our first conclusion is that we find evidence of a selection effect because the estimated coefficient on the inverse Mill's ratio is always positive and significantly different from zero. Thus, we find strong evidence that insurers who seek a second rating expect, on average, to receive a more favorable rating from S&P even after we control for publicly available information to market participants and for the private information revealed to either A. M. Best or S&P itself through other dealings. For example, based on the results shown in Model 3, the insurers strategically choosing a second rating expect to receive, on average, a 0.08 higher rating from S&P than they received from A. M. Best. These results support the contention that better than average insurers within any pre-existing A.M. Best rating category sought to differentiate themselves through a second rating.

The second conclusion we draw is that S&P maintained significantly higher standards relative to A.M. Best because the intercept term in each model is negative and significantly different than zero. Focusing again on Model 3, we see that the estimated mean difference in rating standards is 0.42 grades lower on the S&P scale than under the A.M. Best rating system. This result supports our theory that, conditional upon the rating provided by the incumbent agency, the insurers sought to differentiate themselves by seeking an additional rating from a new entrant agency that required higher standards in order to maintain the same rating.

## 6 Conclusion

In this paper, we examined how the entry of a new credit rating agency to the market served by an incumbent monopolistic credit rating agency changes the information content of ratings. In doing so, we departed from the literature that has largely ignored the endogeneity of the CRA's rating standards and shown that an entrant's rating standards

may be significantly different from those used by the incumbent agency. Our analysis implies that although it may be easy to understand that two rating agencies have a category they assign to only firms of the highest quality, say AAA for S&P and A++ for A.M. Best, the standards necessary to achieve those ratings may differ across the agencies. The theory presented here predicts new entrants have incentives to require higher standards relative to the incumbent rater in order for a firm to achieve a similar rating. The empirical analysis of the market for insurance ratings is consistent with this hypothesis as we show, all else equal, insurers of the same quality received a lower rating by the new entrant relative to the incumbent. The inconsistency of standards across rating agencies will have no cost to market participants as long as these differences in standards are perfectly transparent. That is, market participants can infer the expected quality and precision of a rating from the rating scale of a particular CRA. Our empirical analysis of the insurance market suggests that this was exactly the case because firms saw through the verbal descriptions offered by the CRAs and recognized that the entrant was applying higher standards. Thus, competition allows the better-than-average insurers to signal their status, thereby providing incentives for firms to improve their credit quality.

From a policy perspective, our work suggests that the benefits of competition can only be achieved when the CRAs disclose the process of assigning ratings and their historical performance. Otherwise, differences in rating standards across multiple rating agencies are likely to create confusion about the meaning of ratings and decrease the precision of information. Indeed, suppose that the verbal descriptions of ratings are taken at face value. Thus, a AAA rating by one agency is seen to be identical to a AAA rating by another agency. We opened this paper with a prediction from the CEO of Moody's who suggested that competition will induce a "race to the bottom". If an investor (or regulator) cannot recognize the differences in rating standards, its choice of a CRA will likely be guided by the ability to obtain the highest rating at the lowest cost. As a result, firms will go to the most lax of the CRAs to obtain their desired rating. The ratings of structured products is an example of such behavior because the absence of historical

performance information and the opaque rating process may reduce an investor's ability to assess the true value of AAA collateralized debt obligations (CDOs). Similarly, one may be concerned about the negative effects of competition if regulators fail to acknowledge the differences in rating standards in identifying assets that count when measuring a bank's or insurer's regulatory capital. For the market to benefit from competition among CRAs, regulators should take into account the multiplicity of the CRAs' rating standards and focus on increasing the disclosure of the rating process and the ratings historical performance.

## Appendix: Proofs (Not for Publication)

**Proof of Proposition 1.** We first prove the uniqueness of equilibrium under full disclosure. Consider a set of nonrated types  $V_N$ . Then the valuation of these types in the eyes of buyers is

$$E(v|V_N) - a\text{Var}(v|V_N),$$

where

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

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

If  $V_N = [0, 1]$ , then the valuation is equal to  $\max(0, \frac{1}{2} - \frac{1}{12}a)$ . If type  $v = 1$  is the only one rated, it is paid 1. When  $t < 1 - \max(0, \frac{1}{2} - \frac{1}{12}a) = \max(1, \frac{1}{2} + \frac{1}{12}a)$ , among the nonrated 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.

We now derive the optimal market coverage  $v_F$ . Consider two cases,  $u_N > 0$  and  $u_N < 0$ .  $u_N > 0$  is equivalent to

$$\frac{1}{2} - \frac{1}{12}av_F > 0. \tag{6}$$

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

$$(1 - v_F)\left(\frac{1}{2}v_F + \frac{1}{12}av_F^2\right)$$

subject to (6).

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

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

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

$$(1 - v_F)v_F$$

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 2.** Define a disclosure policy correspondence

$$s(v) = \{[s_i(v), s_{i+1}(v)]_{i=1}^{K(v)}\} \text{ for all } v \in [0, 1],$$

where  $v \in s(v)$ ,  $s_i(v) \leq s_{i+1}(v)$ ,  $s_1(v) \geq 0$ ,  $s_{K(v)}(v) \leq 1$ . Under this policy a rating assigned to type  $v$  is a union of intervals and points with elements from  $[0, 1]$  containing  $v$ . For example,  $v = \frac{1}{5}$  and  $s(\frac{1}{5}) = \{[\frac{1}{6}, \frac{2}{5}], [\frac{1}{2}, \frac{2}{3}], \frac{9}{10}\}$  means that if type  $v = \frac{1}{5}$  is rated, the rating agency discloses that the seller's type can be in intervals  $[\frac{1}{6}, \frac{2}{5}]$  or  $[\frac{1}{2}, \frac{2}{3}]$ , or equal to  $\frac{9}{10}$ . Note that  $\frac{1}{5} \in s(\frac{1}{5})$  and  $K(\frac{1}{5}) = 3$ . The disclosure policy can also be an infinite sequence of elements, for example,  $v = \frac{5}{9}$  and  $s(v) = \{(\frac{i}{i+1}, \frac{2i+1}{2i+3})_{i=1}^{\infty}\}$ . Clearly, any disclosure policy can be characterized as  $s(\cdot)$ .

Denote  $\underline{v}(s)$  the lowest rated type under disclosure policy  $s$ . Assume that all types  $v > \underline{v}$  are rated and obtain a valuation of at least  $u(s(\underline{v}))$ . Then the participation constraint of

type  $\underline{v}$  determines the fee  $t = u(s(\underline{v})) - \max\{u([0, \underline{v}]), 0\}$ , where  $u([0, \underline{v}])$  is the valuation of nonrated types  $[0, \underline{v}]$ . The lowest payoff of type  $\underline{v}$  equals to  $\underline{v}$  and obtains when the signal  $s(\underline{v})$  contains only  $\underline{v}$ . Thus, the fee can be increased only if  $s(\underline{v})$  contains some higher types  $v > \underline{v}$ .

Suppose that  $s(\underline{v})$  consists of a system of disjoint intervals,  $s(\underline{v}) = \{[\underline{v}, v_1], \dots, [v_{K(\underline{v})-1}, v_{K(\underline{v})}]\}$  with  $v_{2j-1} < v_{2j}$  for all  $j$  such that  $2j < K(\underline{v}) \leq \infty$ . Then, for any distribution of types  $F(v)$ ,

$$\begin{aligned}\mu(s(\underline{v})) &= \frac{\int_{\underline{v}}^{v_1} v dF(v) + \int_{v_2}^{v_3} v dF(v) + \dots + \int_{v_{K(\underline{v})-1}}^{v_{K(\underline{v})}} v dF(v)}{F(v_1) - F(\underline{v}) + F(v_3) - F(v_2) + \dots + F(v_{K(\underline{v})}) - F(v_{K(\underline{v})-1})}, \\ \sigma^2(s(\underline{v})) &= \frac{\int_{\underline{v}}^{v_1} (v - \mu(s(\underline{v})))^2 dF(v) + \int_{v_2}^{v_3} (v - \mu(s(\underline{v})))^2 dF(v) + \dots + \int_{v_{K(\underline{v})-1}}^{v_{K(\underline{v})}} (v - \mu(s(\underline{v})))^2 dF(v)}{F(v_1) - F(\underline{v}) + F(v_3) - F(v_2) + \dots + F(v_{K(\underline{v})}) - F(v_{K(\underline{v})-1})}.\end{aligned}$$

Define  $\widehat{s}(\underline{v}) = [\underline{v}, \widehat{v}]$  where  $\widehat{v}$  is such that

$$\frac{1}{F(\widehat{v}) - F(\underline{v})} \int_{\underline{v}}^{\widehat{v}} v dF(v) = \mu(s(\underline{v})).$$

That is, under disclosure policy  $\widehat{s}$ , type  $\underline{v}$  is pooled with types  $[\underline{v}, \widehat{v}]$  in the same signal, and  $\widehat{v}$  is such that  $\mu(\widehat{s}(\underline{v})) = \mu(s(\underline{v}))$ . Then it is easy to show that the signal  $\widehat{s}(\underline{v}) = [\underline{v}, \widehat{v}]$  results in lower variance  $\sigma^2(\widehat{s}(\underline{v}))$  than  $\sigma^2(s(\underline{v}))$ . Since increasing  $\sigma^2$  for fixed  $\mu$  reduces the fee  $t$ , we conclude that it is optimal to pool type  $\underline{v}$  with neighboring types  $(\underline{v}, \widehat{v}]$ ,  $\underline{v} \leq \widehat{v}$ .

It remains to prove that under an optimal disclosure policy all types  $v > \widehat{v}$  are rated and obtain a valuation of at least  $\mu(s(\underline{v})) - \sigma^2(s(\underline{v}))$ . Suppose that there is a rated type  $\widehat{\widehat{v}} > \widehat{v}$  such that  $\mu(s(\widehat{\widehat{v}})) - a\sigma^2(s(\widehat{\widehat{v}})) < \mu(s(\underline{v})) - a\sigma^2(s(\underline{v}))$ . It means that  $\widehat{\widehat{v}}$  is either pooled with lower types resulting in lower  $\mu(s(\widehat{\widehat{v}}))$ , or with types that are higher, but are very distinct, resulting in high  $\sigma^2(s(\widehat{\widehat{v}}))$ , or both. At the same time,  $\widehat{\widehat{v}}$  can always obtain a payoff  $\widehat{\widehat{v}} > \mu(s(\underline{v})) - a\sigma^2(s(\underline{v}))$  if the type is fully disclosed, and  $s(\widehat{\widehat{v}}) = \widehat{\widehat{v}}$ . As long as  $\widehat{\widehat{v}}$  obtains a rating, its valuation has no impact on the fee charged by the agency. Thus

the rating agency cannot benefit by designing a disclosure policy resulting in the payoff of  $\widehat{v}$  lower than  $\mu(s(\underline{v})) - a\sigma^2(s(\underline{v}))$ . For the same reason, the rating agency cannot benefit from excluding types  $v > \widehat{v}$  from the rating. We conclude that under an optimal rating system all types  $v > \underline{v}$  are rated, types  $[\underline{v}, \widehat{v}]$ ,  $\underline{v} \leq \widehat{v} \leq 1$  are pooled in one rating, and types  $v > \widehat{v}$  obtain a valuation of at least  $\mu(s(\underline{v})) - a\sigma^2(s(\underline{v}))$ .

There are multiple disclosure policies for types  $v > \widehat{v}$  that are compatible with the last condition. In particular, any interval disclosure system that results in the valuation of at least  $\mu(s(\underline{v})) - a\sigma^2(s(\underline{v}))$  is an equilibrium.

As the value of information increases,  $a \rightarrow +\infty$ , pooling has infinite costs. Consequently, the support of each rating contains only one type and has zero variance. It implies that, as the value of information tends to infinity, the optimal disclosure policy converges to full disclosure. ■

**Proof of Proposition 3.** Consider a rating system when the agency pools companies  $[v_M, v_M + b_M]$  in one rating. 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

$$\max_{(b_M, v_M)} (1 - v_M)(u_R(v_M, v_M + b_M) - u_N) = (1 - v_M)\left(\frac{1}{2}v_M + \frac{1}{12}av_M^2 + \frac{1}{2}b_M - \frac{1}{12}ab_M^2\right)$$

$$\frac{1}{2} - \frac{1}{12}av_M \geq 0, \tag{7}$$

$$1 - b_M - v_M \geq 0. \tag{8}$$

Constraint (7) is equivalent to  $u_N > 0$ , and (8) is a feasibility condition. Denote  $\lambda \geq 0$  and  $\mu \geq 0$  the Lagrangian multipliers of these constraints. The first-order conditions of the problem are

$$\begin{aligned} b_M : & (1 - v_M)\left(\frac{1}{2} - \frac{1}{6}ab\right) - \mu = 0, \\ v_M : & -\frac{1}{4}av_M^2 + \frac{1}{6}(a - 6)v_M + \frac{1}{2} - \frac{1}{2}b_M + \frac{1}{12}ab_M^2 - \frac{1}{12}a\lambda - \mu = 0. \end{aligned}$$

Suppose that  $\lambda > 0$  and  $\mu > 0$ . Then  $v_M = \frac{6}{a}$  and  $b_M = 1 - \frac{6}{a}$ . 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  $b_M = \frac{3}{a}$  and  $v_M = \frac{6}{a}$ . It implies that  $\lambda = \frac{9(2a-21)}{a^2}$ , and  $\lambda > 0$  when  $a > \frac{21}{2}$ .  $\mu = 0$  implies that (8) 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  $b_M = 1 - v_M$ , and  $\mu = (1 - v_M)(\frac{1}{2} - \frac{1}{6}a(1 - v_M))$ . The first-order condition with respect to  $v_M$  writes  $\frac{1}{4}a - \frac{1}{3}av_M - \frac{1}{2} = 0$ , and  $v_M = \frac{3}{4} - \frac{3}{2a}$ .  $v_M > 0$  when  $a > 2$ .  $\mu = \frac{36-a^2}{96a}$ , and  $\mu > 0$  when  $a < 6$ .  $\lambda = 0$  implies that (8) must be satisfied,  $\frac{3}{4} - \frac{3}{2a} \leq \frac{6}{a}$ , or  $a < 10$ . Then this case is possible when  $2 < a < 6$ . The profit of the rating agency in this case is  $\frac{(a+6)^2}{96a}$ . If  $a < 2$ , then  $v_M = 0$ , and  $b_M = 1$ . The profit of the rating agency in this case is  $\frac{1}{2} - \frac{1}{12}a$ .

Suppose that  $\lambda = \mu = 0$ . Then  $b_M = \frac{3}{a}$ , and the first-order condition with respect to  $v_M$  writes  $-\frac{1}{4}av_M^2 + (\frac{1}{6}a - 1)v_M + \frac{1}{2} - \frac{3}{4a} = 0$  implying that  $v_M = \frac{2}{3} - \frac{1}{a}$ .  $\lambda = 0$  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  $u_N > 0$ .

$a$	$v_M$	$b_M$	$t_m$	$\pi_M$
$0 \leq a \leq 2$	0	1	$\frac{1}{2} - \frac{1}{12}a$	$\frac{1}{2} - \frac{1}{12}a$
$2 \leq a \leq 6$	$\frac{3}{4} - \frac{3}{2a}$	$\frac{1}{4} + \frac{3}{2a}$	$\frac{1}{4} + \frac{1}{24}a$	$\frac{(a+6)^2}{96a}$
$6 \leq a \leq \frac{21}{2}$	$\frac{2}{3} - \frac{1}{a}$	$\frac{3}{a}$	$\frac{(a+3)^2}{27a}$	$\frac{(a+3)^3}{81a^2}$
$a \geq \frac{21}{2}$	$\frac{6}{a}$	$\frac{3}{a}$	$\frac{27}{4a}$	$\frac{27(a-6)}{4a^2}$

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

$$\begin{aligned} \max_{(b_M, v_M)} (1 - v_M)u_R(v_M, v_M + b_M) &= (1 - v_M)(v_M + \frac{1}{2}b_M - \frac{1}{12}ab_M^2) \\ -\frac{1}{2} + \frac{1}{12}av_M &\geq 0 \text{ and (8)}. \end{aligned}$$

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

$$\begin{aligned} b_M : (1 - v_M)(\frac{1}{2} - \frac{1}{6}ab_M) - \mu &= 0, \\ v_M : 1 - 2v_M - \frac{1}{2}b_M + \frac{1}{12}ab_M^2 + \frac{1}{12}a\lambda - \mu &= 0. \end{aligned}$$

Suppose that  $\lambda > 0$  and  $\mu > 0$ . Then  $v_M = \frac{6}{a}$  and  $b_M = 1 - \frac{6}{a}$ . 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  $v_M = \frac{6}{a}$  and  $b_M = \frac{3}{a}$ . It implies that  $\lambda = \frac{3(51-4a)}{a^2}$ , and  $\lambda > 0$  when  $a < \frac{51}{4}$ .  $\mu = 0$  implies that (8) 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  $b_M = 1 - v_M$ , and  $\mu = (1 - v_M)(\frac{1}{2} - \frac{1}{6}a(1 - v_M))$ . The first-order condition with respect to  $v_M$  becomes  $av_M^2 - 2(a+2)v_M + a = 0$ , implying that  $v_M = \frac{a+2-2\sqrt{a+1}}{a}$ . 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  $b_M = \frac{3}{a}$  and  $v_M = \frac{1}{2} - \frac{3}{8a}$ .  $\lambda = 0$  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  $u_N < 0$ .

$a$	$v_M$	$b_M$	$t_M$	$\pi_M$
$6 \leq a \leq 9$	$\frac{6}{a}$	$1 - \frac{6}{a}$	$\frac{3}{2} - \frac{1}{12}a$	$\frac{(a-6)(18-a)}{12a}$
$9 \leq a \leq \frac{51}{4}$	$\frac{6}{a}$	$\frac{3}{a}$	$\frac{27}{4a}$	$\frac{27(a-6)}{4a^2}$
$a \geq \frac{51}{4}$	$\frac{1}{2} - \frac{3}{8a}$	$\frac{3}{a}$	$\frac{3}{8a} + \frac{1}{2}$	$\frac{(4a+3)^2}{64a^2}$

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.

$a$	$v_M$	$b_M$	$t_M$	$\pi_M$
$0 \leq a \leq 2$	0	1	$\frac{1}{2} - \frac{1}{12}a$	$\frac{1}{2} - \frac{1}{12}a$
$2 \leq a \leq 6$	$\frac{3}{4} - \frac{3}{2a}$	$\frac{1}{4} + \frac{3}{2a}$	$\frac{1}{4} + \frac{1}{24}a$	$\frac{(a+6)^2}{96a}$
$6 \leq a \leq \frac{21}{2}$	$\frac{2}{3} - \frac{1}{a}$	$\frac{3}{a}$	$\frac{(a+3)^2}{27a}$	$\frac{(a+3)^3}{81a^2}$
$\frac{21}{2} \leq a \leq \frac{51}{4}$	$\frac{6}{a}$	$\frac{3}{a}$	$\frac{27}{4a}$	$\frac{27(a-6)}{4a^2}$
$a \geq \frac{51}{4}$	$\frac{1}{2} - \frac{3}{8a}$	$\frac{3}{a}$	$\frac{3}{8a} + \frac{1}{2}$	$\frac{(4a+3)^2}{64a^2}$

It completes the proof. ■

**Proof of Proposition 4.** Consider an interval disclosure policy,

$$\{[v_M, v_M + b_M], [v_M + b_M, v_M + b_M + b_1], \dots, [v_M + b_M + \sum_{i=1}^{N-1} b_i, v_M + b_M + \sum_{i=1}^N b_i]\},$$

where  $v_M$  and  $b_M$  are derived in Proposition 3 and the valuation of all rated types is at least  $u([v_M + b_M, v_M + b_M + b_1])$ , that is,  $u_k([v_M + b_M + \sum_{i=1}^{k-1} b_i, v_M + b_M + \sum_{i=1}^k b_i]) \geq u([v_M + b_M, v_M + b_M + b_1])$ . A disclosure policy where the valuation of a seller is non-decreasing in rating must satisfy  $u_{k+1}([v_M + b_M + \sum_{i=1}^k b_i, v_M + b_M + \sum_{i=1}^{k+1} b_i]) \geq u_k([v_M + b_M + \sum_{i=1}^{k-1} b_i, v_M + b_M + \sum_{i=1}^k b_i])$ , or

$$\begin{aligned} v_M + b_M + \sum_{i=1}^{k-1} b_i + b_k + \frac{1}{2}b_{k+1} - \frac{1}{12}ab_{k+1}^2 &\geq v_M + b_M + \sum_{i=1}^{k-1} b_i + \frac{1}{2}b_k - \frac{1}{12}ab_k^2, \\ \Leftrightarrow b_{k+1} &\leq b_k + \frac{6}{a}. \end{aligned}$$

It implies that  $b_{k+1} - b_k \leq \frac{6}{a}$ , and the size of an interval decreases as  $a$  increases. ■

**Proof of Proposition 5.** In each rating interval  $k$ , denote  $\hat{v}_k$  the type that is indifferent between full disclosure and pooling,

$$\hat{v}_k = v_M + b_M + \sum_{i=1}^{k-1} b_i + \frac{1}{2}b_k - \frac{1}{12}ab_k^2.$$

Types  $v \in [v_M + b_M + \sum_{i=1}^{k-1} b_i, \hat{v}_k]$  prefer pooling, and types  $v \in [\hat{v}_k, v_M + b_M + \sum_{i=1}^{k-1} b_i + b_k]$  prefer full disclosure. The measures of types in each group are, respectively,  $\frac{1}{2}b_k - \frac{1}{12}ab_k^2$  and  $\frac{1}{2}b_k + \frac{1}{12}ab_k^2$ . Hence, for any  $a > 0$ , the measure of types that prefer full disclosure is higher than the measure of types that prefer pooling. ■

**Proof of Proposition 6.** Consider an interval rating system of the incumbent  $N$ ,  $R_1, R_2, \dots, R_K$  where types  $v \in N = [0, v_M]$  are not rated and types  $v \in R_i = [v_{i-1}, v_i]$ ,  $i = 1, \dots, K$ ,  $v_0 = v_M$  are rated  $R_i$ . The valuation of the seller rated  $R_i$  by the incumbent is

$$u(R_i) = \frac{1}{2}(v_{i-1} + v_i) - \frac{1}{12}a(v_i - v_{i-1})^2.$$

Denote  $R_e(R_i; v)$  a rating that an entrant assigns to type  $v$  rated  $R_i$  by the incumbent. This rating is purchased by type  $v$  if it increases the valuation of the seller,  $u(R_i, R_e(R_i; v)) > u(R_i)$ .

Entrant's rating  $R_e(R_i; v)$  can be characterized as a system of disjoint intervals,  $R_e(R_i; v) = \{[v_{j-1,i}^e, v_{j,i}^e]\}_{j=2, \dots, J(i)}$  where  $v \in R_e(R_i; v)$ ,  $v_{j-1,i}^e \leq v_{j,i}^e$ ,  $v_{1,i}^e \geq 0$ ,  $v_{J(i),i}^e \leq 1$ . The proof proceeds in five steps. In Step 1 we establish the entry strategy in the best rating category of the incumbent. In Steps 2 and 3 we characterize entry strategy for the lower categories of the incumbent and non-rated sellers. In Step 4 we characterize the optimal entrant's rating system as a solution to an optimization problem and show how it can be implemented as a system of interval ratings. In Step 5 we provide the results on the mean and variance of the entrant's rating system.

**Step 1.** Consider a highest rating interval of the incumbent  $R_K$ . Type  $v \in R_K$  purchases the rating of the entrant if it either increases the expected type or reduces the variance of the type, that is

$$\begin{aligned} & u(R_K, R_e(R_K; v)) - u(R_K) \\ &= \mu(R_K, R_e(R_K; v)) - \mu(R_K) - a(\sigma^2(R_K, R_e(R_K; v)) - \sigma^2(R_K)) > 0. \end{aligned}$$

If rating  $R_e(R_K; v)$  contains any types below those pooled in the incumbent's rating  $R_K$ ,  $v < v_{K-1}$ , then  $\mu(R_K, R_e(R_K; v)) < \mu(R_K)$  and  $\sigma^2(R_K, R_e(R_K; v)) > \sigma^2(R_K)$ . In this case types  $v \in R_K$  will not purchase the entrant's rating. Thus,  $R_e(R_K; v) \subset R_K$ .

Rating  $R_e(R_K; v)$  does not contain disjoint intervals. Indeed, suppose to the contrary

that  $J(K) > 2$ . Then

$$\begin{aligned}\mu(R_e(R_K; v)) &= \frac{\int_{v_{1,K}^e}^{v_{2,K}^e} v dF(v) + \int_{v_{3,K}^e}^{v_{4,K}^e} v dF(v) + \dots + \int_{v_{J(i)-1,K}^e}^{v_{J(i),K}^e} v dF(v)}{F(v_{2,K}^e) - F(v_{1,K}^e) + \dots + F(v_{J(i),K}^e) - F(v_{J(i)-1,K}^e)}, \\ \sigma^2(R_e(R_K; v)) &= \frac{\int_{v_{1,K}^e}^{v_{2,K}^e} (v - \mu(R_e(R_K; v)))^2 dF(v) + \dots + \int_{v_{J(i)-1,K}^e}^{v_{J(i),K}^e} (v - \mu(R_e(R_K; v)))^2 dF(v)}{F(v_{2,K}^e) - F(v_{1,K}^e) + \dots + F(v_{J(i),K}^e) - F(v_{J(i)-1,K}^e)}.\end{aligned}$$

Define  $\widehat{v}_K$  is such that

$$\frac{1}{F(\widehat{v}_K) - F(v_{1,K}^e)} \int_{v_{1,K}^e}^{\widehat{v}} v dF(v) = \mu(R_e(R_K; v)).$$

Consider a rating of the entrant where types  $[v_{1,K}^e, \widehat{v}]$  are pooled and  $\widehat{v}$  is such that  $\mu([v_{1,K}^e, \widehat{v}]) = \mu(R_e(R_K; v))$ . Then the rating  $[v_{1,K}^e, \widehat{v}]$  results in lower variance  $\sigma^2([v_{1,K}^e, \widehat{v}])$  than  $\sigma^2(R_e(R_K; v))$ . Since decreasing  $\sigma^2$  for fixed  $\mu$  increases the seller's willingness to pay for the entrant's rating, ratings containing disjoint intervals are suboptimal for the entrant.

Rating  $R_e(R_K; v)$  contains the best types in interval  $R_K$ . Indeed, keeping fixed the mass of types that are rated by the entrant,  $\Delta = \widehat{v}_K - v_{1,K}^e$ , seller's willingness to pay for the second rating is increasing in  $\widehat{v}_K$ . Thus,  $\widehat{v}_K = 1$ .

Denote  $v_K^e = v_{1,K}^e$ . Then the rating system of the entrant is such that types  $[v_K^e, 1]$ ,  $v_K^e \geq v_{K-1}$  are pooled in one rating. The participation constraint for sellers  $v \in [v_K^e, 1]$  is  $t_e \leq u([v_K^e, 1]) - u([v_{K-1}, 1])$ .

**Step 2.** Consider types  $v \in [v_{K-2}, v_{K-1}]$  rated  $R_{K-1}$  by the incumbent. Denote  $R_e(R_{K-1}; v)$  a rating assigned by the entrant to type  $v$  rated  $R_{K-1}$ . Step 1 implies that  $R_e(R_{K-1}; v)$  does not contain types  $v < v_{K-2}$ . Thus,  $R_e(R_{K-1}; v) \subset R_{K-1}$ . For the arguments analogous to those developed in step 1, the entrant's rating system is such that types  $[v_{K-1}^e, v_{K-1}]$ ,  $v_{K-1}^e \geq v_{K-2}$  are pooled in one rating. The participation constraint for sellers  $v \in [v_{K-1}^e, v_{K-1}]$  is  $t_e \leq u([v_{K-1}^e, v_{K-1}]) - u([v_{K-2}, v_{K-1}])$ .

**Step 3.** By induction, the arguments of Step 2 apply to lower ratings  $R_{K-2}, \dots, R_1$  and non-rated sellers  $N$ . The participation constraint of types rated  $R_i$  by the incumbent is  $t_e \leq u([v_i^e, v_i]) - u([v_{i-1}, v_i])$ . The participation constraint of non-rated sellers is  $t_e \leq u([v_N^e, v_M]) - u([0, v_M])$ , where  $v_N^e \leq v_M$  is the lowest type that was not rated by the incumbent and obtains a rating from the entrant.

**Step 4.** The optimal rating system of the entrant  $(v_N^e, v_1^e, \dots, v_K^e)$  maximizes the profit of a new rating agency,

$$t_e \sum_{i=0}^K (v_i - v_i^e),$$

where  $v_0 = v_M$ ,  $v_0^e = v_N^e$ , subject to the participation constraints of the sellers,  $t_e \leq u([v_i^e, v_i]) - u([v_{i-1}, v_i])$ ,  $i = 1, \dots, K$  and  $t_e \leq u([v_N^e, v_M]) - u([0, v_M])$ . The optimal rating system can be implemented as a sequence of intervals  $R_K^e = [v_K^e, 1]$ ,  $R_{K-1}^e = [v_{K-1}^e, v_K^e]$ ,  $\dots$ ,  $R_0^e = [v_N^e, v_1^e]$ . In each of these intervals  $R_i^e$  the rating is requested only by types  $[v_i^e, v_i]$  and not requested by types  $[v_{i-1}, v_i^e]$ . Thus a combination of ratings  $R_i$  and  $R_i^e$  results in valuation  $u([v_i^e, v_i])$ .

**Step 5.** Since  $v_i^e \geq v_{i-1}$ , the variance of types that obtain two ratings from the incumbent and the entrant is lower than the variance of  $R_K$ . Also it implies that the mean valuation of a seller rated by two rating agencies is higher than the mean under the initial rating of the incumbent. ■

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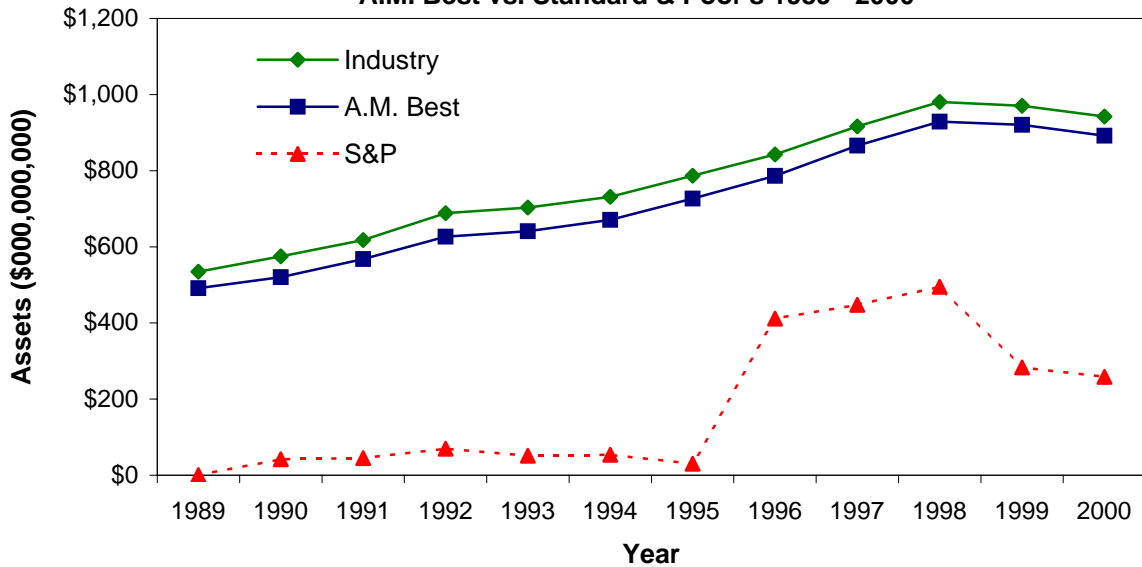
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**Table 1**  
**Coverage of the U.S. Property-Liability Insurance Industry**  
**By A.M. Best vs. Standard & Poor's 1989 - 2000**

Table 1 displays the number of property-liability insurers operating in the United States, the number of firms rated by A.M. Best Company, and the number of firms that requested a rating from 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 numbers in parantheses show the percentage of firms (or assets) of the industry receiving a rating from either firm.

Year	Number of Companies			Total Assets (\$ billions)		
	NAIC	A.M. Best	S&P	NAIC	A.M. Best	S&P
1989	1904	1110 (58.3%)	3 (0.2%)	534.6	491.6 (91.9%)	0.6 (0.1%)
1990	1898	1176 (62.0%)	12 (0.6%)	575.2	520.2 (90.4%)	42.1 (7.3%)
1991	1973	1266 (64.2%)	25 (1.3%)	618.0	567.9 (91.9%)	44.9 (7.3%)
1992	2031	1370 (67.5%)	26 (1.3%)	688.6	626.7 (91.0%)	69.6 (10.1%)
1993	2068	1444 (69.8%)	30 (1.5%)	703.3	640.9 (91.1%)	51.3 (7.3%)
1994	2068	1517 (73.4%)	29 (1.4%)	731.5	670.9 (91.7%)	53.9 (7.4%)
1995	2097	1563 (74.5%)	36 (1.7%)	786.8	726.9 (92.4%)	30.2 (3.8%)
1996	2127	1603 (75.4%)	281 (13.2%)	842.6	786.4 (93.3%)	411.4 (48.8%)
1997	2115	1617 (76.5%)	314 (14.8%)	916.1	865.9 (94.5%)	447.7 (48.9%)
1998	2136	1660 (77.7%)	354 (16.6%)	980.7	928.8 (94.7%)	495.3 (50.5%)
1999	2072	1647 (79.5%)	297 (14.3%)	970.6	920.5 (94.8%)	283.4 (29.2%)
2000	1964	1582 (80.5%)	258 (13.1%)	942.2	892.0 (94.7%)	258.7 (27.5%)

**Figure T1**  
**U.S. Property-Liability Industry Assets Covered by**  
**A.M. Best vs. Standard & Poor's 1989 - 2000**



**Table 2**  
**Insurer Rating Categories: A.M Best vs. Standard & Poor's**

Table 2 displays the mapping used in this study to compare financial strength rating categories across A.M. Best and Standard & Poor's. The terms shown in the column labeled "Verbal Description" are the descriptive words that each agency uses in their rating manuals to characterize a specific rating. The terms shown in the column labeled "Category" are the two broad terms each agency uses to group the individual ratings. Sources: A.M. Best (1991, 1992) and Standard & Poor's (1995).

<b>Number</b>	<b>A.M. Best</b>			<b>Standard &amp; Poor's</b>		
	<b>Verbal Description</b>	<b>Rating</b>	<b>Category</b>	<b>Verbal Description</b>	<b>Rating</b>	<b>Category</b>
3	Superior	A++,A+	Secure	Extremely Strong	AAA	Investment Grade
2	Excellent	A, A-	Secure	Very Strong	AA, A	Investment Grade
1	Good	B++,B+	Secure	Good	BBB	Investment Grade
0	Marginal	B and below	Vulnerable	Marginal	BB and below	Non-Investment Grade

**Table 3: 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 217 firm-year observations in the insolvent sample and 24,236 in the solvent sample.

FAST Ratios and Other Control Variables	Solvent Insurers		Insolvent Insurers		Test Statistic $H_0: \mu_{sol} = \mu_{ins}$
	$\mu_{sol}$	$\sigma_{sol}$	$\mu_{ins}$	$\sigma_{ins}$	
Kenney Ratio: Net Premiums Written to Equity Capital	1.13	0.85	1.87	1.12	9.654
Insurance Reserves to Equity Capital	1.03	0.94	1.64	1.24	7.229
1 Yr. Growth in Net Premiums Written (%)	11.85	41.58	11.18	60.92	0.160
1 Yr. Growth in Gross Premiums Written (%)	11.90	37.48	10.86	52.45	0.292
Aid to Equity Capital due to Reinsurance	2.05	4.34	6.04	7.50	7.838
Investment Yield (%)	5.71	1.38	5.42	1.54	2.778
1 Yr. Growth in Equity Capital (%)	8.81	16.33	-8.74	19.84	12.990
Adverse Reserve Development to Equity Capital (%)	-2.72	10.84	4.18	11.73	8.635
Gross Expenses to Gross Premiums Written	0.58	0.76	0.55	0.64	0.839
1 yr. Change in Gross Expenses (%)	0.05	0.46	0.08	0.57	0.877
1 yr. Change in Liquid Assets (%)	1.17	2.67	0.35	1.78	6.694
Investments in Affiliates to Equity Capital	0.58	1.32	0.95	1.75	3.105
Receivables from Affiliates to Equity Capital	0.02	0.04	0.04	0.05	5.237
Misc. Recoverables to Equity Capital	0.03	0.05	0.07	0.08	6.735
Non-investment Grade Bonds to Equity Capital	0.69	2.51	0.76	2.70	0.353
Other Invested Assets to Equity Capital	0.01	0.03	0.02	0.04	3.567
Dummy = 1 if insurer has a large single agent	0.12	0.33	0.22	0.42	3.414
Dummy = 1 if insurer has a large single agent they control	0.08	0.28	0.12	0.32	1.437
Losses, Exp's, Div's and Taxes Paid to Premiums Collected	1.29	0.73	1.60	0.84	5.364
Total Assets (000000's in 2000 \$)	435.88	2218.95	134.63	695.43	6.109
Ind. = 1 if Insurer is Part of a Mutual Group	0.26	0.44	0.08	0.28	9.070

**Table 4: Discrete-Time Hazard Bankruptcy Model Regression Results**

**Panel A:**

Table displays the results of the discrete-time hazard regression model. The dependent variable  $y_{it} = 1$  for each insurer that has a formal regulatory action taken against the insurer in year  $t+1$ . Otherwise  $y_{it} = 0$  for all other observations. All U.S. property-liability insurers from 1989 - 2000 are included assuming they have adequate data. There are 24,236 healthy firm-year observations and 217 insolvent company observations.

Independent Variable	Coefficient Estimate	Standard Error	$\chi^2$ Statistic	
Intercept	-0.2458	0.9069	0.0734	
Kenney Ratio: Net Premiums Written to Equity Capital	0.6619	0.0995	44.2155	***
Insurance Reserves to Equity Capital	0.2637	0.0910	8.4058	***
1 Yr. Growth in Net Premiums Written (%)	0.0019	0.0018	1.1025	
1 Yr. Growth in Gross Premiums Written (%)	0.0007	0.0022	0.0969	
Aid to Equity Capital due to Reinsurance	0.0453	0.0114	15.9287	***
Investment Yield (%)	-0.0538	0.0534	1.0180	
1 Yr. Growth in Equity Capital (%)	-0.0469	0.0056	69.7371	***
Adverse Reserve Development to Equity Capital (%)	0.0282	0.0069	16.9760	***
Gross Expenses to Gross Premiums Written	-0.1024	0.1112	0.8489	
1 yr. Change in Gross Expenses (%)	0.1509	0.1580	0.9120	
1 yr. Change in Liquid Assets (%)	-0.0821	0.0421	3.7955	*
Investments in Affiliates to Equity Capital	0.1527	0.0481	10.0745	***
Receivables from Affiliates to Equity Capital	3.3804	1.4911	5.1395	**
Misc. Recoverables to Equity Capital	1.3329	1.0189	1.7112	
Non-investment Grade Bonds to Equity Capital	0.0144	0.0285	0.2559	
Other Invested Assets to Equity Capital	4.6585	1.9498	5.7083	**
Dummy = 1 if insurer has a large single agent	0.4375	0.2001	4.7827	**
Dummy = 1 if insurer has a large single agent they control	-0.2045	0.2580	0.6285	
Losses, Exp's, Div's and Taxes Paid to Premiums Collected	0.5949	0.1028	33.4640	***
Ln(Total Assets in \$2000)	-0.3856	0.0519	55.2763	***
Ind. = 1 if Insurer is Part of a Mutual Group	-1.1267	0.2653	18.0353	***
Log Likelihood Function Value	-876.46			
Pseudo R <sup>2</sup>	26.21%			

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

The pseudo R<sup>2</sup> equals 1 minus the ratio of the log likelihood 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	1 <sup>st</sup> Percentile	99 <sup>th</sup> Percentile
Solvent	24,236	0.81%	0.20%	2.50%	0.01%	11.48%
Insolvent	217	9.22%	4.36%	12.55%	0.08%	68.69%

**Panel C:**

The classification table displays the number of actual insolvent and solvent firm-year observations versus the number of predicted insolvent and solvent firm-year observations using the estimated hazard model. Observations were predicted to be insolvent (solvent) that had one-year probabilities of default estimated to be greater than the population average over this time period (0.89 percent).

Firm Type	Predicted Firm Type		Totals
	Insolvent	Solvent	
Insolvent	177	40	217
Solvent	4,240	19,996	24,236

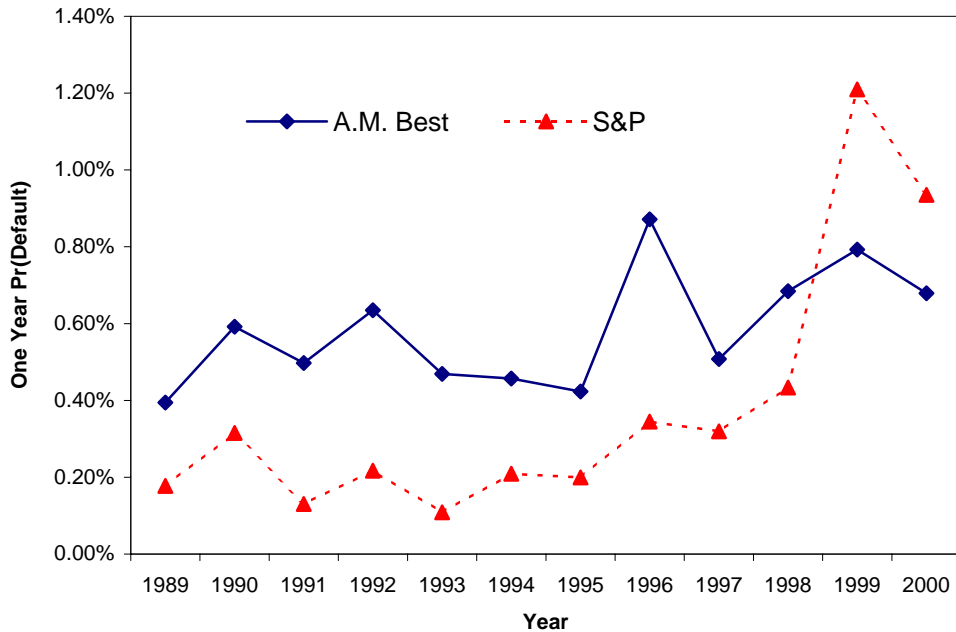
**Table 5**  
**Summary Statistics One-Year Probability of Default for**  
**U.S. Property-Liability Insurers Rated By**  
**A.M. Best vs. Standard & Poor's: 1989 - 2000**

Table 5 displays the average and median probability of default of the firms that receive ratings by A.M. Best and from Standard & Poor's. The t-test column reports the results of the null hypothesis of equal means for the probability of default for A.M. Best rated insurers versus S&P rated insurers assuming unequal variances against the alternative hypothesis the average probability of default for S&P rated insurers is lower than the average for A.M. Best rated insurers. The chart below displays the average probability of default time series for each agency over time period of this study.

Year	A.M. Best			Standard & Poor's			Test Statistic	
	Num	Mean	Median	Num	Mean	Median	$H_0: \mu_{Best} = \mu_{S\&P}$	
1989	1110	0.39%	0.14%	3	0.18%	0.24%		
1990	1175	0.59%	0.26%	12	0.32%	0.11%	-1.991	**
1991	1261	0.50%	0.14%	25	0.13%	0.11%	-7.735	***
1992	1352	0.63%	0.15%	26	0.22%	0.12%	-5.071	***
1993	1437	0.47%	0.12%	30	0.11%	0.05%	-6.479	***
1994	1515	0.46%	0.14%	29	0.21%	0.13%	-4.492	***
1995	1551	0.42%	0.10%	36	0.20%	0.04%	-2.357	***
1996	1577	0.87%	0.18%	281	0.35%	0.18%	-6.253	***
1997	1598	0.51%	0.14%	314	0.32%	0.14%	-3.448	***
1998	1620	0.68%	0.16%	354	0.43%	0.15%	-2.965	***
1999	1620	0.79%	0.19%	297	1.21%	0.21%	2.149	
2000	1570	0.68%	0.20%	258	0.94%	0.25%	1.371	

\*\*\*, \*\*, or \* - significant at the 1, 5, or 10 percent level, respectively

**Figure T5**  
**Average One-Year Probability of Default for U.S. Property-Liability Insurers**  
**Rated By A.M. Best and Standard & Poor's 1989-2000**



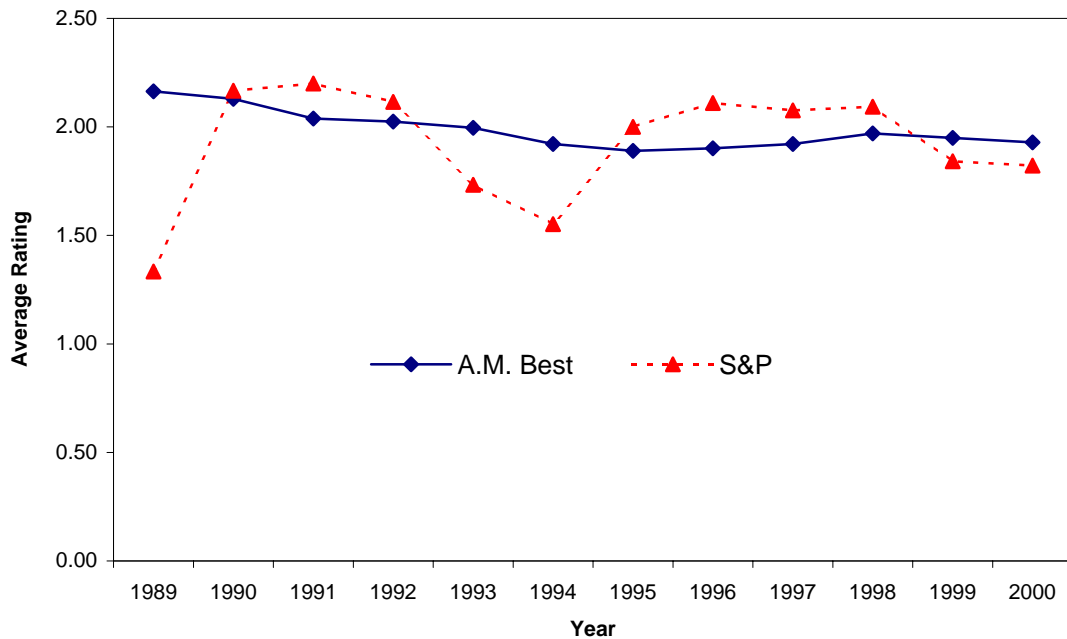
**Table 6**  
**Average Rating Assigned by A.M. Best vs. Standard&Poor's by Year: 1989 - 2000**

Table displays summary statistics of the ratings assigned by A.M. Best and S&P to U.S. property-liability insurers over the years 1989 - 2000. The final two columns display t-statistics reporting the difference in means test assuming unequal variances

Year	A.M. Best				Standard & Poor's				Difference in Means Test Statistics S&P - A.M. Best	
	Num	$\mu_{Best}$	$\sigma_{Best}$	Min Max	Num	$\mu_{S\&P}$	$\sigma_{S\&P}$	Min Max	$H_0: \mu_{Best} = \mu_{S\&P}$	
1989	1110	2.16	0.82	1 3	3	1.33	1.15	0 2	-	
1990	1176	2.13	0.86	1 3	12	2.17	0.72	1 3	0.18	
1991	1266	2.04	0.87	1 3	25	2.20	0.58	1 3	1.37	*
1992	1370	2.02	0.86	1 3	26	2.12	0.65	0 3	0.70	
1993	1444	2.00	0.85	1 3	30	1.73	0.91	0 3	1.57	*
1994	1517	1.92	0.86	1 3	29	1.55	0.83	0 2	2.38	***
1995	1563	1.89	0.84	1 3	36	2.00	0.63	0 3	1.03	
1996	1603	1.90	0.84	1 3	281	2.11	0.45	1 3	6.17	***
1997	1617	1.92	0.81	1 3	314	2.08	0.45	1 3	4.76	***
1998	1660	1.97	0.81	1 3	354	2.09	0.42	1 3	4.13	***
1999	1647	1.95	0.84	1 3	297	1.84	0.54	0 3	2.84	***
2000	1582	1.93	0.85	1 3	258	1.82	0.54	0 3	2.67	***

\*\*\*, \*\*, or \* - significant at the 1, 5, or 10 percent level, respectively

**Figure T6**  
**Average Rating for U.S. Property-Liability Insurers Rated By A.M Best and Standard & Poor's 1989-2000**



**Table 7**  
**Comparing A.M. Best and Standard & Poor's**  
**Ratings for Common Insurers: 1989 - 2000**

Table compares the ratings assigned by A.M Best and S&P for insurers that receive a rating from both firms. The data includes all firm-year observations over the years 1989 - 2000 that received a rating from A.M Best and a rating from S&P. Each cell of the matrix,  $c_{ij}$ , equals the number of firm-year observations that receive rating  $i$  from A.M. Best and rating  $j$  from S&P where  $i, j \in \{\text{Superior, Excellent, Good, Marginal}\}$ .

**Panel A**

A.M. Best Rating	S&P Full Rating			
	Marginal	Good	Excellent	Superior
Marginal	23	5	6	0
Good	12	31	38	0
Excellent	1	63	706	15
Superior	0	0	567	162

Total number of firm-year observations: 1629

S&P gives the same rating as A.M. Best:	56.60%
S&P rates higher than A.M. Best:	3.93%
S&P rates lower than A.M. Best:	39.47%

Table 8

## Summary Statistics of A.M. Best Rated Insurers that also Request a Rating from Standard &amp; Poor's: 1990 - 2000

The sample includes insurer-year observations that receive an A.M. Best rating over the years 1990 - 2000. The columns labeled "A.M. Best and Standard & Poor's" displays summary statistics for just those insurer-year observations that requested a rating by both the incumbent and the new entrant agency. The columns labeled "A.M. Best Only" are insurer-year observations for firms that requested a rating only from A.M. Best. The variable labeled "[Median Pr(Def. | A.M. Best Rating) - Insurer Pr(Def.)]" equals the median probability of default for all insurers within the A.M. Best rating category as firm  $i$  minus insurer  $i$ 's own estimated default probability.

	A.M. Best Only		A.M. Best and Standard & Poor's		Test Statistics
	$\mu_{\text{BestOnly}}$	$\sigma_{\text{BestOnly}}$	$\mu_{\text{both}}$	$\sigma_{\text{both}}$	$H_0: \mu_{\text{BestOnly}} = \mu_{\text{both}}$
S&P Rating	-		1.989	0.506	-
A.M. Best Rating	1.955	0.835	2.339	0.684	20.2 ***
S&P Rating - A.M. Best Rating	-		-0.350	0.564	-
[Median Pr(Def.   A.M. Best Rating) - Insurer Pr(Def.)]	-0.003	0.010	-0.004	0.011	3.0 ***
Ind. = 1 if Insurer is Part of a Mutual Group	0.319	0.466	0.171	0.377	14.0 ***
Total Assets (000000's in 2000 \$)	494.8	2339.9	1,860.4	5,963.9	8.8 ***
% Net Premiums Written in Retail Lines of Insurance	0.373	0.362	0.288	0.311	9.9 ***
Ind. = 1 if Insurer had Corporate Debt Rating from S&P	0.196	0.397	0.717	0.451	42.9 ***
Ind. = 1 if Insurer Requested S&P rating year t-1	0.017	0.128	0.684	0.465	55.4 ***
Ind. = 1 if Insurer was Assigned Qualified Rating by S&P Year t-1	0.388	0.487	0.144	0.351	24.5 ***
Ind. = 1 for Marginal A.M. Best Rating	0.071	0.257	0.024	0.153	10.4 ***
Ind. = 1 for Good A.M. Best Rating	0.159	0.365	0.050	0.218	16.9 ***
Ind. = 1 for Excellent A.M. Best Rating	0.515	0.500	0.489	0.500	1.9 **
Ind. = 1 for Superior A.M. Best Rating	0.256	0.436	0.437	0.496	13.6 ***
Ind. = 1 if year = 1990	0.079	0.270	0.007	0.081	23.1 ***
Ind. = 1 if year = 1991	0.082	0.274	0.016	0.125	16.5 ***
Ind. = 1 if year = 1992	0.091	0.287	0.015	0.123	18.7 ***
Ind. = 1 if year = 1993	0.096	0.295	0.015	0.123	19.9 ***
Ind. = 1 if year = 1994	0.100	0.300	0.017	0.128	19.8 ***
Ind. = 1 if year = 1995	0.105	0.307	0.023	0.151	17.4 ***
Ind. = 1 if year = 1996	0.090	0.287	0.174	0.380	8.3 ***
Ind. = 1 if year = 1997	0.086	0.280	0.185	0.388	9.6 ***
Ind. = 1 if year = 1998	0.086	0.281	0.212	0.409	11.6 ***
Ind. = 1 if year = 1999	0.092	0.290	0.174	0.379	8.1 ***
Ind. = 1 if year = 2000	0.092	0.289	0.162	0.369	7.2 ***

\*\*\* - 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 only received a rating from A.M. Best was 13,353. The number of firm-year observations that received both an A.M. Best and Standard & Poor's rating was 1503.

**Table 9**  
**Probit Regression Results Predicting Whether Insurer Requested a Rating from Standard & Poor's: 1990 - 2000**

Table displays Probit regression results where the dependent variable equals 1 when insurer *i* was assigned a rating by Standard & Poor's in year *t* and 0 otherwise. Panel A displays the estimated coefficients on the independent variables. Panel B displays the marginal effects. The model also contains year indicator variables but the results are suppressed to save space. The full results with the estimated coefficients for the year indicator variables are available upon request.

<b>Panel A: Regression Results</b>	<b>Did Insurer Request a Rating from S&amp;P?</b>			
	<b>Model 1</b>	<b>Model 2</b>	<b>Model 3</b>	<b>Model 4</b>
Intercept	-1.019 *** (0.040)	-4.640 *** (0.222)	-4.090 *** (0.277)	-4.265 *** (0.306)
[Median Pr(Def.   A.M. Best Rating) - Insurer Pr(Def.)]	47.233 *** (9.552)	53.604 *** (11.650)	41.192 *** (12.727)	43.149 *** (13.113)
[Median Pr(Def.   A.M. Best Rating) - Insurer Pr(Def.)] x (Year - 1988)	-4.843 *** (0.915)	-5.652 *** (1.108)	-4.531 *** (1.254)	-4.932 *** (1.295)
Ln(Assets in \$2000)		0.179 *** (0.011)	0.114 *** (0.014)	0.108 *** (0.014)
Ind. = 1 if Insurer is Part of a Mutual Group		-0.165 *** (0.047)	-0.159 *** (0.058)	-0.168 *** (0.058)
Ind. = 1 if Insurer had Corporate Debt Rating from S&P		1.049 *** (0.037)	0.687 *** (0.047)	0.656 *** (0.048)
% Net Premiums Written in Retail Lines of Insurance		-0.189 *** (0.054)	-0.149 ** (0.068)	-0.143 ** (0.069)
State of Business of Herfindahl		-0.304 *** (0.056)	-0.294 *** (0.068)	-0.269 *** (0.069)
Ind. = 1 if Insurer Requested S&P rating year t-1			2.465 *** (0.063)	2.461 *** (0.063)
Ind. = 1 if Insurer was Assigned Qualified Rating by S&P Year t-1 for Years 1989-1994			0.088 (0.124)	0.075 (0.124)
Ind. = 1 if Insurer was Assigned Qualified Rating by S&P Year t-1 for Years 1995-1999			0.104 * (0.056)	0.098 * (0.057)
Ind. = 1 for Good A.M. Best Rating				0.158 (0.151)
Ind. = 1 for Excellent A.M. Best Rating				0.304 ** (0.139)
Ind. = 1 for Superior A.M. Best Rating				0.344 ** (0.143)
Log-likelihood function value	-4186.7	-3200.3	-2042.1	-2037.5
Pseudo R <sup>2</sup>	13.99%	34.25%	58.05%	58.14%
<b>Panel B: Estimated Marginal Effects</b>				
[Median Pr(Def.   A.M. Best Rating) - Insurer Pr(Def.)]	5.946 ***	3.629 ***	2.128 ***	2.190 ***
[Median Pr(Def.   A.M. Best Rating) - Insurer Pr(Def.)] x (Year - 1988)	-0.610 ***	-0.383 ***	-0.234 ***	-0.250 ***
Ln(Assets in \$2000)		0.012 ***	0.006 ***	0.005 ***
Ind. = 1 if Insurer is Part of a Mutual Group		-0.011 ***	-0.008 ***	-0.009 ***
Ind. = 1 if Insurer had Corporate Debt Rating from S&P		0.071 ***	0.035 ***	0.033 ***
% Net Premiums Written in Retail Lines of Insurance		-0.013 ***	-0.008 **	-0.007 **
State of Business of Herfindahl		-0.021 ***	-0.015 ***	-0.014 ***
Ind. = 1 if Insurer Requested S&P rating year t-1			0.127 ***	0.125 ***
Ind. = 1 if Insurer was Assigned Qualified Rating by S&P Year t-1 for Years 1989-1994			0.005	0.004
Ind. = 1 if Insurer was Assigned Qualified Rating by S&P Year t-1 for Years 1995-1999			0.005 *	0.005 *
Ind. = 1 for Good A.M. Best Rating				0.008
Ind. = 1 for Excellent A.M. Best Rating				0.015 **
Ind. = 1 for Superior A.M. Best Rating				0.017 **

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

The pseudo R<sup>2</sup> equals 1 minus the ratio of the log likelihood function value divided by the log likelihood function value where all coefficients are constrained to be zero (see Greene 1997 p. 891). Standard errors are shown in parentheses.

**Table 10**  
**Regression Results Explaining Rating Difference**  
**Between Standard & Poor's and A.M. Best Ratings: 1990 - 2000**

Table displays OLS regression results where the dependent variable is the difference between the rating assigned by Standard & Poor's minus the rating assigned by A.M. Best in year t. The inverse Mill's terms in each model were calculated using the results of the corresponding Probit regression shown in Table 9.

<b>Independent Variable</b>	<b>Did Insurer Request a Rating from S&amp;P?</b>			
	<b>Model 1</b>	<b>Model 2</b>	<b>Model 3</b>	<b>Model 4</b>
Intercept	-0.5832 *** (0.075)	-0.5066 *** (0.033)	-0.4213 *** (0.021)	-0.4337 *** (0.021)
Inverse Mills Ratio	0.1531 *** (0.048)	0.1344 *** (0.026)	0.0983 *** (0.020)	0.1156 *** (0.020)
R <sup>2</sup>	0.67%	1.82%	1.53%	2.09%
Expected change in rating due to insurer strategic choice	0.233	0.157	0.071	0.084
Expected change in ratings due difference in S&P vs. A.M. Best standards	-0.583	-0.507	-0.421	-0.434
Average Rating Difference S&P Rating - A.M. Best Rating	-0.350	-0.350	-0.350	-0.350